A RISK-BASED VERIFICATION FRAMEWORK FOR OFFSHORE WIND FARM DEVELOPMENT: DESIGN, INSTALLATION, OPERATIONS AND MAINTENANCE OF OFFSHORE WIND TURBINES

Ifeanyi Christian Ikewete

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DECLARATION

"This thesis is primarily a sole work of my own. I can confirm that to the best of my knowledge, it contains no materials previously published or accepted for the award of any other degree or diploma of the university or other institutions of higher learning, except where acknowledgements are made to various relevant sources and/or other researchers and as such are duly referenced in the thesis"

Signature: …………………………………... Date: ………………………..…..........

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ABSTRACT

This thesis encompasses a holistic review of the development trends in wind turbine technology (onshore and offshore) and the challenges perceived at the stages of design, construction and operations of modern-day wind energy technology (Friedrich and Lukas, 2017). The main focus of this study is to evaluate the risks associated with offshore wind farm development (OWFD). This is achieved by first estimating those perceived risks, understanding the relative importance of each individual risk, and carrying out an assessment using a specialist analytical tool known as AHiP-Evi. AHiP-Evi was developed through a combination of application of Analytic Hierarchy Process (AHP) and Evidential Reasoning (ER) techniques. The AHP was used to ascertain the weighting of the respective risk variables according to their relative importance, while the ER was used to evaluate the aggregated influence of the collective risk variables associated with the OWFD.

Finally, a specific modelling tool known as BN-SAT (Bayesian Network Sensitivity Analysis Technique) was developed to evaluate the probabilities of occurrence of the variable nodes and their overall impacts on the decision node (OWFD). The BN-SAT is comprised of a combination of Bayesian networks (BNs) concepts and a sensitivity analysis (SA) approach. The AHiP-Evi model initially developed in this study is transformed into the BN structure in order to compute the conditional and unconditional prior probability for each starting node using the NETICA analytical software to determine the aggregated impact of the specific risk variables on the OWFD. The outcome from this modelling analysis is then compared to the initial assessment carried out by the application of the AHiP-Evi modelling tool in order to validate the robustness of both modelling tools. In the case study of this research, the percentage difference of the outcomes of the two models is insignificant, which demonstrates the fact that both systems are effective.

The Fuzzy Analytic Hierarchy Process (FAHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) were integrated to develop a specific model for the selection of best-case risk management technique (RMT).

Based on the decision makers' (DMs) aggregated judgements, it was possible to compute the values and determine the best-case RMT dependent on the decision variables driving the decision - for example, costs and benefits, through the developed integrated model known as FAHP-FTOPSIS. The outcome of this selection model has been seen to be reasonably practical and a successful conclusion of the research contribution. Awareness of the aggregated impact of the risk variables is important in making the decision about appropriate investments in a strategic improvement of risk management and efficient resource allocations to the offshore wind industry.

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ABBREVIATIONS USED IN THIS THESIS INCLUDE:

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
API	Application Programming Interface
BBN	Bayesian Belief Network
BBNs	Bayesian Belief Networks
BDM	Belief Degree Matrix
BMT	British Maritime Technology
BN	Bayesian Network
BNM	Bayesian Network Modelling
BNs	Bayesian Networks
BN-SAT	Bayesian Network Sensitivity Analysis Technique
BNT	Bayesian Networks Theory
BPA	Basic Probability Assignment
CCC	Committee on Climate Change
CI	Consistency Index
CLM	Checklists Method
CPTs	Conditional Probability Tables
CR	Consistency Ratio
CWIF	Caithness Wind Farm Information Forum
DA	Decision Alternative
DAG	Directed Acyclic Graph
DBN	Dynamic Bayesian Networks
DBNs	Dynamic Bayesian Networks
DEMATEL	Decision Making Trial and Evaluation Laboratory
DM	Decision Maker
DMs	Decision Makers
DoBs	Degree of Beliefs
DoC	Degree of Competency
DP	Dynamic Positioning
DTI	Department of Trade and Industry
EC	Evaluation Criteria
ELECTRE	ELimination and Choice Expressing Reality
EM	Expectation Maximisation
EMV	Expected Monetary Value
ER	Evidential Reasoning
ETA	Event Tree Analysis
FAHP	Fuzzy Analytical Hierarchy Process
FLB	Fuzzy Link-Based
FMADM	Fuzzy Multi-Attribute Decision-Making
FMCDM	Fuzzy Multi-Criteria Decision-Making
FMECA	Failure Modes, Effects and Criticality Analysis

FN	Fuzzy Number
FNIS	Fuzzy Negative Ideal Solution
FOREX / FX	Foreign exchange
FPIS	Fuzzy Positive Ideal Solution
FPP	Fuzzy Preference Programming
FRA	Fuzzy Risk Assessment
FRB	Fuzzy Rule Based
FSM	Fuzzy Set Modelling
FST	Fuzzy Set Theory
FTA	Fault Tree Analysis
FTM	Fuzzy TOPSIS Modelling
GBF	Gravity-Based Foundation
GENOP	Generation and Operating
GGM	General Graphical Model
GIS	Geographic Information System
GW	Giggawatts
HAWT	Horizontal Axis Wind Turbine
HAWTs	Horizontal Axis Wind Turbines
HAZOPS	Hazard and Operability Studies
IDA	Informal Direct Assessment
IPCC	Intergovernmental Panel on Climate Change
JF	Jacket Foundation
JPD	Joint Probability Distribution
KPIs	Key Performance Indicators
LFPP	Logarithmic Fuzzy Preference Programming
LoC	Loss of Containment
MADA	Multiple-Attribute Decision-Analysis
MADM	Multi-Attribute Decision-Making
MAEA	Multi-Alternative Evaluations of Alternatives
MAGDM	Multiple-Attribute Group Decision-Making
MCDM	Multi-Criteria Decision Making
MCGP	Multi-Choice Goal Programming
MTBF	Mean Time Between Failures
MTTR	Mean Time To Repair
MW	Megawatt(s)
NFFO	Non Fossil Fuel Obligation
NIS	Negative Ideal Solution
OREIs	Offshore Renewable Energy Installations
OWF	Offshore Wind Farm
OWFD	Offshore Wind Farm Development
OWFT	Offshore Wind Farms Turbines
PBA	Probability Basic Assignment
PICs	Probability-Impact Calculations
PIS	Positive Ideal Solution

PRA	Probabilistic Risk Assessment
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
PT	Probability Theory
PV	Priority Vector
RAMS	Reliability, Availability, Maintainability and Safety
RBV	Risk-Based Verification
RCC	Relative Closeness Coefficient
RED	Renewable Energy Directive
RES	Renewable Energy Source
RI	Random Index
RIS	Risk Indicator Scales
RMT	Risk Management Technique
SA	Sensitivity Analysis
TF	Tripod Foundation
TFN	Triangular Fuzzy Number
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TP	Transition Piece
UCPTs	Unconditional Probability Tables
UN	United Nations
UXO	Unexploded Ordinance
VaR	Value-at-Risk
VAWT	Vertical Axis Wind Turbine
VAWTs	Vertical Axis Wind Turbines
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje (multi-criteria optimization and compromise solution)
WMO	World Meteorological Organisation
WTG	Wind Turbine Generator

CHAPTER ONE: INTRODUCTION

Summary

This research draws on the literature of wind energy generation, development trends, risk estimation, risk analysis and selection of best-case risk management approaches. The aims, objectives and hypothesis of this thesis form the rational framework with a view to analysing and managing the inherent risks estimated. Through in-depth case studies, this research aims to identify the risk variables associated with wind energy development, evaluate the risk weighting and apply the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) approach for selection of best-case Risk Management Technique (RMT). This is achievable through the development of a well-structured research methodology and study scope.

1.1 Background

Renewable Energy Sources (RESs) such as wind have existed for centuries; however, the drive to harness them on an industrial scale has been lacking. Increasing concerns about global warming due to greenhouse gas emissions from such activities as the use of automobiles, industrial processes, deforestation and generation of electricity from fossil fuels over the past decades have sparked a global search for solutions (United Nations, 1997). This dated reference demonstrates the growth trend and also an indication of when the global community developed a vested interest in harnessing energy from RES. Some scientific models predict that the global temperature is likely to increase by approximately 1.4 to 5.8 degrees Celsius by 2100 (United Nations, 1997). This potential global warming challenge is expected to cause melting of the polar ice caps, rises in mean sea levels and subsequent flooding of low-lying regions. The predicted precipitation patterns are also likely to change, causing shifts in climatic zones that will disturb human habitations and natural global ecosystems. Whilst the human populations may be in a position to adjust relatively quickly to these changes, many natural systems may be more sensitive to change or slower to adapt to these changes (United Nations, 2002).

Considering the fact that the causes and effects of climate change are global and complex, international communities and corporations have commenced actions in various capacities to seek solutions to curb the greenhouse gas emissions. The World Meteorological Organisation (WMO) and the United Nations (UN) environment programme collaborated to form the Intergovernmental Panel on Climate Change (IPCC) in 1988 (United Nations, 2002). The IPCC now plays a major role in assessing the relevant scientific, technical and socio-economic data for an understanding of the risk of climate change especially caused by human activities. Thus, the IPCC provides a platform for international discussions and cooperation on climate change issues (IPCC, 1990).

The Kyoto Protocol sets out binding targets for the reduction of greenhouse gas emissions by signatory countries (IPCC, 2001). The developed countries collectively committed to reducing greenhouse gas emissions by 5% from 1990 levels by 2012. The EU, Switzerland, Central and Eastern European states set estimated targets tasking individual reduction of their carbon footprint by at least 8%, the target was 7% in the United States and 6% in Canada, Hungary, Japan and Poland. New Zealand, Russia and Ukraine also accepted the need to stabilise their emissions. Other countries, such as Norway, Australia and Iceland were not committed to this protocol.

The electricity sector is said to be responsible for over one-third of energy-related CO_2 (Laurikka, 2002; OECD, 2001). This sector is often the subject of government programmes and policies to reduce greenhouse gas emissions, since centralised electricity generation is a large and stationary pollution source that is easier to regulate than the transportation sector (IPCC, 2001a; IPCC, 2001b), hence the emergence of significant investments in RESs on such industrial scales as experienced in the past two decades and most especially in the wind energy sector. Significant advances have recently been made in methods and technologies to reduce carbon dioxide emissions resulting from electricity production. These include more efficient conversion techniques and end use of energy, improved energy management, and the use of low-carbon and renewable fuels (IPCC, 200 1a; IPCC, 2001b).

Offshore wind energy development has experienced substantial global growth in recent decades. For instance, 9% of the 9,616 MW installed wind energy capacity in the EU in 2011 was from offshore wind installations (866 MW), bringing the EU's total offshore wind power capacity to 3,810 MW as of 2011 (EWEA, 2012). The EU has forecast that offshore wind energy generation will contribute at least 14% of its electricity demand by 2030.

The drivers of wind energy growth in the United Kingdom and Europe include but are not limited to policy incentives by means of support schemes such as feed-in-tariff, energy subsidy, improved technology and more reliable infrastructures (Blanco, 2009). However, the risks to investments in the wind energy sector are becoming increasingly complex and the unavailability of adequate insurance is a contributory factor to the challenges of wind farm development, especially in the offshore environment. Therefore, robust risk management instruments are vital to alleviating the challenges facing the industry, which is the primary concern of institutional investors such as insurers, banks, governments, private investors, financial management firms, pension funds and the likes (Boomsma *et al.,* 2012). A holistic estimation of the risks associated with wind energy development and application of the appropriate risk management technique will ensure sustainable energy development through wind sources.

Wind energy in particular plays a major role in the global energy turnaround due to the higher efficiency of energy production with much lower Generating and Operating (GENOP) costs in the long run. Aside from the steady rapid growth in onshore wind technology in recent years, the industry has gradually moved towards offshore wind energy development with a view to accessing the stronger and more stable wind speeds required for the efficient operation of wind turbines (EEL, 1993). However, the shift towards offshore wind farms has introduced considerable risks resulting from the complexity of working in the offshore environment. These associated risks span across the design of the turbine, support structures, other ancillaries and control systems, up to the construction of the wind park and its operation and maintenance challenges ((Friedrich and Lukas, 2017). The uncertainty of this offshore environment has also made provision of insurance very difficult in recent years. According to Turner *et al.,* (2013), the growth of renewable energy and the increasing market risk exposures will require more complex financing conditions and changes in regulations (support schemes). The estimated annual expenditure on risk management services including insurance solutions is expected to be up to USD 2.8 billion by 2020 (Turner *et al.,* 2013). Therefore, robust advancements in the risk estimation, risk assessment and risk control systems need to be made in the renewable energy industry as a matter of urgency. Because of the significant growth in wind energy development, it has seen increasing accidents, incidents and near misses given that it is a relatively new industry; thus, the motivation for undertaking this study.

1.2 Research Aim and Objectives

The aim of this research work is to develop a framework for assessing the influencing risk factors associated with offshore wind farm development (OWFD) including developing a sustainable methodology for selecting suitable risk management technique for the OWFD process. The research will entail proposal of a systematic risk management approach and alternatives to alleviate the wind farm design, installation, operational and maintenance challenges with a view to developing innovative tools for assessing the risk challenges currently facing the offshore wind industry. This approach will be based on the system lifecycle model, risk influence factors, generic and specific risk management framework.

The following objectives have been set out in order to fulfil the aim of this study:

- Undertake a literature review of the risks associated with offshore wind farm turbines (OWFTs).
- Identify the inherent risk factors of wind farm design, pre-construction, construction and operational phases.
- Discuss the challenges facing the key aspects of offshore wind farm development in relation to the inherent risk factors.
- Develop a risk assessment model for the residual risk factors and a decision-making tool.
- Develop an innovative risk-based management tool aimed at improving the design, inspection and maintenance of OWFT.
- Create a commercial-scale mechanism for managing the risk levels.

1.3 Problem Statement

As wind energy development is a relatively new industry, the data is understandably scarce. However, this unavailability of data challenge is also compounded by the fact that most of the investors and producers are well-known national and international brand names. Therefore, most of these companies tend to shy away from sharing such information as accident and incident records. There are only a handful of organisations who are trying to pull together as much information as possible amid the restrictions of what information the wind energy stakeholders are willing to release to them and what they are allowed to put in the public domain. Moreover, due to a lack of regulatory control in some of the areas, the stakeholders do not seem to be currently under any obligation to provide the information. The UK HSE may have access to information on some of the accidents and incidents, but the data is not readily available. Although there have been reasonable improvements in recent times, more work is still required in this area so that all cases of incidents, accidents and near misses are reported and the data made available to the public but, most importantly, to make people aware of the risks and lessons to be learned.

The general lack of awareness of application of robust risk assessment modelling tools and effective risk management approaches has been found to be a contributory factor exacerbating the challenges currently faced by the renewable energy industry. More efforts are required in advising and/or regulating such dynamic industry considering the rate of rapid growth recorded in the past two decades (Islam, *et al.,* 2013).

Pillay and Wang (2003) established that the process of data collation through experts' opinions can be problematic in terms of recruiting the participants as well as in relation to the data accuracy. However, the industry experience of the researcher has made a valuable contribution in understanding some of the challenges and potential risks characterising the development of offshore wind farms. This experience was also helpful in identifying the experts to participate in the data-gathering process. It is worth noting that the subjective data gathered from the experts required standardisation with existing data in order to establish consistency and ensure confidence in the modelling outcomes. In some cases, objective and subjective data can be combined and may require elicitation in order to establish datasets required to apply the proposed modelling techniques to the development of an offshore wind farm (OWF). There is a general lack of robust advance-level risk management technique in the offshore renewable energy sector. The current practice in the sector is not in-depth enough to identify the relevant risk factors and efficient risk management techniques across all phases of the OWF development.

1.4 Delimitations of the Research

The delimitations of this research include but are not limited to the lack of specific studies in the critical areas of the wind farm industry. A confidentiality and data protection policy governing the organisations makes it difficult to collate, use and/or expressly publish the outcome of the investigations. Due to these delimitations, the data utilised in this study is the outcome of collaborative efforts by several experts, which the author specifically synthesised for the purpose of the test cases.

1.5 Research Methodologies and Research Scope

The methodology of this research work comprises the advancement of a risk-based framework for modelling associated risks of OWFD. The research work integrates the fuzzy set modelling, Bayesian networks and multi-criteria decision-making modelling approaches to provide optimised information for improvement of the offshore wind farm development process.

The research will discuss the developmental trends relating to wind energy, identification of the influencing risks factors associated with OWFD, evaluation of the risks and proposition of the method for selection of the best-case risk management technique. The scope of the research is summarised into a risk-based framework methodology for offshore wind farm development, by utilising varying objective and subjective data available through reliable sources. The benefits of this risk-based evaluation may include but are not limited to: (a) understanding the underlying risks inherent in the design, construction, operations and maintenance process of OWFD, (b) reducing the risk exposures associated with the OWFD systems including the potential environmental impact, (c) reducing the costs associated with the design, construction, operation and maintenance of OWFD systems.

1.6 Thesis Structure

This thesis structure shown in Figure 1.1 is comprised of six chapters as described below:

Chapter One outlines a brief introduction relating to the research background, research hypothesis, problem statement of the research, highlighted methodology and research scope.

Chapter Two is the literature review detailing the components of the wind turbine and its operating principles. It also highlights the historical developments and the technological trend in the wind energy (windmill and wind turbine) industry over the centuries, and related works on offshore wind farm risk assessment. The overwhelming support and attention currently being received by the wind energy industry through various investments and incentives, and the sudden surge in both installed and generating capacities in Europe, are discussed in this chapter. The advantages and disadvantages of the various types of wind turbines are also reviewed, as well as the projected generating capacity targets that these turbine types are expected to meet. This chapter also highlights the various risks associated with wind energy development resulting in a catalogue of accidents, incidents and near misses; thus demonstrating the rationale of this research study. This chapter equally introduces the various risk-based modelling techniques applied in this research in order to evaluate the highlighted risks associated with the development of OWFs and propose a best-case RMT through a decision-making modelling tool.

Chapter Three includes the estimation of OWF risk factors and the development of a risk model for evaluation and validation of the risk factors using the AHP and ER. A hierarchical structure of OWF risks is developed and used to perform pairwise comparisons of the risk variables identified in order to determine the risk weightings. The ER is applied to demonstrate a structured method that decision makers can employ to handle the multi-attribute decision-making (MADM) scenarios under uncertainties by establishing the relevance of the risk factor in the hierarchical structure, as detailed in section 2.10.4 of Chapter Two.

Chapter Four describes the test case of the risk evaluation using the Bayesian networks to determine the influence of each risk variable on the other. The output data obtained from analytical evaluation of pairwise comparisons of the influencing risk factors were applied as the input data in this chapter. The proposed model developed in this chapter is known as *BN-SAT* . The result obtained from the application of *BN-SAT* analytical model was used to validate the result outcome obtained from the *AHiP-Evi* model developed in Chapter Three.

Chapter Five presents the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) model applied for selection of the best-case risk management technique. This involves the aggregation of the decisions of a group of experts, and normalisation and defuzzification of the values obtained in order to obtain the ranking order for the final values.

This chapter has presented an effective fuzzy MCDM method that is suitable for solving multiple-attribute group decision-making (MAGDM) cases under a fuzzy environment where the available information is subjective, incomplete and imprecise. The proposed approach allows a group of decision makers to collaborate and aggregate their subjective opinions. The application of the basic Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) analytical approach is such that the chosen alternative has the farthest distance from the Fuzzy Negative to Ideal Solution (FNIS) and shortest distance from the Fuzzy Positive to Ideal Solution (FPIS). The proposed FAHP-FTOPSIS model and solution outcomes have both a practical and a scientific interest in the industry.

Chapter Six is a summary of the entire thesis and the interdependencies of its chapters. Chapter One involves the structural outlines of each of the chapters. Chapter Two encompasses a thorough review of the literature into renewable energy generation from wind resources, the trend in development over the years, review of accidents and incidents in the industry, decision making tools and risk assessment techniques. Chapter Three describes the application of AHP to determine the weights of the influencing risk factors. Then, the ER approach is applied to demonstrate a structured method that decision makers can employ to handle the multi-attribute decision-making (MADM) scenarios under uncertainties by establishing the relevance of the risk variables in the hierarchical structure. Chapter Four involves the determination of the probability of occurrence of the influential risk factors through the fuzzy set theories and linguistic terms. Chapter Five demonstrates the application of Fuzzy Analytic Hierarchy Process-Technique for Order of Preference by Similarity to Ideal Solution for selection of best-case risk management technology.

Chapter Seven presents the conclusions and recommendations of the study. This encompasses the aims and objectives of the research, results outcomes from the risk modelling, analytical and decision-making processes, knowledge gap and contributions. It also contains a summary as set recommendations for future work.

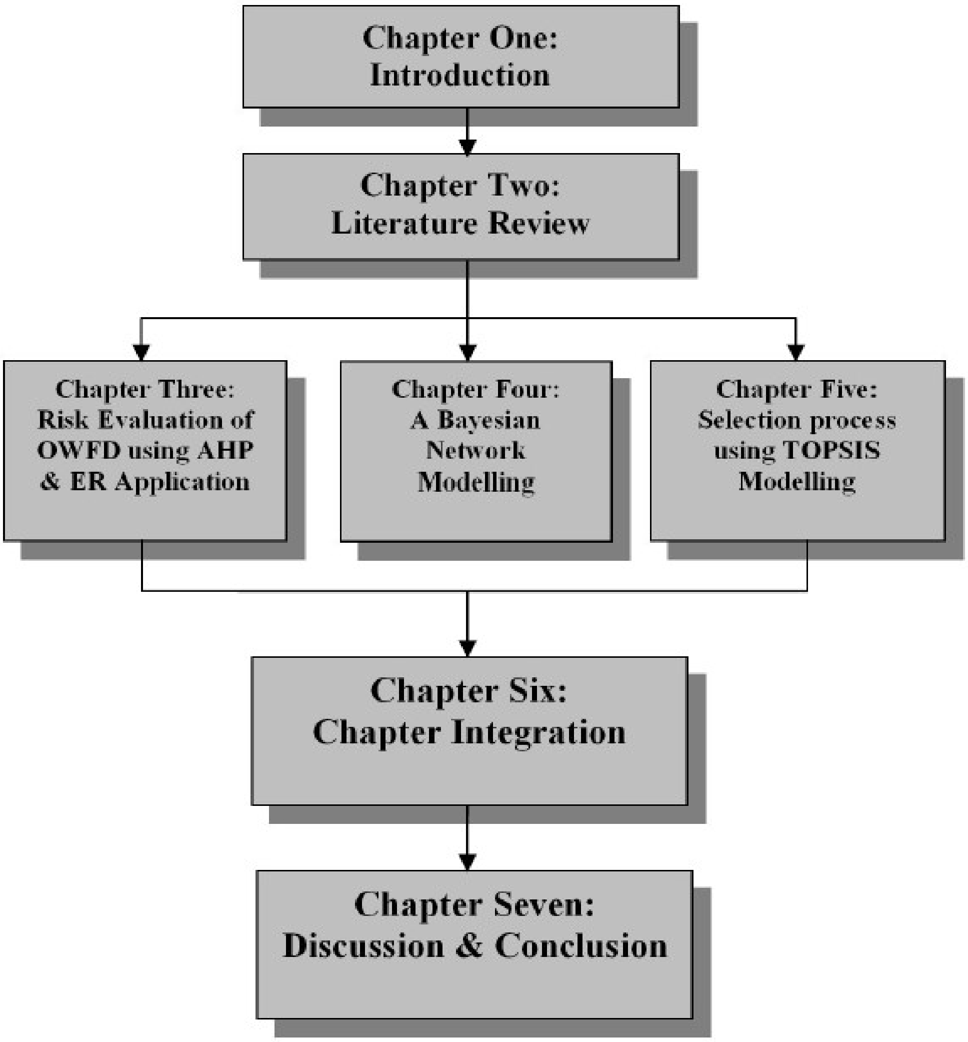


Figure 1.1 Thesis structure

1.7 Publications Developed from this Research

The following publications have been developed from this research and are under review:

- I.C. Ikewete, D.R. Allanson, E.D. Blanco, J. Wang, "A Bayesian Network Approach to Offshore Wind Farm (OWF) Development Risk Analysis".

- I.C. Ikewete, D.R. Allanson, E.D. Blanco, J. Wang, "An Integrated Framework for Selecting a Strategic Risk Management Technique for the Improvement of Offshore Wind farm Development Using FAHP and FTOPSIS".

- I.C. Ikewete, D.R. Allanson, E.D. Blanco, J. Wang, "Chapter Three: Risk Evaluation of Offshore Wind Farm Development by Application of Analytic Hierarchy Process and Evidential Reasoning".

CHAPTER TWO: LITERATURE REVIEW

Summary

This chapter encompasses the review of the development trend in wind energy and wind turbine critical components. It also covers the causes and potential for failure of these components, including historical data on reported accidents, incidents and near misses in the wind energy industry.

2.1 Introduction

This section of the research work will focus on the study of the development trend in wind turbine generator (WTG) technology, previous studies completed in the subject area, and the general understanding of the components of wind farm turbines. Vast improvements have been made in the design, installation and operation of wind turbines over the years, leading to substantial improvements in efficiency and cost reduction in the current WTG design and build. Therefore, this research study will not look into the cost reduction and efficiencies recorded so far in the areas of WTG design, installation, operations and maintenance. This is because there are already existing projections and evidence of steady reduction in the associated costs of OWFD since 2009 (Froese, 2017). On the other hand, the number of accidents, near-misses and incidents are increasing at an alarming rate (CWIF, 2015). As part of a radical campaign by the Committee on Climate Change (CCC) for decarbonisation of the economy, the UK is expected to generate 30% of its electricity from wind energy (a combination of both onshore and offshore wind capacity) by 2030 (Fankhauser *et al.,* 2009).

2.2 Offshore and Onshore Wind Technology Development

Wind turbines are either sited inland or out at sea; an array of turbines installed inland is known as an onshore wind farm and an array of turbines installed offshore is known as an offshore wind farm. Onshore wind farms are prevalent in the UK and other countries in Europe because the expertise to develop them has been available for a while. There are pros and cons of both onshore and offshore wind farm development, some of which are highlighted below. At a reasonably windy site, average modern 2.5 MW turbines are capable of generating sufficient units of electricity each year to meet the yearly consumption requirements of 1,400 households, make around 230 million cups of tea, or run a computer for 2,250 years (Renewable Solution, 2012).

2.2.1 Offshore wind farm

Wind farms developed in offshore locations have several advantages, which include more availability of strong winds. Wind availability is required for efficient functioning of the WTG and generation of higher wind energy capacity. Offshore wind farms do not suffer such restrictions as is the case of onshore wind farms that are often sheltered by houses, hills or other structures from optimum wind directions. There are no protests from local communities against the development of OWFs, which is normally the case in onshore wind farm development (EWAE, 2013). Such protests are usually organised either to protect the environmental scenery or due to the potential noise pollution generated by a wind farm located within close proximity to residential areas. The cost of offshore OWFD remains one of the most challenging factors for investors. Offshore wind farms in the UK are generally being constructed in water depths of up to 30 metres, with the exception of the Beatrice wind farm, installed at a demonstration site in Scotland in 2006. This wind farm consists of only two REPower 5 MW turbines in a depth of 45 metres (EWEA, 2013).

2.2.2 Onshore wind farm

The cost of onshore wind farm development is relatively cheaper than it is in the offshore sector due to its less complex logistics arrangements and the ease of grid connection. As of the end of 2018, the onshore wind generating capacity increased to 7,899 megawatts. There is less voltage drop usually experienced on long cabling due to the proximity of the wind farm to the grid connection or consumers. However, some of the concerns of onshore wind farms include the noise pollution, accident impact radius and complaints from local communities about damage to the landscape (NES, 2016). The first UK onshore wind farm was built at Delabole in 1991

(Rudolph *et al.,* 2014); since then, onshore wind energy development in the UK has been evolving into a much more commercial investment. The wind energy development surpassed the hydropower industry to become the largest renewable power generation source in 2007 (Nixon, 2008).

2.3 Types of Wind Turbine Generator

There are currently only two types of WTG, namely the horizontal axis wind turbine (HAWT) designs and the vertical axis wind turbine (VAWT) system. In 2013, the HAWT type was said to dominate 99% of the WTG market in the UK (Verkinderen, and Imam, 2015; Grieser *et al.,* 2015). Statistics show that the VAWT systems installed in the UK alone increased by 20% in 2011, but dropped steeply in 2012 by 46%.

The VAWT is comparatively more efficient, cheaper and easier to maintain than the HAWT. The following are some of the known advantages of VAWT over HAWT:

- The VAWTs always faces the wind and as such does not have to be steered into the wind.
- It has a larger surface area for energy capture.
- It is considered more efficient in gusty winds as it is already facing the gusts by nature of its design.
- It has more flexibility for being installed in various locations such as house rooftops, along highways, in parking lots, etc.
- It is generally considered safer for wildlife; for example, it moves slowly and the blades are not sharp enough to kill birds.
- It has the flexibility of being easily scaled to any size depending on power output requirements (from milliwatts to megawatts).
- It is considerably cheaper to construct due to its simplicity when compared with the HAWT.
- It has low maintenance downtime – mechanisms are at or near ground level.
- Due to its low-speed design, it generates less noise.

- It is more aesthetically pleasing.

Disadvantages of the vertical axis wind turbines include but are not limited to:

- Dynamic stall of the rotor blades has been known to constitute a significant challenge to the system. Dynamic stall occurs as a result of the abrupt varying angle of attack.
- Due to significant variable forces exerted on the components during rotation, the rotor blades are prone to fatigue (Borg et al; 2012).
- Although the VAWT has fewer components and are less likely to suffer breakdown or require repairs, the forces acting on the equipment are considered far more turbulent than those acting on HAWT.
- VAWTs are ideal for lower areas; therefore, they are limited in the amount of energy they can trap. In effect, they trap less energy than the HAWTs (Borg et al; 2012).
- VAWTs are also prone to stalling during strong winds irrespective of the fact that they are installed at lower heights than HAWTs.
- Most of the old designs are known to break apart after prolonged use. However, the design may have vastly improved over the past decades.
- An initial energy is required for the machine to startup, which uses up energy. Most VAWTs can only operate one blade at a time. There is also tendency for additional drag when blades rotate. These factors make the VAWTs less efficient than HAWTs (Kragten, 2004).
- Due the high vibration resulting from the airflow near the ground level, a strong turbulent flow is created and causes the bearing to wear. This in turn results in increase generating and operating (GENOP) cost.
- VAWTs have no known aerodynamic theory to design the rotor (Darrieus rotor), whereas the HAWTs aerodynamic theory is simple to apply Kragten, 2015).

According to Ackermann and Söder (2000), the first horizontal axis windmill was in operation in England in the year 1150. The typical windmill was 30m tall with a rotor 25m in diameter. The horizontal windmill type was also later found in France, Belgium, Germany, Denmark and the rest of Europe. France continued to invest in wind energy development over the years and had up to 20,000 operational windmills in 1800.

The HAWT contains an electrical generator and rotor shaft at the top of a tower. It is important to build a tower because the HAWT's wings or blades need relatively high-speed air to rotate. A gearbox is used to generate high-speed rotation from slow-moving blades. These high-speed rotations are then used to generate electricity. These turbines have their own merits and demerits, as listed below.

Advantages of the horizontal axis wind turbine:

- The pitch of their blades can be adjusted according to the wind. This allows the turbine to rotate at the optimum speed and generate a maximum amount of electricity at any given instance.
- The HAWT towers can be used to generate more power because, for every 10 metres elevation from the ground level, the wind speed increases by 20%, which can be used to increase power by up to 34%.
- HAWT blades move perpendicular to the wind, which allows them to generate electricity easily without any reciprocating action.

Disadvantages of the horizontal axis wind turbine:

- Transportation is very difficult; turbines with 90-metre towers are very hard to move.
- Its tall structure can affect the various signals of different telecom companies.
- It requires a very heavy and expensive gearbox, generator, and blades.
- Extra yaw control is required to turn blades in the direction of the wind.
- It also affects the beauty of the landscape, which is usually opposed by residents and the general public.

Comparison between HAWT and VAWT design systems installed annually (as adapted from Tjiu *et al.,* 2015; Eriksson *et al.*, 2008):

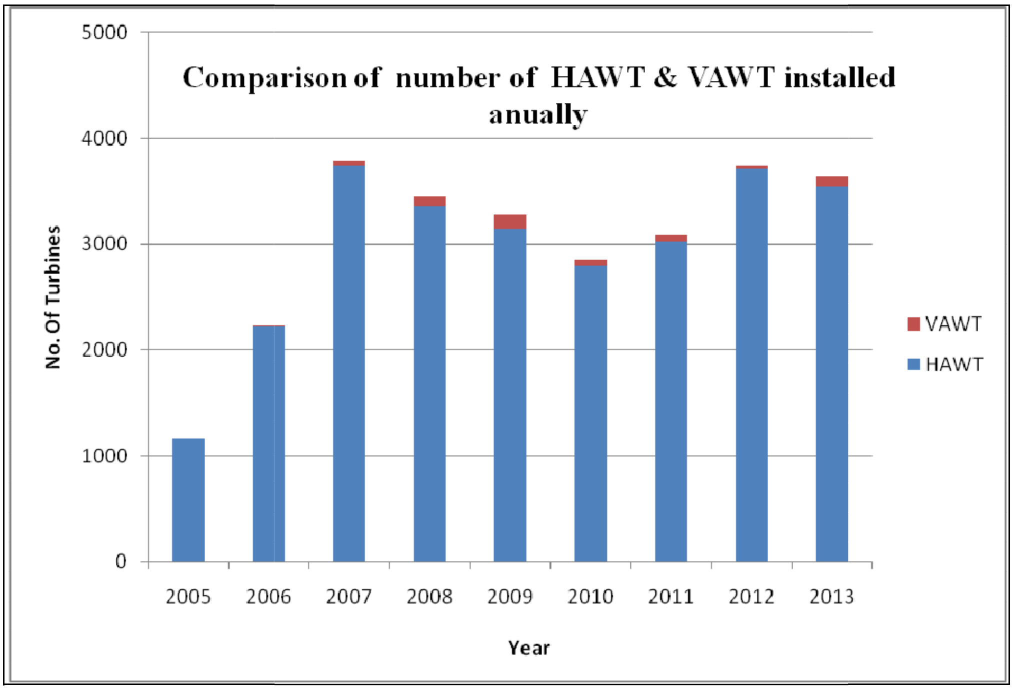


Figure 2.1 Comparison of the number of HAWTs and VAWTs installed annually in the UK and Europe 'source: Tjiu *et al.,* 2015; Eriksson *et al.,* 2008'.

The above figure, Figure 2.1, illustrates a sharp contrast between the installation of the HAWT and the VAWT. As can be seen on the chart, the HAWT is widely installed and commonly used in the UK and Europe, which is due to the specific advantages highlighted above.

2.4 Critical Components of the Wind Turbine

A wind turbine has various functional components that come together as an operating machine. However, this section will deal with the major components of the wind turbine such as:

- Foundation
- Tower section
- Turbine and
- Transition piece (TP)

- Nacelle & Hub
- Cables.

The wind turbine system is mainly comprised of the seven main functional units as listed above, i.e. the foundation, transition piece, tower, turbine, and the nacelle & hub and cables (Stiesdal, 1999). The monopile and transition pieces sections are generally classed as the support structures. The tower supports the nacelle and its rotor whereas the tower is supported by the support structure, which is driven into the seabed, as commonly seen in most offshore wind farm projects. The support structures are usually rigid and suitably sturdy enough to withstand offshore environmental elements, such as cyclic loading, vortex-induced vibrations, cyclonic wind gusts, high waves and fast current speeds (Henderson and Zaaijer, 2004). These environmental conditions are capable of causing damage to offshore wind turbines or structures due to impact forces, constant fatigue stress impact, resonant vibrations, etc. (Magoha, 2004).

On offshore sites, the monopile is driven into the seabed in line with the prescribed installation specifications; the tower is mounted on the monopile and the nacelle is finally lowered onto the tower receptacle (World Steel Association, 2012). The monopile and the tower make up a hollow steel support structure, which is designed with a tapered shape at one end. The monopile foundations are usually installed in water with a depth of 25m. Other relevant types of foundation structures mainly deployed in offshore wind farms projects include:

- Gravity-Based Foundation (GBF) –usually suitable for turbines up to 5MW, and which has been shown to be effective for OWTs of this capacity.
- Tripod Foundation (TF) – made of heavy steel structures and known to be suitable for water depths of up to 35 metres. TF can usually be used for 5 MW turbines.
- Jacket Foundation (JF) – comprised of heavy steel in a lattice configuration, which can be used to install big turbines. The advantage of this type of foundation is its ability to be deployed in deep waters (World Steel Association, 2012).

The shafts, generator gearbox, mechanical brakes, yaw drive, control systems, electrical generator, etc. are the other main ancillaries of the wind turbine. Other measuring devices such as the wind vane and anemometer are installed on the external part of the nacelle, in order to monitor the wind speed and direction. The nacelle also forms a platform for installation of navigation lights and site marking lights. The wind force exerted on the blades initiates the motion on the turbine by rotating the blades, and a corresponding rotation of the mechanical shafts causes electricity to be generated and transmitted through the cable to the transformer and the grid.

The nacelle houses the majority of the wind turbine ancillary equipment. The most relevant equipment found in the nacelle is the drive train including the mechanical transmission (rotor shaft, bearings and the gearbox) if applicable, the electrical generator, and other equipment such as the power electronic interface, the yaw drive, the mechanical brake, and the control system, such as Pitch control and Stall control (IRENA, 2012). The nacelle is installed at the uppermost end of the tower with the aid of a bearing system, which allows it to be rotated into the wind direction if required.

Submarine cables connect the turbine arrays in the wind farm. The cables are usually made of aluminium or copper cores of three cables in a bundle with two communication cables known as fibre optic cables. They are also used to export the power generated from the wind farm to the onshore grid connection. The installation of submarine cables comes with increased risks in the areas of anchor damage from construction vessels or other marine traffic, fishing trawler damage, sea motion and material damage, abrasion and so on. The risks are usually reduced to be as low as reasonably practical (ALARP), and managed by applying avoidance strategies, reasonable routing calculations, the use of protection mattresses, cable burial and the robust design of cable systems.

2.5 Overview of Wind Energy Development in Europe

The European Union (EU) has committed efforts in the research and development of energy from renewable energy sources (RES), especially the wind energy. In 2009, the EU launched an initiative dubbed vision 2020 through its Renewable Energy Directive (RED), which set a mandatory target for the member states to derive their 20% energy consumption from RES by 2020 (EEA, 2018). This initiative made the EU a world leader in renewable energy capacity per capita up until 2016, when other emerging markets in other parts of the world started overtaking them in terms of RES deployment. According to EEA, (2018b), the EU-wide renewable energy share increased from 16.7% in 2015 to 17.0% in 2016 and to the estimated 17.4% in 2017 indicating an upward trend. The EU has already met its indicative trajectory for 2016-2017 and is expected to achieve the 2020 vision as set out in the RED (2009/28/EC), as well as the trajectory from the NREAPs adopted by the member states.

2.5.1 Wind energy contributions of the various EU countries

Germany made the highest annual increase between 2016 & 2017 in contribution of installed wind energy electricity demand, from 16% to 20%. It also has the highest installed capacity of wind energy in the EU, followed by Spain, the UK and France, as presented in Table 2.1.

Table 2.1 Installed capacity of 28 EU countries between 2000 and 2017 (as adapted from EWEA, 2018)

28 EU Countries	2017 Installed Capacity		Total Installed Capacity
	Onshore	Offshore	
Austria	196	-	2,828
Belgium	302	165	2,843
Bulgaria	-	-	691
Croatia	147	-	613
Cyprus	-	-	158
Czech Republic	26	-	308
Denmark	342	-	5,476
Estonia	-	-	310
Finland	475	60	2,071
France	1,692	2	13,759
Germany	5,334	1,247	56,132
Greece	282	-	2,651
Hungary	-	-	329
Ireland	426	-	3,127
Italy	252	-	9,479
Latvia	-	-	66
Lithuania	-	-	493
Luxembourg	-	-	120

Malta	-	-	-
Netherlands	81	-	4,341
Poland	41	-	5,848
Portugal	-	-	5,316
Romania	5	-	3,029
Slovakia	-	-	3
Slovenia	-	-	3
Spain	96	-	23,170
Sweden	197	-	6,691
UK	2,590	1,680	18,872
Total	12,484	3,154	168,727

Six European Union (EU) countries made a substantial contribution to the total installed capacity in 2016, as follows: 6.6 GW was contributed by Germany, 4.3 GW by the UK, 1.7 GW by France, 476 MW by Belgium, 426 MW by the Ireland and 147 MW by Croatia as presented in Table 2.1. This table shows the statistics for the 2017 installed capacity and the cumulative installed capacity up to the end of 2017. The European Wind Energy Association's report of 2018 revealed that Denmark has the highest electricity demand share of 44%; however, it has not made a significant contribution to the EU installed capacity (EWEA, 2018).

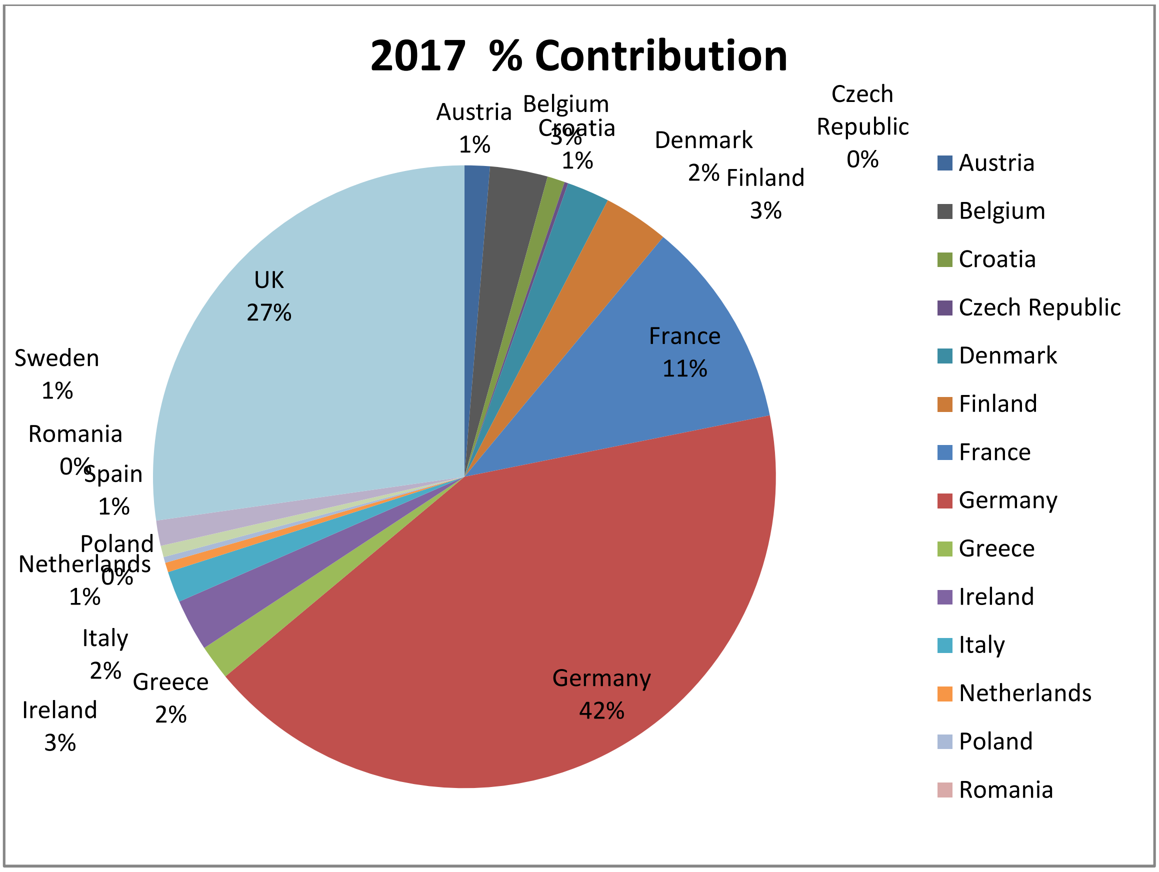


Figure 2.2 Distribution of the 2017 installed capacity (as adapted from EWEA, 2018).

The above Figure 2.2 shows the percentage proportion of the contributions made to the installed capacity of wind energy in 2017 by various EU nations. A total of 168.7 GW of wind energy (both onshore and offshore) was installed in the EU as of 2017, which shows a significant growth of 10% when compared to 2016 installations.

2.5.2 Wind energy trend statistics between 2000 and 2017

According to the annual report published in 2016 by the European Wind Energy Association (EWEA), 12,800MW of wind energy capacity was the total installed capacity that was connected to the grid in the European Union in 2015. This installed capacity indicates an increase of 6.3% when compared to installed capacity in 2014 (EWEA, 2016). The installed wind energy capacity exceeded any other energy generation source installed in 2015, therefore accounting for 44.2% of the total installed energy regardless of source in 2015. Overall installed energy capacity from RESs in 2015 represents 77% of the EU total installed capacity for all energy sources (EWEA, 2016). The energy capacity installed from RESs alone in 2015 accounted for 22.3GW of the total new installed energy capacity of 29GW.

Annual installed capacity of all energy sources (MW) and RES share (%):

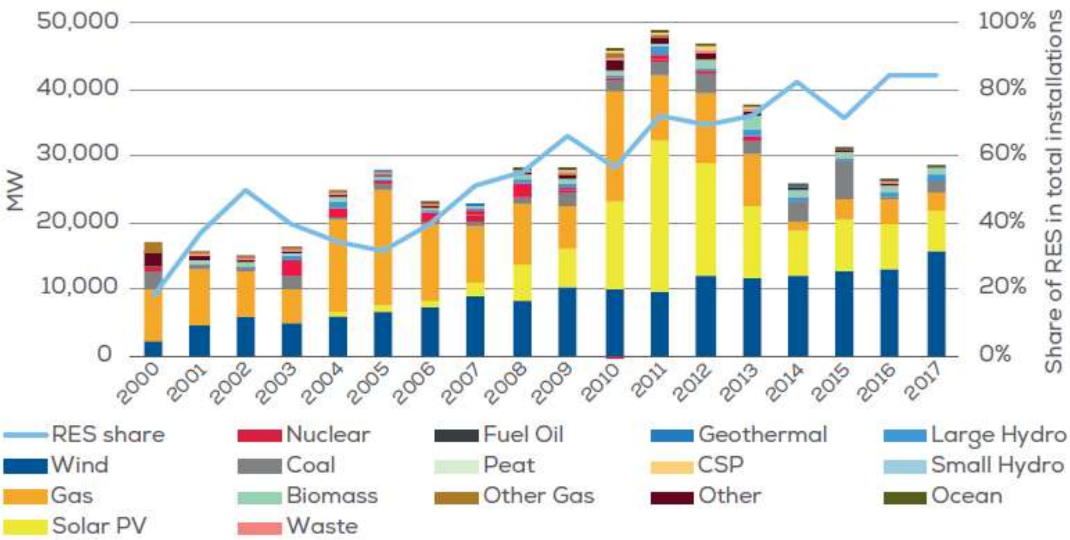


Figure 2.3 Annual installed capacity and comparison with RES (source: (EWEA, 2018).

As indicated above, Figure 2.3 summarises the annual installed capacities of all sources of energy in Europe between the years 2000 and 2015. Energy generated from gas had the most consistent installed capacity until its sudden decline in 2014 and 2015 (EWEA, 2014). The installed capacity of wind energy has seen a consistent increase from the year 2000, with peak installations recorded in 2012, 2014 and 2015. Solar PV installations gradually picked up from the year 2003and hit peak installation in 2011 before experiencing as low decline from 2012. Nuclear energy has seen the least installed capacity in Europe since the year 2000. However, there was a small installed capacity from nuclear energy sources in 2007 and a very negligible capacity in 2009.

The wind energy installed capacity as of year 2000 was just 2.7 GW. By 2007, renewable energy contributed over 50% of annual power installations and this was over 70% by 2011 with an annual installed capacity of between 20 and 34 GW. Wind energy installation has contributed about 33% of total installed capacity, and other energy from RESs contributed about 60% of the total installed capacity in Europe between the years 2000 and 2017 (EWEA, 2018).

2.6 Historical Accidents and Incidents of OWFTs

A research study by Woebbeking (2008) of 2,500 datasets of wind turbine failures revealed that 26% of these were due to gearbox failure, 17% were due to generator/bearings failure, 13% were due to drive train, 19% were due to electrical installation and 25% were due to other factors, as shown in Figure 2.4 below.

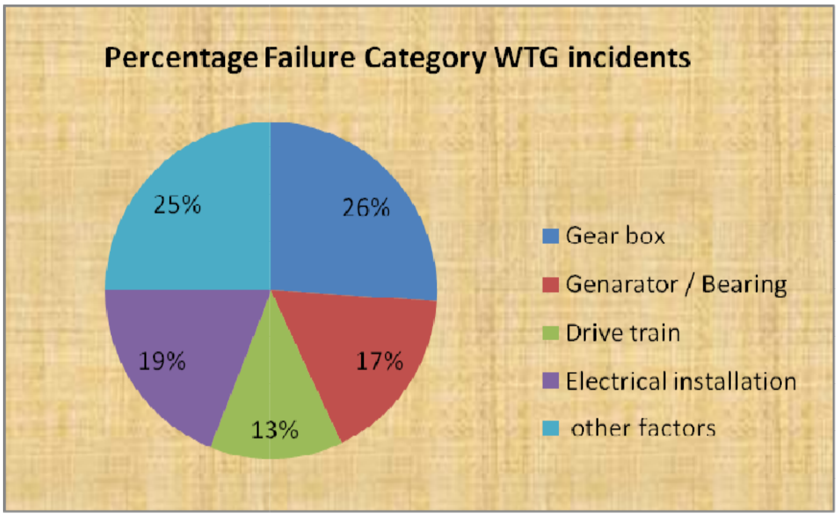


Figure 2.4 Percentage failure categories of historical incidents of WTG components (as adapted from CWIF, 2015)

Morgan *et al.,* (1998) investigated the loading impact of ice on OWFTs and the hazard posed to public safety. The investigation found that ice build-up is capable of causing damage to the WTG blades and as such recommended special features be incorporated into the WTG to prevent ice build-up. The study also encourages the display of warning signs to personnel in order to prevent injuries and potential claims or fines. CWIF (2015) holds useful information about the reported incidents in both onshore and offshore wind farms.

The data held by the Caithness Wind Farm Information Forum (CWIF) spans across three decades, ranging from the 1990s to September 2015 of 1,781 reported incidents around the world. According to the CWIF, 142 incidents were reported in the UK alone. However, it is worth noting that Renewable UK in 2011 reported 1,500 accidents and incidents which took place in the previous five years in the UK. The trend of the accidents indicates a progressive increase in the number of reported accidents, which directly relates to the sudden increase in the number of installed turbines. The average numbers of accidents reported over the decades, as reflected in Figure 2.5 are as follows: 16 per year between 1995 and 1999, 49 per year between 2000 and 2004, 108 per year between 2005 and 2009, and 156 accidents per year between 2011 and 2015 (CWIF, 2015).

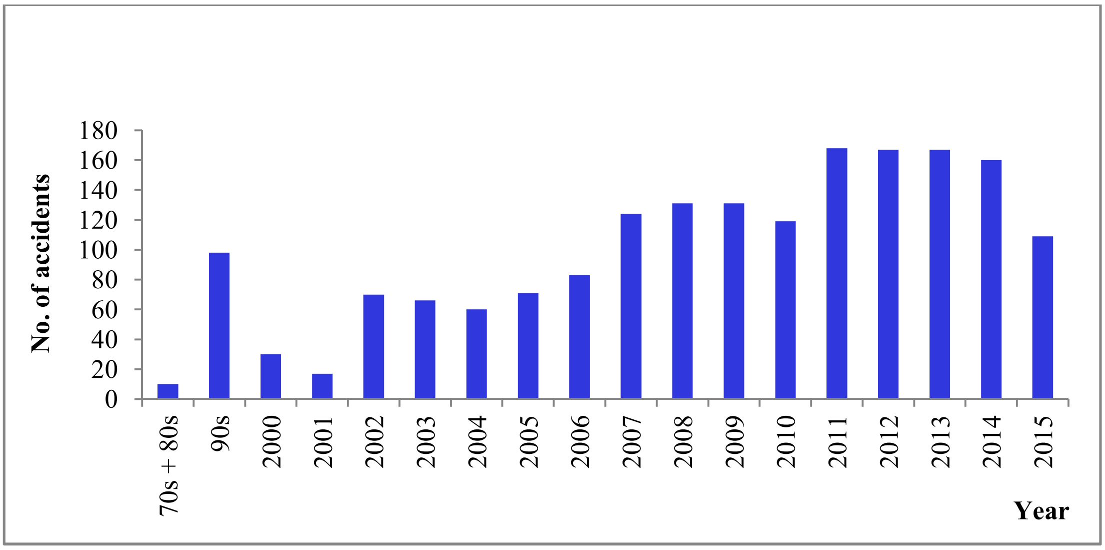


Figure 2.5 Total number of globally reported accidents in wind farms between the 1970s and 2015 (as adapted from CWIF, 2015)

Recent research suggests that fatality/injury in the wind farm industry can be reduced by increasing the distances between turbines and local residents from 2km to 2.5km, particularly in the case of onshore wind farms, as proposed by the Scottish government. The most common accident on wind farms has been found to be blade failure, which is mainly caused by fire and poor maintenance (CWIF, 2015). This statement is in line with the findings of GCube, which is the largest provider of insurance to the renewable industry (Anaheim, 2017).

According to the WindPower Monthly publication in June 2015, annual blade failure in the industry is estimated to be around 3,800 (Campbell, 2015). The total number of accidents recorded in the chart represented in Figure 2.5 is 1,781. The number of fatal accidents reported in Figure 2.6 below is 116, with details shown in the chart below (CWIF, 2015).

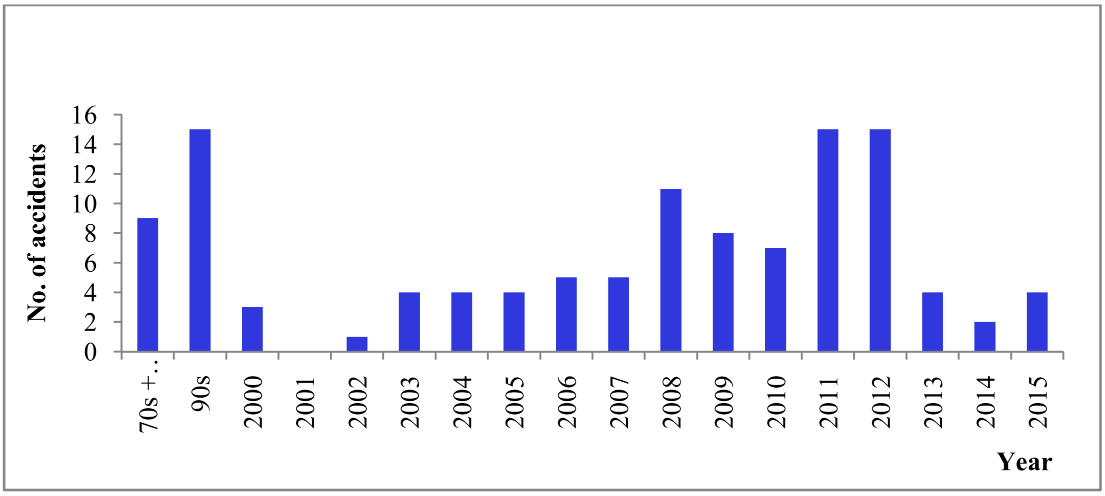


Figure 2.6 Total number of globally reported fatal accidents in wind farms between 1970 and 2015 (as adapted from CWIF, 2015)

The number of accidents reported may appear to be lower than the number of fatalities, given that one particular accident may well cause multiple fatalities. The 116 fatal accidents resulted in 162 fatalities, of which 95 were directly wind farm activity-related involving industry personnel. The number of fatalities not directly related to wind farms is only 67 (CWIF, 2015). This figure includes personnel such as fire fighters, logistics and transportation support handlers.

2.6.1 Human injury

The number of reported accidents involving human injury is 136 (CWIF, 2015). Only 118 of these accidents directly involved a wind farm, 24 of those involved the public, and six of the injuries as reported involved the general public in the UK (see Figure 2.7 below). Other resources or sources of information both reported and unreported have not been considered in this literature review.

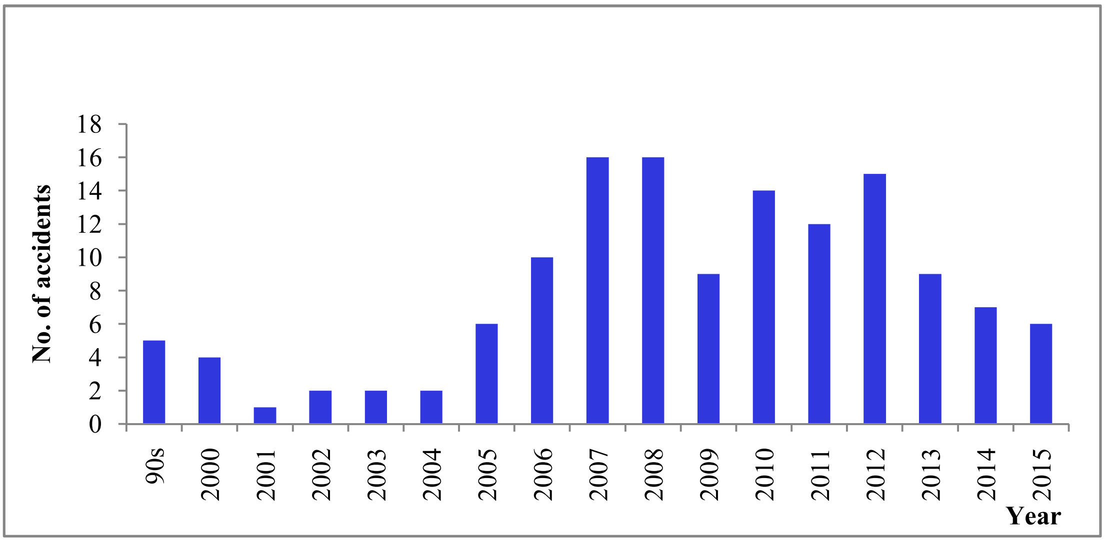


Figure 2.7 Total number of globally reported human injury accidents in wind farms between the 1990s and 2015 (as adapted from CWIF, 2015).

2.6.2 Incidents affecting human health

Between 2012 and September 2015, only 60 incidents of wind farms affecting human health were reported (CWIF, 2015). The incident types reported in this category include ill health, discomfort due to turbine noise, shadow flicker, etc. The details of the assessments of risks associated with WTG noise pollution will be further discussed in a subsequent section of this research work.

2.6.3 Blade failure

According to the CIFW (2015), this category records the biggest number of failures in the wind farm industry. The total number of blade failures reported is 326 as of

2015, as shown in Figure 2.8. Blade failure occurs when part of or the whole blade breaks away from the turbine due to a number of different reasons (Yang *et al.*, 2016).

The records show that pieces of the blades are capable of flying up to one mile and can also penetrate roofs and walls of occupied buildings. Hence, the reason for suggesting a 2km (1.6 miles) space between turbines and public buildings is to promote safety and minimise other issues including noise and shadow flicker (Campbell, 2015). The details of the assessments of risks associated with WTG blade failure will be further addressed in a subsequent section of this research work.

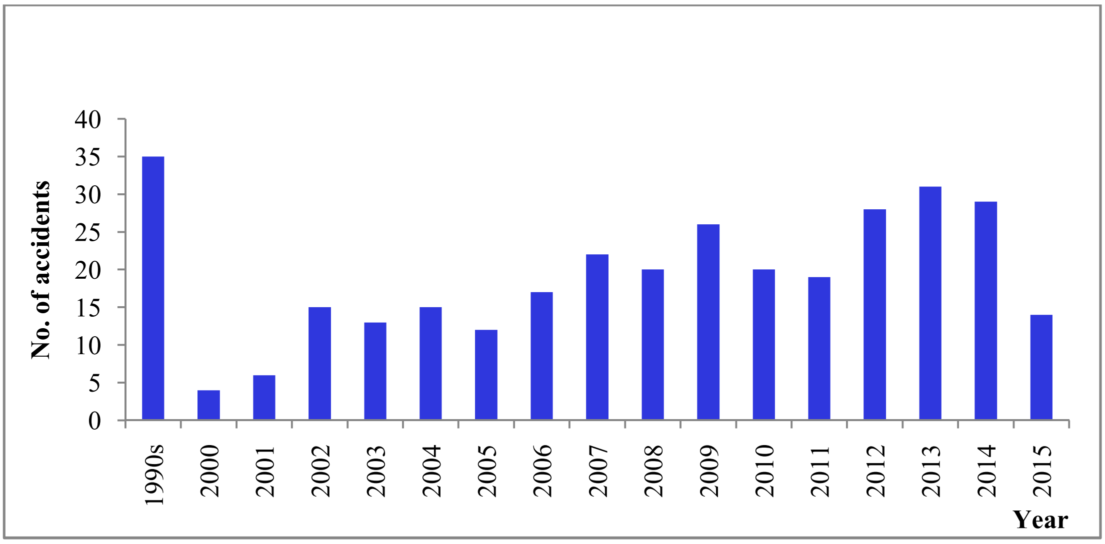


Figure 2.8 Total number of globally reported blade failure accidents in wind farms between the 1990s and 2015 (as adapted from CWIF, 2015).

2.6.4 Fire incidents

According to the data held by the Caithness Wind Farm Information Forum (CWIF, 2015), the second most common incident leading to casualty and fatality is fire, with a record high of 258 reported incidents as of 2015. Whilst fire is common on wind farm turbines, the potential for occurrence may slightly vary with turbine type and manufacturer. The risk of fire increases dramatically in onshore wind farms during inclement weather conditions such as thunder, lightning and wind storms.

There is also the risk of wild fires or property damage in dry weather conditions with turbines sited in forests or built-up areas. Due to the height of wind farm turbines, they are often inaccessible by the fire service, and the logistics requirements of the OWFT, by virtue of its location, make it near impossible to be accessed by a trained competent emergency service. However, in the case of offshore wind farms, the construction vessels and other vessels in the area may be in the position to fight the fire, providing the situation is adequately assessed for impending danger. Figure 2.9 shows the record of reported fire incidents in the wind energy industry between 1990 and 2015.

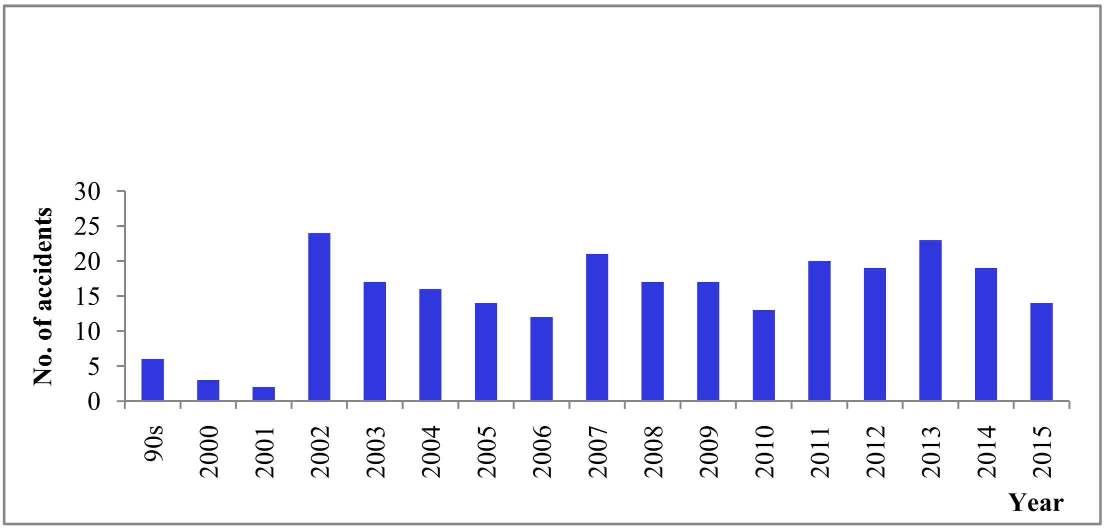


Figure 2.9 Total number of globally reported fire incidents in wind farms between the 1990s and 2015 (as adapted from CWIF, 2015).

2.6.5 Structural failure

Structural failure refers mainly to such challenges as the deterioration of foundation structures due to grout failure, transition piece slippage and the failure of other components.

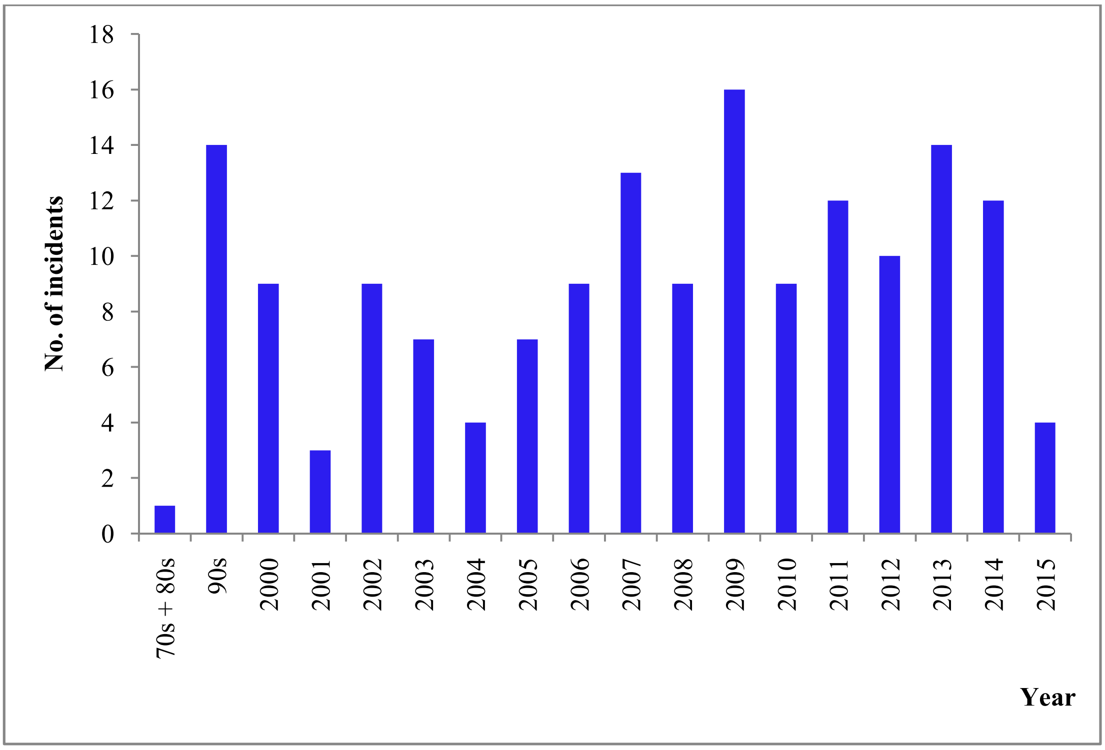


Figure 2.10 Total number of globally reported structural failures in wind farms between the 1980s and 2015 (as adapted from CWIF, 2015).

This often leads to other major component failures and collapse of the tower in some cases. According to the data held by the CWIF (2015), structural failure in the wind farm industry has been noted as a serious issue. This is supported by 162 cases, as represented in Figure 2.10, which established structural failure as having the third-highest occurrence in the wind farm industry. Although the financial cost of structural failure outweighs that of blade failure, the damage caused by blade failure could be far more on some onshore wind farms due to their proximity to residential areas (Yang *et al*., 2016).

2.6.6 Ice throw

Ice throw has been recognised as a potential hazard on wind farm turbines, especially in onshore wind farms (Durstewitz *et al*., 2004). In some instances, ice throw travels to distances of up to 140m.

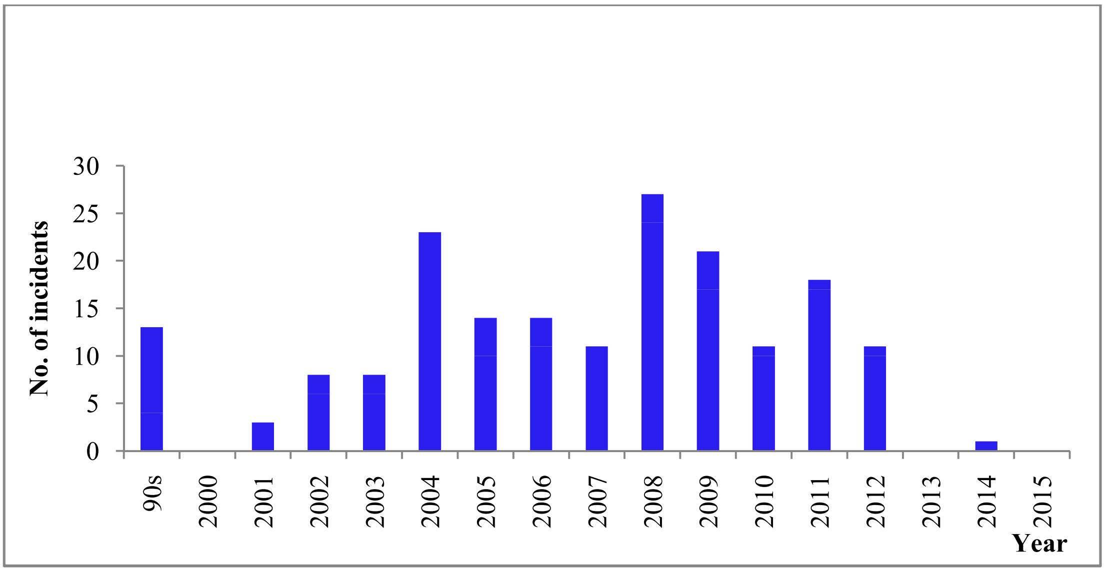


Figure 2.11 Total number of globally reported ice throw incidents in wind farms between the 1990s and 2015 (as adapted from CWIF, 2015).

Therefore, exclusion zones are usually advised. Although the CWIF recorded only 35 incidents, a report published in Germany in 2003 indicates that 880 icing incidents took place between 1990 and 2003 (Durstwitz, 2003). A further report published in 2005 recorded 94 incidents of ice throw, and 27 incidents were reported in 2006 (CWIF (2015). The chart in Figure 2.11 only represents records held by CWIF (2015) of 35 reported incidents.

2.6.7 Transportation incidents

Transportation hazards make up a considerable proportion of accidents and incidents in the wind farm industry. However, the data held by the CWIF (2015) shows that only 148 accidents were reported (see Figure 2.12). Some of the reported accidents include a turbine section crashing through a house during transportation, falling of a turbine section from a turbine, turbine sections falling into the sea during passage, etc.

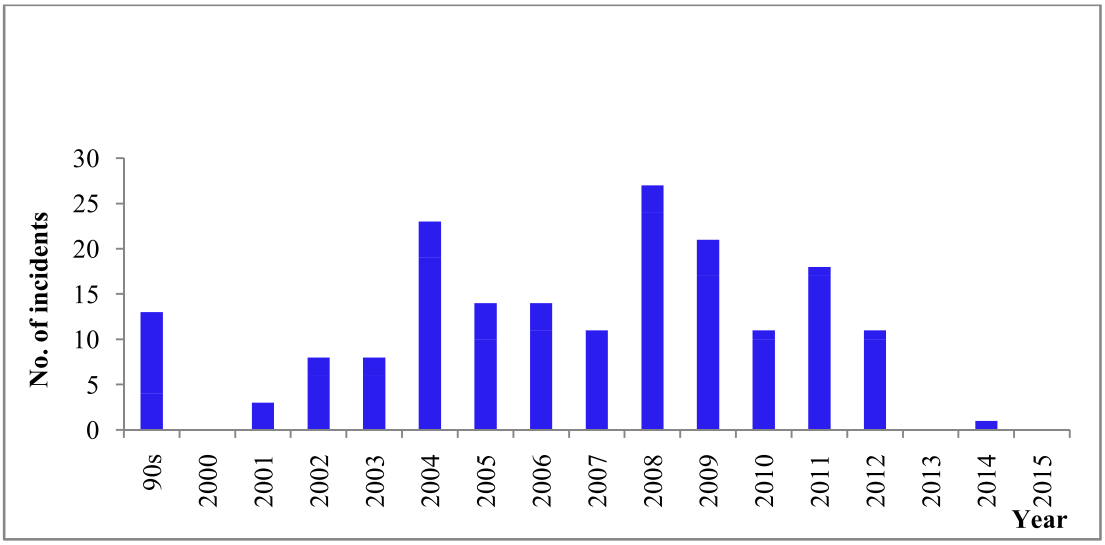


Figure 2.12 Total number of globally reported transportation incidents in wind farms between 2002 and 2015 (as adapted from CWIF, 2015).

2.6.8 Environmental damage

Environmentalists around the world seriously disagree with the development of wind farm turbines for reasons such as causing injury or death to birds, damage to landscape, etc. The CWIF has recorded 117 such incidents. The statistics indicate that 2,400 protected golden eagles and about 10,000 protected raptors were killed in a space of 20 years at Altamont wind farm in California, USA alone (CWIF, 2015).

Global statistics also confirmed 32 deaths of protected white-tailed eagles in Germany, and that 22 endangered Tasmanian eagles were killed by the Woolnorth Wind Farm development in Australia. An estimated 600,000 bats were killed in the United States of America by wind farm turbines in 2012 (CWIF, 2015). An estimated 1,500 birds in Australia are killed each year by the MacArthur Wind Farm. Figure 2.13 below represents a summary of the reported incidents.

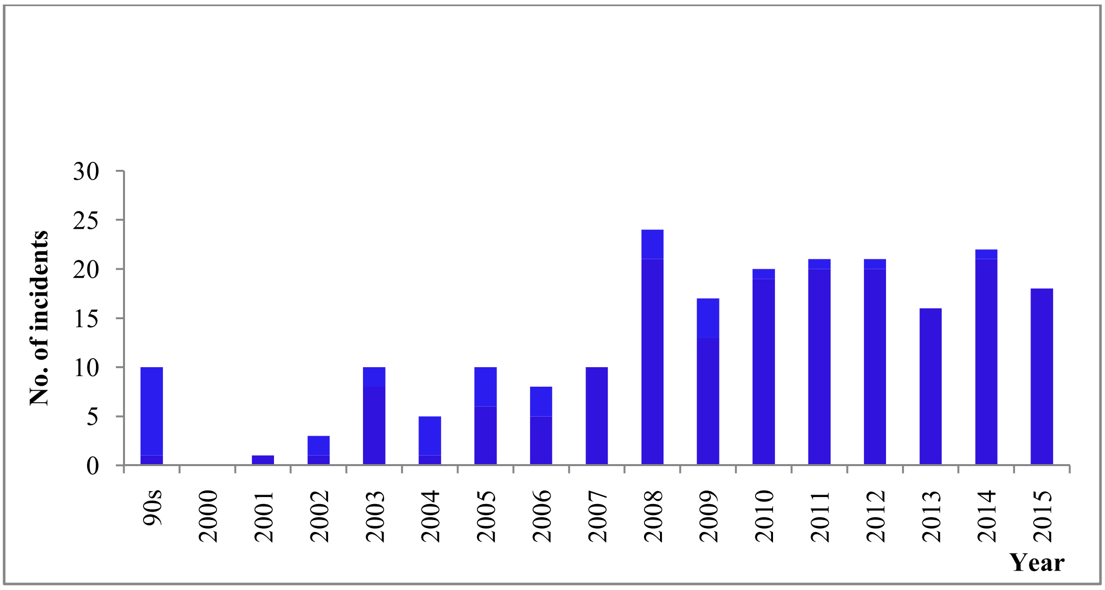


Figure 2.13 Total number of globally reported environmental incidents in wind farms between 2002 and 2015 (as adapted from CWIF, 2015).

2.7 Risk-Modelling Approach

In wind farm development processes, there is always the need to make a decision that contains some elements of risk. Therefore, any such decision will require risk estimation and analysis, which is critical to the understanding of the extent of the risks involved. Understanding the risks will also aid their effective management in order to minimise the effect of the potential impact.

The word "risk" may also imply the probability of a defined outcome; for instance, the risk of being injured from go-karting or jet skiing is high. Risk is comprised of two parameters known as frequency and consequence. It can be defined as the product of the frequency with which an event is anticipated to occur and the consequence of the event's outcome. Mathematically, it is expressed as Risk = Probability x Impact or Risk = Frequency × Consequence. Hazard or threat is an existing condition or possible situation that has the potential to generate an undesirable event or disaster.

Vulnerability may be defined as an assessment of how well or how poorly protected one is against an event. One may or may not be vulnerable to a hazard within the immediate surroundings; for instance, someone who lives on a flood plain may be vulnerable to floods whereas someone who lives on higher ground will not be vulnerable to floods. Impact is an assessment of the interaction of hazard outcome with vulnerabilities.

Vulnerability may be assessed by the determination of the following factors:

- Criticality: by assessing how crucial the affected subject or asset is.
- Exposure: assessment of the extent of threat caused by the exposure to vulnerable conditions.
- Time: assessment of the unit time considered in respect of the changes in vulnerability, e.g. day, week, month or quarterly, etc.

Consequence is the result of the interaction of the impact of the event with other systems. It may induce future events or reduction of vulnerability through mitigation and preparedness. Although the terms consequence and impact may ordinarily appear to be synonymous, they do not connote the same meaning. Impacts are related to the effects of the event and are also shorter (anything from hours to decades) in nature than the consequences (anything from weeks to centuries). Consequences are not automatic and are not irreversible. They are also mainly caused by human factors whereas the impacts are event driven.

Probability is a mathematical assessment of how likely it is that a specific event will occur. This may be expressed in a number of ways as the chances of the occurrence of particular events. It may also be described as a qualitative assessment expressed as the likelihood or unlikelihood of occurrence. For instance, there is a 45% chance of rainfall today; four hurricanes are expected to happen this year.

Likelihood is an imprecise, qualitative statement of how probability is assessed. It is generally expressed in a range of broad probability values, e.g. high may be described as likely and low may be described as unlikely. In some cases, likely may be interpreted as ‘yes, it will’ and unlikely as ‘no, it will not’.

Uher and Toakley (1999) investigated various factors concerned with the implementation of risk management in the conceptual phase of a project life cycle. It was discovered that, although most industry practitioners were familiar with risk management, its application in the conceptual phase was relatively low and qualitative rather than quantitative analysis methods being generally applied. Due to lack of experience and training, low knowledge and skill hamper risk management.

Chapman (2001) elaborated on design risks, which included but were not limited to the difficulty in capturing and specifying the user requirements, difficulty of estimating the time and resources required to complete the design and difficulty of measuring progress during the development of the design. Chapman also stated that the design team's in-depth knowledge of the sources of risk can greatly influence the identification of risks in the design phase of a project. Abdou (1996) classified construction risks into three groups, i.e. construction finance, construction time and construction design, and addressed these risks in detail in light of the different contractual relationships existing among the functional entities involved in the design, development and construction of a project.

2.8 Risk Assessment Methodology

Although risk-informed decisions are critical, it is often challenging to make such decisions in the project management process. In recent times, it has become crucial in industry to ensure the risks associated with any project tasks are well understood and properly managed by putting control measures in place (ABS, 2003).

Governments around the world and their agencies have stepped up their efforts to protect lives and environments. Most governments also further require companies to operate risk-assessed work processes; apply risk-reducing measures and be able to demonstrate that they can operate at certain acceptable risk levels (Andersen *et al*., 2011). Between the 1980s and 1990s, countries such as the US and the UK started putting the onus on corporate bodies to demonstrate the level of risks associated with their operations, especially in the offshore oil & gas sector (ABS, 2010). Nowadays, corporate bodies have become familiar with risk assessment techniques which are applied to improve the decision-making process whether or not there is a regulatory or legal requirement to do so.

The most widely used causal modelling techniques in risk analysis are fault tree analysis (FTA) and event tree analysis (ETA). A number of direct causes of disruption (e.g. loss of containment (LOC)) of a system can be analysed and modelled as a joint event consisting of an initiating event and failure of one or more safety functions. Experience has shown that detailed models for these types of direct causes can be built using FTA and ETA, which provide system insights resulting in computation of uncertainty/probability indices (Papazoglou *et al.,* 2003).

Usually, the computation of these indices can be based on generic data or more specific data for the relevant system being studied in a systematic manner. Wang and Ruxton (1998) revealed that risk analysis can be divided into two broad categories of quantitative and qualitative nature depending on data availability. However, in situations of unavailability or lack of data, expert opinions are required to implement such risk analysis (Wang *et al.,* 2004).

2.9 Risk Analysis Methodology

Risk analysis can be defined as the systematic use of available data to identify sources of risk, and to estimate the possible risk of failure. The information used in risk analysis may include historical data, theoretical analysis, informed opinions and stakeholder concerns (API, 2002). Risk analysis methods are generally categorised as qualitative or quantitative. There may be an intermediate category known as semi-qualitative, depending upon how quantitative the risk analysis is. The American Petroleum Institute's Recommended Practice 580 on risk-based inspection describes a 'continuum of approaches' ranging from the qualitative to quantitative (API, 2002). Figure 2.14 below shows the level of detail in risk analysis corresponding to a wholly qualitative approach on one end of the spectrum to a wholly quantitative one on the other, with intermediate approaches in between.

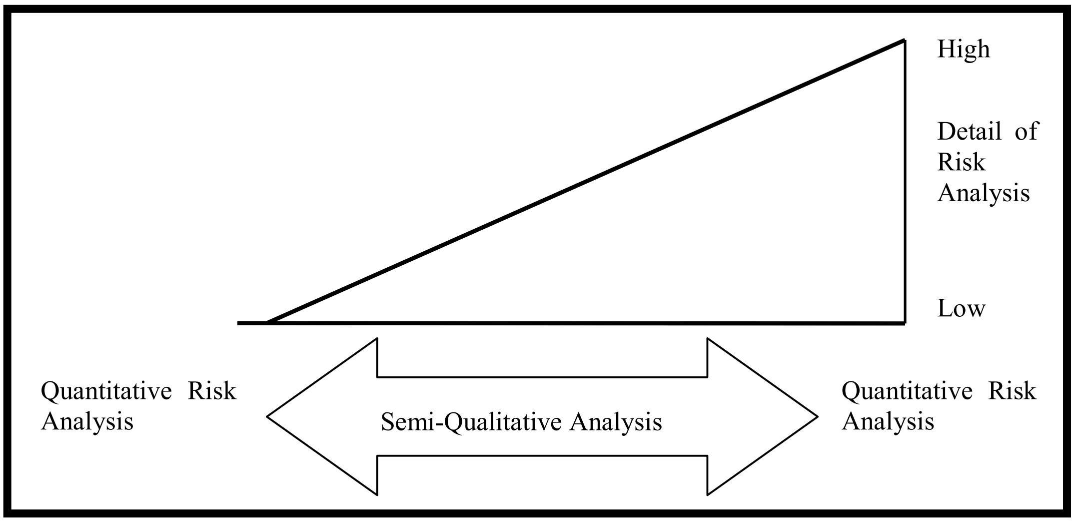


Figure 2.14 Continuum of risk analysis methods (API, 2002)

2.9.1 Qualitative analysis

This method employs engineering judgement and experience as the basis for risk analysis. The outcome of the analysis is wholly dependent on the expertise of the user. Qualitative risk analysis is usually adopted in a scenario where there is a lack of detailed numerical data. It is also the first sensible approach to observe prior to conducting a quantitative risk analysis, which rules out factors of no or less significance. Moreover, the outcomes may be used as a reality check on the outcome of quantitative analysis (API, 2000). However, it is not a very detailed analysis and provides only a broad categorisation of risk. Failure Modes, Effects and Criticality Analysis (FMECA), Hazard and Operability Studies (HAZOPS) and the Risk Matrix approach are examples of qualitative risk analysis. In the Risk Matrix approach, the likelihoods and consequences of failure are qualitatively described in broad ranges such as high, medium or low (API, 2000). Figure 2.15 shows the risk profiles of some selected components of a wind turbine plant. The risk profiles are for demonstration only; the risk profiling in practice requires the attention of industry experts.

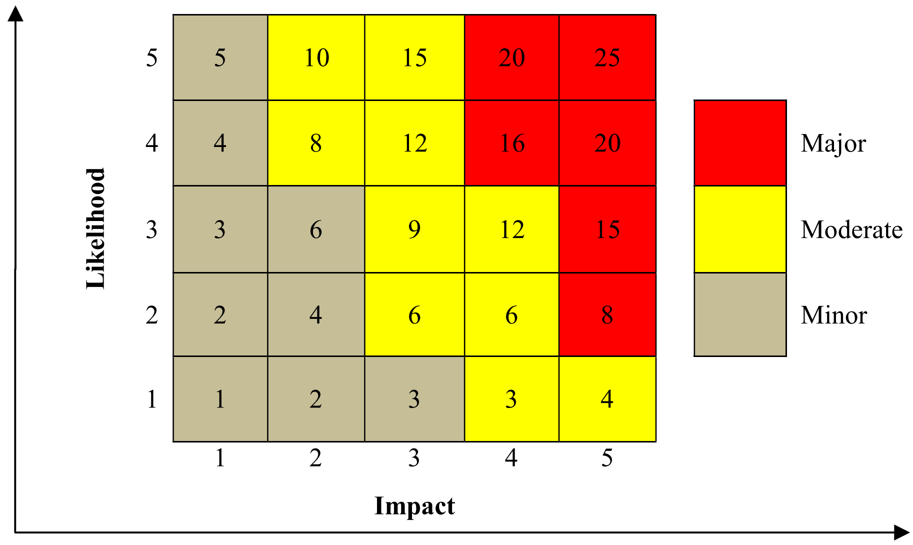


Figure 2.15 Qualitative risk analysis using a risk matrix

2.9.2 Quantitative analysis

Qualitative risk assessments will potentially yield the wrong judgement when applied to a complex system; therefore, quantitative analysis is recommended for a system of components. Quantitative analysis assigns numerical values to the probability (e.g. 10^{-5} failure events per year) and the consequences of failure (e.g. inventory released over 1,100m^2). Qualitative analysis techniques such as FMECA and HAZOPS can become quantitative when the values of failure consequence and failure probability are numerically estimated. The numeric values can be determined from a variety of references such as generic failure databases and elicited expert opinion, or calculated by specific engineering and statistical analysis (ASME International, 2003).

2.10 Decision-Making Analysis Methods

Decision-making techniques are the established rational process of identifying choices between alternatives, gathering information and assessing alternative resolutions. The use of a well-structured systematic decision-making approach often results in a more logical and objective outcome. This sort of approach is recognised as a subset of decision theory (Matheson, 1989). Probability Theory (PT) is one of the modern-day risk analysis tools; it was developed in the 16^{th} and 17^{th} centuries by notable researchers, namely Girolamo Cardano, Galileo Galilei, Blaise Pascal, Pierre de Fermat and Chevalier de Méré (Garrick *et al.*, 2004).

Thomas Bayes developed the Bayesian probability theory in the middle of the 18th century and became widely known as an expert in contemporary risk assessment (Garrick *et al.,* 2004). The greatness of the theory lies in the Bayesian theorem rooted in the fundamental logic that enables the combination of old information with new information for the assignment of probabilities (Cowell, 1998). Such an advantage was made use of in the subjects of early analytical explorations and precursors to the new science of risk assessment such as gambling strategies, military strategies and determining mortality rates.

The most important factors of a rational decision-making approach are the risks, benefits and costs. Most of the decision-making techniques expected to be employed in this research work will be quantitative risk assessment (QRA) approaches where possible. However, qualitative risk assessment techniques may also be used in some rare cases. Therefore, some of the relevant decision-making analysis tools will be discussed in this section of the research work.

2.10.1 Fuzzy set modelling

The fuzzy logic approach is based on degrees of truth rather than the standard true or false (1 or 0) Boolean characteristic logic on which modern computer technology is based. Dr. Lotfi Zadeh of the University of California at Berkeley first advanced the idea of fuzzy logic in 1965 (Zadeh, 1965). Fuzzy sets are sets whose elements have degrees of membership, and fuzzy set theory (FST) is a mathematical model established to handle imprecise data or incomplete data that cannot otherwise be analysed by the use of conventional algorithms (Pillay and Wang, 2003). A classic example of this is common in bioinformatics practice. According to Wang and Trbojevic (2007), fuzzy variables facilitate a gradual transition between states and consequently possess a natural capability to convey events of uncertainties in an unambiguous approach.

A fuzzy set system may consist of various states. For instance, the temperature of an engine may be described using the terms ‘cold’, ‘warm’, ‘hot’ and ‘very hot’ to represent the following temperatures: 0-250°C, 251-500°C, 501-750°C and 751-1,000°C respectively. These states are consequently referred to as `crisp' variables; and can be disregarded when dealing with crisp variables known as bivalent set theory (Zadeh, 1987). The practicality of presenting a set of information in this format is challenging by its very nature in actual circumstances even though it makes mathematical sense. The temperature ranges attain their maximum at the border of each higher figure of the range, i.e. a temperature region of 250°C - 500°C falls within the 'warm' region. However, an oversight or error of 1°C is capable of altering the state to the 'hot' region, thereby giving rise to uncertainty during a maintenance decision whether or not to shut down. FST can be applied as explained earlier in order to deal with these linguistic variables and the practicality of a smooth transition from warm to hot. FST is capable of handling the sharp transition from one state to another, thus allowing fuzziness between states (Metaxiotis *et al.,* 2003).

Further to the above descriptions, if a universe U is made up of a multitude of u and various combinations of these elements make up set A on the universe, then for crisp sets an element u in the universe U is either a member of the crisp set A or is not. Therefore, non-membership is represented by 0 whereas full membership is represented by 1. Further investigations completed by Zedah established that this model is able to accommodate various degrees of membership from 0 (non-membership) to 1 (full membership) (Zedah, 1965). According to Ross (2005), the difference between a crisp set and a fuzzy set is the membership function. Crisp sets have a unique membership function whereas fuzzy sets (denoted by $\widetilde{A}$) have an infinite number of memberships to represent the situation. Typical fuzzy set notation is shown in Equation (2.1) below.

$$\mu\widetilde{A}(u) \in [0,1] \qquad (2.1)$$

where $\mu\widetilde{A}(u)$ represents the degree of membership of elements u in a fuzzy set, therefore $\mu\widetilde{A}(u)$ is equal to the degree to which $u \in \widetilde{A}$ and $\in$ denotes an element of or a member of the set.

In the fuzzy set theory (FST) analysis, data may be represented in various shapes or values assigned to membership functions dependent on the requirements of the investigation. The most commonly used shapes in FST are triangular curves, S-curves, $\pi - curves$ and trapezoidal curves, as shown in Figure 2.16 (Pillay and Wang, 2003).

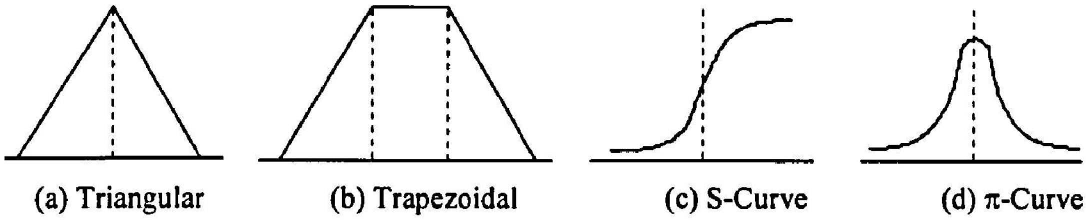


Figure 2.16 Fuzzy set theory shapes

The membership functions (MFs) constitute the building blocks of fuzzy set theory. This means that the fuzziness in a fuzzy set is wholly dependent on its MF. Any of the above shapes may be applied in fuzzy set theory cases and each of them will produce the same or similar outcomes. The only condition common to all the shapes is that a MF must vary between 0 and 1. For the purpose of this study, only the triangular and trapezoidal shapes will be widely applied. Moreover, triangular and trapezoidal shapes MFs have been widely applied in other studies and industries and have proven to be suitable approach to be employed in this study. In addition, they are both less complex to use for computation of analysis.

Fuzzy rule-based (FRB) systems are linguistic 'if then' rules simply represented in a general qualitative descriptors format (Sii *et al.*, 2001). For example, 'If A then B' where A and B are (collections of) positions containing linguistic variables. A is called the 'premise' and B is called the 'consequence of the rule'. The FRB decision-making tool can be combined with fuzzy logic theory to obtain an ideal methodology for handling incomplete and imprecise yet useful information. However, the fuzzy rule-based decision-making technique may generate an undesirable complex analytical (mathematical calculations) process, which includes the construction of multiple hierarchical fuzzy rule-based scenarios and inferences between fuzzy input and output. However, if such a challenge is faced during a multiple hierarchical attribute decision-making process, a new simplified process known as a fuzzy link-based (FLB) decision model may be employed to simplify the process (Yang, 2006). This technique is capable of unifying all hierarchical fuzzy rule bases in order to convert the fuzzy input element with the lowest attributes into the corresponding fuzzy output on a shared utility space that is established by the linguistic variables of the highest-level attributes (Yang, 2006).

According to Bowles and Palaez (1995) and Pillay and Wang (2003), ‘IF-THEN’ rule interpretation comprises two distinct parts, namely, i) the antecedent part evaluation, which involves fuzzification of the input and application of any necessary fuzzy operators (stating conditions of the input variable), and ii) applying the result to the consequent known as ‘implication’ (describing the values of the output variables). In the case of a two-valued logic or binary logic, the ‘IF-THEN’ rules are not complex and as such do not present any trouble. For instance, if the premise of the scenario is true, then the conclusion is true. On the other hand, even if the condition of the two-valued logic is relaxed and introduces an antecedent with the fuzzy statement, and the antecedent is true to some degree of membership, the consequent will also be true to that same degree. Hence,

- $in\, binary \log ic : p \rightarrow q \; (p\, and\, q\, are either\, both\, true\, or\, both\, false)$

- $in\, fuzzy \log ic :\, 0.5p \rightarrow 0.5q \; (p\, and\, q\, antecedents\, provide\, partial\, implication)$

Therefore, both the antecedent of a rule and the consequent of a rule can have multiple parts.

The classical set consists of objects that satisfy precise properties of membership. Fuzzy sets, on the other hand, consist of objects that satisfy the imprecise properties of membership.

As described in equation (2.1) above, the membership of an object in a fuzzy set can be partial. For classical sets, element u in a universe U either is a member of a crisp set A or is not. This binary issue of membership can be represented mathematically as follows:

$$X_A = \begin{cases} 1, u \in A \\ 0, u \notin A \end{cases} \tag{2.2}$$

In this study, two unusual kinds of fuzzy numbers, triangular fuzzy numbers and trapezoidal fuzzy numbers, are employed. A triplet can define a triangular fuzzy number as follows:

$$\tilde{\mu}_A(u) = \begin{cases} 0, u \le a_1 \\ \dfrac{u-a_1}{a_2-a_1}, u \in [a_1, a_2] \\ 1, u = a_2 \\ \dfrac{a_3-u}{a_3-a_2}, u \in [a_2, a_3] \\ 0, u \ge a_3 \end{cases} \tag{2.3}$$

where a_2 is known as the mean value of $\tilde{A}$, and a_2 and a_3 represent the lower bound and the upper bound respectively. Let the $\tilde{A} = (a_{1,} a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$ be two triangular fuzzy numbers. Therefore, the extended fuzzy operation may be represented as follows:

Change of sign: $-(a_{1,} a_2, a_3) = (-a_3, -a_2 - a_1)$ (2.4)

Additional $\oplus (a_1, a_2, a_3) \oplus (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3)$ (2.5)

Subtraction $-(a_1, a_2, a_3) - (b_1, b_2, b_3) = (a_1 - b_1, a_2 - b_2, a_3 - b_3)$ (2.6)

Multiplication $\otimes (a_1, a_2, a_3) \otimes (b_1, b_2, b_3) = (a_1 b_1, a_2 b_2, a_3 b_3)$ (2.7)

Inverse: $(a_1, a_2, a_3)^{-1} = \left(\dfrac{1}{a_3}, \dfrac{1}{a_2}, \dfrac{1}{a_1}\right)$ (2.8)

Division: $\div (a_1, a_2, a_3) \div (b_1, b_2, b_3) = \left(\dfrac{a_1}{b_3}, \dfrac{a_2}{b_2}, \dfrac{a_3}{b_1}\right)$ (2.9)

Let $\tilde{A} = (a_1, a_2, a_3, a_4)$ represent the trapezoidal fuzzy number, where $[a_1, a_4]$ is the support of $\tilde{A}$ and $[a_2, a_3]$ is the modal set.

$$\tilde{\mu}_A(u) = \begin{cases} 0, u \le a_1 \\ \dfrac{u-a_1}{a_2-a_1}, u \in [a_1, a_2] \\ 1, u = a_2 = [a_3, a_4] \\ \dfrac{a_4-u}{a_4-a_3}, u \in [a_2, a_3] \\ 0, u \ge a_4 \end{cases} \tag{2.10}$$

Let $\widetilde{A}=(a_1,a_2,a_3,a_4)$and $\widetilde{B}=(b_1,b_2,b_3,b_4)$ represent the trapezoidal fuzzy number. Similarly, the proposed fuzzy numbers can be mathematically expressed as in the same way as shown in Equations (2.4), (2.5), (2.6), (2.7), (2.8) and (2.9). However, these equations can be extended to accommodate scenarios where trapezoidal fuzzy number approach is applied as represented in Equations (2.11) to (2.16).

Change of sign: $-(a_{1,}a_2,a_3,a_4)=(-a_4-a_3,-a_2-a_1)$ (2.11)

Additional:

$\oplus(a_1,a_2,a_3,a_4)\oplus(b_1,b_2,b_3,b_4)=(a_1+b_1,a_2+b_2,a_3+b_3+a_4+b_4)$

(2.12)

Subtraction:

$-(a_1,a_2,a_3,a_4)-(b_1,b_2,b_3,b_4)=(a_1-b_1,a_2-b_2,a_3-b_3,a_4-b_4)$ (2.13)

Multiplication:

$\otimes(a_1,a_2,a_3)\otimes(b_1,b_2,b_3)=(a_1b_1,a_2b_2,a_3b_3)$ (2.14)

Inverse: $(a_1,a_2,a_3)^{-1}=\left(\frac{1}{a_4},\frac{1}{a_3},\frac{1}{a_2},\frac{1}{a_1}\right)$ (2.15)

Division: $\div(a_1,a_2,a_3,a_4)\div(b_1,b_2,b_3)=\left(\frac{a_1}{b_4},\frac{a_2}{b_3},\frac{a_3}{b_2},\frac{a_4}{b_1}\right)$ (2.16)

According Iancu (2012) and Mamdani (1977), the degree of fulfilment defines the contribution of the rule to fuzzy set potential output values. The crisp output value can be derived from defuzzification. Other risk-based verification (RBV) studies carried out over the years involving the application of fuzzy set theory (FST) include:

- Lee, H.M. (1996) presents the application of fuzzy sets theory in the evaluation of the rate of aggregative risk in software development.
- Lee-Kwang *et al.,* (1994) present a risk assessment technique using a similarity measure between fuzzy sets and between elements.
- Lee *et al.,* (1994) propose a risk assessment methodology using the ranking fuzzy values with satisfaction function.
- De Ru *et al.,* (1996) present a methodology for modelling of the risk analysis process within a computer facility.

- Bowles and Palaez (1995) present a fuzzy logic-based technique for prioritising failures for corrective actions in a Failure Mode, Effects and Criticality Analysis (FMECA). The method allows the analysts to directly evaluate the risks associated with item failure modes using the linguistic terms employed in the criticality assessment.
- Chongfu (1996) employs fuzzy methods to calculate the risk of release, exposure to and consequence of natural urban hazards.
- Huang *et al.,* (1997) investigate the development of a new transformer fault diagnosis system through evolutionary fuzzy logic.
- Huang *et al.,* (2005) apply a fuzzy-based approach to risk assessment for track maintenance incorporated with AHP.
- Moscato (1998) applies the basic concept of fuzzy logic modelling to risk analysis in database gateway systems.
- Bonvicini *et al*., (1998) provide an application of fuzzy logic to the risk assessment of the transport of hazardous materials by road and pipeline to evaluate the uncertainties that affect both individual and societal risks.
- Tah and Carr (2000) and Wirba *et al*., (1996) outline an approach to the assessment of construction project risk by linguistic analysis using FST.
- Wang (2000) presents a subjective safety analysis-based decision-making framework for formal ship safety assessment in situations where a high level of uncertainty is involved.
- Wang *et al.,* (1995), present safety analysis and synthesis using fuzzy set modelling and evidential reasoning.
- Zolotukhin and Gudmestad (2002) illustrate the use of the fuzzy sets method by assessing the risk during the lifting of an offshore module onto a live platform and the risk during an offshore tow operation.
- Ngai and Wat (2005) outline an approach to assess the risks associated with e-commerce (EC) development using FST. A model of fuzzy risk assessment was developed to assist EC project managers and decision makers in formalising the types of thinking that are required in assessing the current risk environment of their EC development in a more simplified manner.
- Sadiq and Husain (2005) develop a methodology for an aggregative environmental risk assessment: a case study of drilling waste.

- Sadiq *et al.,* (2007) apply fuzzy logic and evidential reasoning risk analysis to water quality failures in distribution networks-risk analysis.
- Hu *et al.,* (2007) present a formal safety assessment methodology based on a relative risks model in ship navigation.
- Hsu and Chen (1996) present aggregation of fuzzy opinion under group decision-making by applying fuzzy sets and systems.
- Hadjimichael (2009) presents a fuzzy expert system methodology by which safety knowledge inherent in airline organisations is used for operational risk analysis on a flight-by-flight basis.
- Mokhtari *et al*., (2012) present a decision-support framework for risk management of seaports and offshore terminals using FST and evidential reasoning approach.
- Kuo and Lu (2013) employ a fuzzy multiple criteria decision-making (FMCDM) approach to enhance the assessment of risk for a metropolitan construction project.

2.10.2 Fuzzy rule-based approach

A fuzzy rule-based system for risk estimation in offshore wind energy development will be applied by means of knowledge representation of the data relating to the offshore wind farm development. Several algorithms for the discovery of an easily readable and understandable group of fuzzy rules will be analysed and validated. The accuracy of risk estimation and the interpretability of fuzzy rules will be discussed and evaluated.

Fuzzy rule base is an established system that can deliver a more coherent and intuitive model for evaluating risk in offshore installations and operations. It is a feasible method of assessing the risk posed by a system with inconclusive or incomplete details by the use of a fuzzy *IF-THEN* rule constructed from human understanding, in which case the principles of establishment and conclusions comprise the linguistic variables applied in the description of the risk parameters (Yang *et al.,* 2009). This is the case where probabilistic risk assessment (PRA) is not adequate for evaluating a complex system with a potential high level of uncertainties.

For instance, *IF-THEN* rules with a belief structure can be constructed to model a security risk assessment scenario. An *IF-THEN* rule may be developed as follows:

If Threat Likelihood is “Medium”, system Vulnerability is “High” and Impact or consequent severity is “Serious”, then security risk is “High”.

Due to the high degree of uncertainty associated with the expert judgement when forming or representing a relationship between premise and conclusion, or rather, when the evidence available is not adequate to support any viable decision, or when the expert is not 100% sure whether to believe in an assumption but only to a certain degree of credibility; it is possible to have fuzzy rules with a belief structure as follows:

If Threat Likelihood is “Medium”, system Vulnerability is “High” and Impact or consequent severity is “Serious”, then security risk estimate is {(Very Low, 0), (Low, 0),(Medium, 0.6), (High, 0.4), (Very High, 0)}.

In light of the above, {(Very Low, 0), (Low, 0), (Medium, 0.6), (High, 0.4), (Very High,0)} is a belief distribution of the security risk evaluation where experts are 60% sure that the security risk level is Medium, and 40% sure that the security risk level is High.

2.10.3 Fuzzy analytic hierarchy process (FAHP)

The analytic hierarchy process (AHP) is a methodical technique for organising and analysing complex decisions by using criteria of multiple options structured into a hierarchy system, which includes relative values of all possible criteria, and compares alternatives for each particular criterion with defined average importance of alternatives. The decision-making process of such a complex analytical process simply involves a mathematical and psychological analysis. Thomas L. Saaty developed this system in the 1970s and it has been extensively applied and improved over the years (Saaty, 1980).

Fuzzy Analytic Hierarchy Process (FAHP) is a practical methodology for handling multiple-criteria decision-making (MCDM) in fuzzy environments and has been found to be a very useful application in recent years. Some of the founding works completed in FAHP include one carried out by Laarhoven and Pedrycz (1983) which compared fuzzy ratios described by triangular membership functions. Buckley (1985) subsequently determined the fuzzy priorities of comparison ratios whose membership functions were trapezoidal by application of geometric mean. Boender *et al*., (1989) later improved upon Buckley's approach and came up with a more robust method for the normalisation of local priorities. Their work further revealed that the triangular approximation of fuzzy operations provides fuzzy solutions with a much smaller spread than Buckley's (1985) method.

Chang (1996) developed a new approach, which involved the application of triangular fuzzy numbers for comparison scales and use of extent analysis approach for the synthetic extent values of pairwise comparisons. Cheng (1994) developed a fuzzy judgement matrix using a continuous judgement scale in which a positive bounded closed fuzzy number can represent every element. He also presented a new algorithm for evaluating naval tactical missile systems using FAHP based on grade values of membership functions. Kahraman *et al*., (1998) also proposed a fuzzy weighted evaluation methodology by applying objective and subjective measures. Deng (1999) proposed a simpler and easier fuzzy approach for dealing with qualitative multi-criteria analysis complex cases.

Lee *et al.* (1999) introduced the concept of comparison interval scales and proposed a methodology based on stochastic optimisation to achieve global consistency and to accommodate the fuzzy nature of the comparison process. Cheng *et al*., (1999) proposed a new method for evaluating weapon systems using AHP based on linguistic variable weights. Zhu *et al.,* (1999) unveiled the extent analysis method and demonstrated some practical examples of FAHP. Leung and Cao (2000) proposed a fuzzy consistency definition with consideration of a tolerance deviation for alternatives in FAHP.

According to Wang and Chin (2011), the extent analysis was found to be invalid, as the weights derived by this method do not represent the relative importance of decision criteria or alternatives. Their study further revealed that the fuzzy preference programming (FPP) based nonlinear priority approach equally attributed substantial drawbacks with the potential to produce multiple conflicting priority vectors for a fuzzy pairwise comparison matrix, capable of resulting in entirely different conclusions. Wang and Chin (2011) proposed a logarithmic fuzzy preference programming (LFPP) based methodology for fuzzy AHP priority derivation in order to address these drawbacks and provide a valid yet practical priority method for FAHP. In 2002, Mikhailov proposed the application of AHP in combination with the FPP approach for selection of a company for a partnership process (Mikhailov, 2002).

Other applications of AHP and FAHP include fuzzy group decision-making for selection of computer integrated manufacturing systems, as proposed by Bozdag *et al.,* (2003). Kwong and Bai (2003) presented a methodology for determining the important weights for customer requirements by the application of FAHP with an extent analysis approach. In 2003, multi-criteria supplier selection using fuzzy AHP was proposed by Kahraman *et al.,* (2003). A fuzzy optimisation model for the planning process was introduced in 2004 by applying an analytic network approach (Büyüközkan *et al.,* 2004). Erensal *et al*., (2006) proposed a methodology for determining key capabilities in technology management using fuzzy AHP. Project risk evaluation using a fuzzy analytic hierarchy process was proposed by Tüysüz and Kahraman (2006). Chan and Kumar (2007) presented research entitled Global Supplier Development by considering risk factors using a fuzzy extended AHP-based approach.

FAHP will be applied in this research in order to obtain the weight of each risk item and synthesise the risks of a hierarchical risk framework from the bottom level to the top level. The individual risk factors that make up the cumulative risk factor of the overall risk level are all taken into consideration in order to properly represent the appropriate risk level in wind farm project development. The upside of FAHP is its adaptability and flexibility to be integrated with different analytical approaches such as fuzzy risk assessment (FRA) techniques in risk analysis. Hence, FAHP analysis can generate weighting factors to represent the primary risk factors within each category of risk factors.

Although the AHP methodology is a generally accepted tool for analysing complex multi-criteria decision-making, its fundamental downside remains the fact that it uses a scale of one to nine (1-9), which is unable to handle uncertainty in comparison of the attributes and does not take into account experts' imprecise subjective judgements associated with uncertainty. In reality, experts are often more confident in giving judgements by using qualitative descriptors. Moreover, AHP is mainly applied to nearly crisp (non-fuzzy) decisions by a standardised estimation scheme, which adopts crisp numbers to represent the relative importance between alternatives.

FAHP is built upon a similar framework as AHP in performing rigorous analysis by using fuzzy ratios instead of conventional crisp values. This approach ensures that the existence of any uncertainty in the risk assessment process is properly taken care of at all levels through the system. Mikhailov's method will be employed in the subsequent chapter in order to obtain the weights of risk items at different levels of a hierarchical structure (Mikhailov, 2003). Mikhailov's method involves a fuzzy group prioritization method for deriving group priorities/weights from fuzzy pairwise comparison matrices. This method investigated the different importance weights of multiple DMs by extending the Fuzzy Preferences Programming Method (FPP). Unlike other known fuzzy prioritization techniques, the proposed technique is able to derive crisp weights from incomplete and fuzzy set of comparison judgments and doesn't require additional aggregation procedures. The elements of the group pairwise comparison matrices can be represented as fuzzy numbers rather than exact numerical values in order to model the uncertainty and imprecision in the DMs' judgments (Mikhailov, 2003).

2.10.4 Evidential reasoning theory

The evidence theory (ET) was first presented in the early 1990s to handle the multi-attribute decision-making (MADM) scenarios under uncertainties. It has helped in the development of a novel belief decision-matrix, which can be used to formulate a unique attribute aggregation process based on the Dempster rule of combination (Liu and Gong, 2011; Fu and Yang, 2010; Sen and Yang, 2012). It will be difficult, if not impossible, to make a sound decision under uncertainties without considering all the possible attributes or possible criteria in the MADM (Belton and Stewart, 2002; Yang and Xu, 2002a). In this case, probabilistic theory (PT) may be employed (Pearl, 2014) to represent objective frequency (Pate-Cornell, 1996) or subjective degree of belief (Ng and Abramson, 1990), based on available evidence; and FST can also be employed to handle the imprecise information with fuzzy membership functions (Zadeh, 1965; 1973) (refer to subsection 2.12.1 for full details).

The two major limitations identified in the PT method are the fact that (a) the ignorance is not adequately catered for (Sentz and Ferson, 2002). The ignorance element is represented by assigning equal probabilities to all possible states; as such, the ignorance and randomness are not clearly differentiated. The reason for this failure in the PT approach is that the equal beliefs can either be attributed to complete ignorance or to an equal belief in all possible states; (b) the reinforcement of belief in one state is associated with a decrease of belief in other states. As such, the sum of the probability of all possible states in PT must be equal to 1. This is not a true representation of all cases in a real-life scenario (Zadeh, 1965). For instance, a positive result of a patient's test in a medical diagnosis may increase the belief that the patient has some illness; nonetheless, this will not necessarily decrease the belief that the patient has any other illness.

Because of the above two limitations of PT, Dempster-Shafer theory of evidence (D-S theory) was proposed (Shafer, 1976) as a general framework in representing and reasoning the uncertainty associated with the PT approach. However, irrational results may be produced when D-S theory is applied in an MCDM problem of aggregating conflicting evidence (Murphy, 2000).

Dempster (1967) and Shafer (1976) originally proposed the Dempster-Shafer theory of evidence, or the D-S theory, as a mathematical tool for analysing incomplete and random information. The proposals upon which the D-S theory are based are (a) the proposal of obtaining degrees of belief for one question (hypothesis) from subjective probabilities for a related question (hypothesis), and (b) Dempster's rule for combining such degrees of belief when they are based on independent pieces of evidence (Shafer, and Pearl, 1990; Shafer, 1992).

A typical example of the D-S theory evidence may be illustrated in the murder investigation approach adapted from Beynon *et al.,* (2000). Mr. Jones has been murdered, and it is confirmed that the murderer was one of three suspicious notorious killers, namely Peter, Paul and Mary. Now, we have a set of hypotheses, i.e. a "frame of discernment", Θ = {Peter, Paul, Mary}. If the only available evidence is a witness who is 80% sure that the killer is a man, i.e. *P* (man) = 0.8. The measures of uncertainty, taken collectively in D-S theory, are referred to as a "basic probability assignment" (BPA). Therefore, $bpa = m_1\ of$ 0.8 and is expressed as $m_1(\{Peter, Paul)\} = 0.8$. Given that there is no information on the remaining probability, the whole frame of discernment will be apportioned to it, i.e.

$$m_1(\{Peter, Paul, Mary)\} = 0.2 \qquad (2.17)$$

The various BPAs may be collected and used to communicate general belief. The BPAs can also be collected from various sources and be combined to further ascertain the confidence of the frame. For instance, if additional evidence becomes available that a witness has come up with 60% confidence that Peter was out of the country at the time of the murder, then, the BPA will be $m_2(\{Paul, Mary)\} = 0.6$. As previously considered, there is no other information about the remaining probability. Hence, it is allocated to the whole frame of discernment, i.e.

$$m_2(\{Peter, Paul, Mary)\} = 0.4\ . \qquad (2.18)$$

The two sources of evidence gathered in the murder case above are completely independent in nature. Their assessments of the same scenario provide similar but broader information, which will be aggregated in order to arrive at a conclusion. A complex multiplication rule can be used to aggregate the two pieces of independent information, as shown in Table 2.2.

Table 2.2 Combination of two pieces of evidence (Parsons, 1994)

$\otimes_{\cap}$	$m_1(\{Peter, Paul)\} = 0.8$	$m_1(\{Peter, Paul, Mary)\} = 0.2$
$m_2(\{Paul, Mary)\} = 0.6$	$m_3(\{Paul)\} = 0.48$	$m_3(\{Paul, Mary)\} = 0.12$
$m_2(\{Peter, Paul, Mary)\} = 0.4$	$m_3(\{Peter, Paul)\} = 0.32$	$m_3(\{Peter, Paul, Mary)\} = 0.08$

Summarily, when the two probability assignments are combined, the resultant accruing belief of their intersection will be a product of M_1 and M_2 where M_1 and M_2 are the masses from the probability assignments m_1 and m_2; and the intersecting sets are A and B. This is mathematically expressed as $m_1(\{A\}) = M_1$ and $m_2(\{B\}) = M_2$.

$$m_3(\{Paul, Mary\}) \tag{2.19}$$
$$= m_3(\{Peter, Paul, Mary\}) \times m_2(\{Paul, Mary\})$$
$$= 0.2 \times 0.6$$
$$= 0.12$$

The above new piece of evidence has a wider distribution of probabilities to varying subsets of frame of discernment. This evidence can be aggregated in order to identify some level of belief. The belief of any given set is the sum of all the likely probabilities of all the subsets of that set. For instance:

$$Bel(\{Peter, Paul, Mary\}) \tag{2.20}$$
$$= m_3(\{Peter\}) + (\{Paul\}) + (\{Paul, Peter\})$$
$$= 0 + 0.48 + 0.32$$
$$= 0.8$$

Complex approach of D-S theory

This is slightly different from the probability theory used in the above basic concept. Assuming Θ $= \{h_1, h_2 ..., h_n\}$ is a finite set of frame of discernment (hypothesis), a BPA will be represented as a function m: $2^{\Theta} \rightarrow [0, 1]$

Showing that:

$$m\ (\emptyset) = 0 \tag{2.21}$$

and

$$\sum_{x \in 2^{\Theta}} m(x) = 1 \tag{2.22}$$

where Θ represents the frame of discernment and 2^{Θ} represents number of elements in the power set including all possible subsets obtainable in the frame of discernment, Θ, and Ø is the empty set.

$2^{\Theta}$is a power set of Θ comprising all possible subsets, i.e. $2^{\Theta} = \{Ø, h_1\},... \{h_n\}, \{h_1 \cup h_2\}, ..., \{h_1 \cup h_n\},..., \Theta\}$.

Let *x* be a subset of the framework of discernment Y for which m (*x*) is non zero; this will be referred to as the focal element and represents the exact belief in the subset *x*. The assigned probability is also called the probability of mass, denoted as m (*x*). The probability assigned to *{Ø* represented as m (*Ø*) is known as the degree of ignorance. Based on the BPA as described above, other measures of confidence are derived. The measure of belief is mapping $Bel: 2^{\Theta} \rightarrow [0,1]$ such that for any subset A of Θ

$$Bel(A) = \sum_{B \subseteq A} m(B) \text{, for all } A \subseteq \Theta \tag{2.23}$$

Therefore, *m* can be recovered as proposed by Shafer (1976) such that it represents the confidence that the value lies in A or any of its subsets. A plausibility measure is a function represented as $Plaus: 2^{\Theta} \rightarrow [0,1]$, which is defined as

$$Plaus(A) = \sum_{B \cap A \neq Ø} m(B) \text{, for all } A \subseteq \Theta \tag{2.24}$$

$Plaus(A)$ denotes the extent of failure to disbelieve A; and measures are interrelated, mathematically expressed as $Bel(A) = 1 - Plaus(\neg A)$ and $Palus(A) = 1 - Bel(\neg A)$, where $\neg A$ refers to its complement as "not A", whereas $Bel(\neg A)$ is also expressed as doubt in A. According to Shafer (1976), the difference between the belief and the plausibility of set A describes the ignorance of the assessment for set A.

In the event of evidence being available from more than one source, Dempster's rule is used to combine them. It assumes that the sources of evidence are independent; hence, it applies the orthogonal sum approach to combine the multiple assigned masses: $m = m_1 \oplus m_2 \oplus ... m_k$, where '$\oplus$' represents the operator combination of when two probability masses are assigned, $m_1 \text{ and } m_2$. The $m_1 \text{ and } m_2$ represent the BPA associated with $Bel_1 \text{ and } Bel_2$ where $Bel_1 \text{ and } Bel_2$ are independent;

therefore, the function $m_1 \oplus m_2 : 2^{\Theta} \rightarrow [0,1]$. Hence, Dempster's rule of combination is defined as follows:

The combination process starts by combining two mass functions and the result is later combined with another mass function and so on until the whole combination process is completed. Dempster's rule for combining two mass function m_1 (A_1) and m_2 (A_2) is usually expressed as:

$$m(A) = \begin{cases} 0 & \text{when } A = \emptyset \\ \dfrac{\sum_{A_1 \cap A_2 = A} m_1(A_1) \times m_2(A_2)}{1 - \sum_{A_1 \cap A_2 = \emptyset} \mathrm{m}_1(A_1) \times m_2(A_2)} & \text{when } A \neq \emptyset \end{cases} \tag{2.25}$$

where $\sum_{A_1 \cap A_2 = \emptyset} \mathrm{m}_1(A_1) \times m_2(A_2) = k$ and $k = \deg ree\, of\ conflict$,

and the denominator $1-k$ emphasises the total agreement between the various pieces of evidence and ignores any potential conflict among them through dividing the original combination by $1-k$ (Sentz and Ferson, 2002) . The constant, k is a measure of the degree of conflict between the sources of evidence; k is crucial in the combination as it is considered the normalisation factor. The measure of the degree of conflict simply represents the mass assigned to the empty set if the masses were not normalised. This is particularly crucial for assessing the quality of the combination. For example, if the degree of conflict is high, it may result in difficult or questionable decision-making; in such a case, $k \approx 1$.

Most researchers including Zadeh (1984) have criticised the application of normalisation as it often produces counter discerning results given that most of the masses before normalisation and after combination are assigned to the empty set (Parsons, 1994; Dubois, 1988).

An illustrative example of the limitations of D-S theory:

In the case of two pieces of evidences, such as (1) the weather in Liverpool will be freezing today, (2) the temperature in Liverpool this morning is between 0^0C and 4^0C, and sunshine is expected all day.

Assuming the set A is assigned a probability of 99% and set B is assigned a probability of 1%, this shows that the probability of B is low or unlikely.

The above two pieces of evidence are conflicting:

$$m_1(A)=0.99, m_1(B)=0.01, m_1(C)=0$$

$$m_2(A)=0, m_2(B)=0.01, m_2(C)=0.99$$

If the D-S theory combination approach is applied to the above pieces of evidence (see Table 2.3 below), B will become a certain occurrence with an assigned probability of 100%, which contradicts the conventional approach and seems to make little or no sense.

Table 2.3 Combination of conflicting evidence by application of the D-S combination rule (Wang *et al.,* 2006)

Belief structure	A	B	C
m_1	0.99	0.01	0
m_2	0	0.01	0.99
$m_1 \oplus m_2 (before\ normalisation)$	0	0.0001	0
$m_1 \oplus m_2 (after\ normalisation)$	0	1	0

ER methodology is comprised of three main features, namely belief structure for modelling various types of uncertainty (Yang and Singh,1994), rule- and utility-based information transformation techniques (Yang, 2001), and the ER algorithm for information aggregation (Yang, 2021).

Belief structure: belief structure represents an expectation which was fundamentally created to model a subjective scenario under uncertainty (Yang and Singh, 1994; Sen and Yang, 2012). In general, ER methodology is classed to be in the category of value/utility-based methods. However, its difference from the conventional approaches is that it has a belief structure to represent the measurable criteria as a distributed assessment rather than a single number. For instance, the distributed assessment of the performance of a 7-megawatt wind turbine generator (WTG) could be {(Excellent, 20%), (Good, 40%), (Average, 30%), (Poor, 5%), (Worst, 5%)}, which means the performance of the WTG is assessed to be Excellent with 20%of belief degree, Good with 40% of belief degree, Average with 30% belief degree, Poor with 5% of belief degree, and Worst with 5% of belief degree. Through this type of belief structure, the ER methodology is able to handle MCDM problems with uncertainties and information of a hybrid nature.

A similar example may be applied in assessment of the quietness of a 7-megawatt WTG: an expert's opinion concludes that the quietness of the WTG is 50% good and 30% excellent. This statement represents the certainty of how quiet the WTG is or how confident the expert opinion is. Here, the quietness of the WTG is distinctively described by the expert's evaluation grades, i.e. 'good' or 'excellent', and the values of 50 and 30 represent the degrees of belief indicating the extents to which the respective grades are assessed. Mathematically, this can be expressed as:

$$S(quietness) = \{(good, 0.5), (excellent, 0.3)\},$$

where $S(quietness)$ represents the state of the WTG quietness; the values 0.5 and 0.3 show the degrees of belief of 50% and 30% respectively.

The uncertainties referred to above can be categorised into three main types, as described below:

- Lack of data scenario: if there is no data available to assess a particular criterion, then the belief degrees in the distributed assessments of that criterion will be 0.
- Partial data scenario: if the data for assessing a particular criterion is only partially available, then the incomplete assessments of that criterion mean that

the belief degrees in the distributed assessment of that criterion will be between 0% and 100%.

- Lack of generally acceptable probabilities: if there are no clearly defined probabilities widely accepted, the criterion becomes random in nature, which results in personal judgements in the form of probability distribution. Generally, the distributed assessment in ER is able to address such subjective judgements by transforming the probability distribution into degree of belief distribution of that criterion.

The hybrid nature of the information referred to above may be described in the following ways:

- Combination of data from incommensurable criteria;
- Combination of data from qualitative and quantitative criteria;
- Combination of data from probabilistic and deterministic criteria.

This approach has been broadly applied in MCDM problems such as in design assessment of new products (Chin *et al.,* 2009), quality function deployment (Chin *et al.,* 2009), environmental impact assessment (Wang *et al.,* 2006), pipeline leak detection (Xu *et al*., 2007), maritime security assessment (Yang *et al.,* 2009), fault prediction (Si *et al.,* 2010), engineering system safety analysis (Liu *et al.,* 2005), etc.

2.10.4.1 Rule-based information transformation techniques

Defined evaluation grades for any particular basic attribute are useful in the facilitation of collection of raw data. These predefined grades need to be interpreted and transformed such that they can be applied in the assessment of general attributes (Yang, 2001). These transformations are highly opinionated, as they are formed based on the decision maker's knowledge and experience, simply referred to as 'rules'. Rule-based transformation can be applied to both qualitative and quantitative data assessments.

2.10.4.2 Transformation technique application in qualitative assessment

In this type of assessment, various words may be used to describe a particular situation or the equivalence of that situation; this may be achieved by the application of equivalence rules. For instance, if describing a WTG sound as ‘very noisy’ translates into the quality of the WTG being ‘poor’, then using ‘very noisy’ as the evaluation grade in assessment of WTG quietness can be said to be equivalent to using ‘poor’ as the evaluation grade in quality assessment.

In the same way, if the evaluation grade ‘noisy’ is equivalent to ‘indifferent’, ‘normal’ to ‘average’, ‘quiet’ to ‘good’, and ‘very quiet’ to ‘excellent’, then the set of evaluation grades can be represented as {very noisy, noisy, normal, quiet, very quiet} in the assessment of the WTG’s quietness to ‘good’, and ‘very quiet’ to ‘excellent’ will be equivalent to the set of evaluation grades {poor, indifferent, average, good, excellent} in the assessment of the WTG’s quality.

Assuming $H_{n,i}$ of a basic set H^i is defined as $H^i = \{H_{n,i}, n = 1,..., N_i\}$, and represents a grade $H_{n,}$ of set H defined as $H = \{H_{n,}, n = 1,..., N\}$,

where N is distinctive (mutually exclusive) evaluation grades $H_n(n = 1,...,N)$ and

$$H_{n,i} \text{ means } H_{n,},\ n = 1,...,N \tag{2.26}$$

If $N = N_i$, the basic set H^i will be equivalent to the general set H.

Assuming H^i is equivalent to H and $N = N_i$, then a general assessment may be represented as

$$S(e_i) = \{(H_n, \beta_{n,i}), n = 1,..., N\} \tag{2.27}$$

which will be equivalent to a basic assessment represented as:

$$S^i(e_i) = \{(H_{n,i}, \gamma_{n,i}), n = 1,..., N\} \tag{2.28}$$

If only and if

$$\beta_{n,i} = \gamma_{n,i}, n = 1,..., N. \tag{2.29}$$

Generally speaking, $N = N_i$ may not always be the case and sometimes $H_{n,i}$ in H^i may not really represent any single grade in H but rather represent a number of grades in some degrees. For example, a heavily vibrating WTG could mean that the quality of the WTG is between 'poor' and 'indifferent' in terms of vibration evaluation grades. If a grade $H_{n,i}$ in H^i means a grade H_l in H to a degree of $\alpha_{l,n}(l=1,...,N)$ with $0 \leq \alpha_{l,n} \leq 1$ and $\sum_{l=1}^{N} \alpha_l = 1$, therefore $H_{n,i}$ is equivalent to

$$\{(H_l, \alpha_{l,n}), l = 1...,N\}. \quad (2.30)$$

Based on the above definition, the decision maker needs to provide equivalent rules described in Equation (2.30) and Equation (2.26). This simply implies that the underlying utility of $H_{n,i}$ is said to be the expected utility of the expectation $\{(H_l, \alpha_{l,n}), l = 1,...,N\}$ or $u(H_{n,i}) = \sum_{l=1}^{N} \alpha_{l,n} u(H_1)$

If $\{(H_l, \alpha_{l,n}), l = 1...,N\}$ is a basic assessment of $S^i(e_i)$ as defined above and $S^i(e_i) = \{(H_{n,i}, \gamma_{n,i}), n = 1,...,N\}$ is equivalent to the general assessment of $S(e_i)$ in Equation $S(e_i) = \{(H_n, \beta_{n,i}), n = 1,...,N\}$, if and only if

$$\beta_{l,i} = \sum_{n=1}^{N_i} \alpha_{l,n} \gamma_{n,i}, l = 1,...,N \quad (2.31)$$

2.10.4.3 Transformation technique application in quantitative assessment

As described in subsection 2.11.2 of this chapter, the quantitative basic attribute involves data evaluation using numerical values. In the case of the application of the transformation technique, the process relies on the decision maker to establish the rules that will be transformed into values. The transformed quantitative attributes as well as the qualitative attributes can then be aggregated in order to make an informed decision. For instance, 80% capacity factor of a power station may mean that the efficiency of the power station is 'excellent' as far as efficiency. Similarly, 50%, 45%, 30% and 20% could mean that the efficiency of the power station is 'good', 'average', 'indifferent' and 'poor' respectively. This can be represented mathematically, assuming a value $h_{n,i}$ is used for an attribute e_i and assessed to be equivalent to evaluation grade $H_{n,}$,

where $h_{n,i} = H_n(n = 1,...,N)$ (2.32)

Assuming e_i indicates a 'profit' attribute, which means that a larger value represented as $h_{n+1,i}$ is considered more profitable than a smaller value, $h_{n,i}$. Therefore, let $h_{N,i}$ and $h_{1,i}$ be the largest and the smallest feasible values respectively. In this case, a value h_j on e_i may be represented as equivalent of the following expectation:

$$S^i(h_j) = \{(h_{n.i}, \gamma_{n,j}), n = 1,..., N\}, \tag{2.33}$$

where,

$$\gamma_{n,j} = \frac{h_n + 1,_i - h_j}{h_n + 1,_i - h_{n,i}}, \quad \gamma_n + 1,_j = 1 - \gamma_{n,j} \qquad \text{if } h_{n,i} \le h_j \le h_n + 1_{,} i, \text{ then} \tag{2.34}$$

$$\gamma_{k,j} = 0 \text{ for } k = 1,..., N, k \ne n, n+1 \tag{2.35}$$

Summarily, h_j as shown in Equation (2.33) is calculated by the expected value of $S^i(h_j)$ denoted by $h_j = E(S^i(h_j))$;

whereas,

The utility of h_j is calculated by $u(h_j) = u(S^i(h_j))$.

Similarly, in the equivalence rule shown in Equation (2.32), a value h_j can be represented as;

$$S(h_j) = \{(H_n \beta_{n,j}), n = 1,..., N\} \tag{2.36}$$

where,

$$\beta_{n,j} = \gamma_{n,j}, \ n = 1,..., N. \tag{2.37}$$

As previously explained, it may not always be possible to have a quantitative attribute with a single variable in a real-life decision-making situation. This scenario can be represented mathematically as the following distribution,

$$S^i(e_i) = \{(h_{j,} p_j), j = 1,..., M_i\}, \tag{2.38}$$

where $h_j (j = 1,..., M_i)$ represent possible values of e_i and p_j is the probability that e_i takes the value h_j; given that

$\sum_{j=1}^{M_i} p_j \leq 1$. This simply means that the attribute e_i has a value of h_j with potential probability of $p_j (j = 1,..., M_i)$. Assuming that e_i takes a single value, h_j, as shown in the above Equation (2.38), then $p_j = 1$ and $p_l = 0$ $(l = 1,...M_i, l \neq j)$.

Considering the equivalence rule presented in the above Equation (2.32), $S^i(e_i)$ in Equation (2.38) is equivalent to the expectation using the general evaluation grade set as follows;

$$S(e_i) = \{(H_{n,} \beta_{n,i}), n = 1,..., N\} \text{ with } \beta_{n,i} = \tilde{\gamma}_{n,i} \quad (2.39)$$

2.10.4.4 Utility-based information transformation technique

The rule-based information transformation as explained above is applied to both qualitative and quantitative data assessments in order to establish unified equivalence rules. However, the explicit estimation of the utilities was not required. In the event that the explicit estimation of the utilities is required, then the utility-based information transformation can be applied. In the context of the ER framework, utilities for both the qualitative and quantitative attributes can be explicitly estimated.

2.10.4.5 Utility estimation in the ER framework

Assuming a_l is assessed on the qualitative attribute of e_i with an expectation that $S(e_i(a_l))$, where

$$S(e_i(a_l)) = \{(H_n, \beta_{n,i}(a_l), n = 1,..., N\} \; i = 1,..., L, \; l = 1,..., M, \quad (2.40)$$

The expected utility of the expectation is derived from the utility of assessment as shown in the Equation below:

$$u(S(y(a_l))) = \sum_{n=1}^{N} u(H_n)\beta_n(a_l) \quad (2.41)$$

The utility interval for $S(e_i(a_l))$ can be estimated by the application of these mathematical expressions:

$$u_{\max}(a_l) = \sum_{n=1}^{N-1} \beta_n(a_l)u(H_n) + (\beta_N(a_l) + \beta_H(a_l))u(H_N), \quad (2.42)$$

$$u_{\min}(a_l) = (\beta_1(a_l) + \beta_H(a_l))u(H_1) + \sum_{n=2}^{N} \beta_n(a_l)u(H_n), \quad (2.43)$$

Preferences suggested by the decision maker may be used to estimate $u(H_n)$. In the event that the decision maker has no preferences, it will be assumed that the utilities of the evaluation grades are distributed equidistantly in the normalised utility space, such that $u(H_n) = (n-1)/(N-1)(n = 1,...,N)$. Alternatively, the probability assignment method may be applied for the utility estimation (Keeney and Raiffa, 1976; Farguha, 1984; Winston and Goldberg, 2004).

From equations (2.42) and (2.43), the minimum, maximum, and average utilities of $(U(E))$ can be estimated. Thus, mathematically represented as follow (Yang, 2001):

$$T_{\min}(U(E)) = \sum_{n=2}^{N} \beta_n u(H_n) + (\beta_1 + \beta_H)u(H_1) \quad (2.44)$$

$$T_{\max}(U(E)) = \sum_{n=1}^{N-1} \beta_n u(H_n) + (\beta_N + \beta_H)u(H_N) \quad (2.45)$$

$$T_{average}(U(E)) = \frac{T_{\min}(U(E)) + T_{\max}(U(E))}{2} \quad (2.46)$$

As already mentioned above, a multi-attribute decision analysis can be represented as follows:

$S^i(e_i) = \{(H_{n,i}, \gamma_{n,i}),\ n = 1,..., N\}$ (for qualitative attributes) (2.47)

$S^i(e_i) = \{(h_{n,i}, \gamma_{n,i}),\ n = 1,..., N_i\}$ (for quantitative attributes) (2.48)

The utility-based technique can be used to evaluate both complete and incomplete data in order to achieve a unified result.

Let the general attribute be y and the utilities of the evaluation grades are represented as $H_j(j = 1,..., N)$ and are estimated and denoted by $u(H_j)(j = 1,..., N)$. Assuming y is an intermediate attribute, its utilities can be estimated using the assignment of probability or calculated by applying the following mathematical expressions: Equation 2.49 and 2.52.

$$\underline{u}(H^i) = \underline{A}_i{}^T \times \underline{u}(H), \tag{2.49}$$

where,

$$\underline{A}_i{}^T = \begin{array}{c|c} & H_{1,i} \quad H_{2,i\ldots} \quad H_{N,i} \\ \begin{array}{c} H_1 \\ H_2 \\ \\ \\ \\ H_N \end{array} & \begin{bmatrix} \alpha,1 & \alpha_{1,2\ldots} & \alpha_{1,}N_i \\ \alpha_{2,1} & \alpha_{2,2}\cdots & \alpha_2 N_i \\ . & & \\ . & & \\ . & & \\ x_{N,1} & \alpha_{N,2}\ldots\alpha_{N,N_i} & \end{bmatrix} \end{array} \tag{2.50}$$

$\underline{A}_i$ is referred to as the transformation matrix

The transformation process is not dependent upon the individual alternative assessments. Therefore, the transformation is consistent and easily transformed from one form to the other.

Considering Equation 2.49, the utilities of the basic evaluation can be calculated from the application of this mathematical expression for the utilities of the general evaluation grades as follows: $u(H_n)(n = 1,\ldots,N)$. The process of transformation is considered irrational if an incomplete assessment is transformed to complete assessment and vice versa.

Similarly, $\underline{u}(h^i) = \underline{A}_i \times \underline{u}(H) = \underline{u}(H)$

(2.51)

where, $\underline{b}$ *and* $\underline{u}(H)$ can be evaluated using the following Equation:

$$\underline{b} = \begin{bmatrix} \beta_{1,i} \\ \beta_{2,i} \\ . \\ . \\ . \\ \beta_{N,i} \end{bmatrix}, \quad \underline{A}_i{}^T = \begin{array}{c|c} & H_{1,i} \quad H_{2,i\ldots} \quad H_{Ni,i} \\ \begin{array}{c} H_1 \\ H_2 \\ \\ \\ \\ H_N \end{array} & \begin{bmatrix} \alpha_{1,1} & \alpha_{1,2\ldots} & \alpha_{1,}N_i \\ \alpha_{2,1} & \alpha_{2,2}\cdots & \alpha_2 N_i \\ . & & \\ . & & \\ . & & \\ x_{N,1} & \alpha_{N,2}\ldots\alpha_{N,N_i} & \end{bmatrix} \end{array}, \quad \underline{r}_i = \begin{bmatrix} \gamma_{1,i} \\ \gamma_{2,i} \\ . \\ . \\ . \\ \gamma_{Ni,i} \end{bmatrix}, \tag{2.52}$$

Also,

$$\underline{u}(H^i) = \begin{bmatrix} u(H_{1,i}) \\ u(H_{2,i}) \\ . \\ . \\ . \\ u(H_{N,i}) \end{bmatrix}, \ \underline{u}(H) = \begin{bmatrix} u(H_1) \\ u(H_2) \\ . \\ . \\ . \\ u(H_N) \end{bmatrix}, \tag{2.53}$$

However, considering $u(H_j)(j=1,...N)$ and $u(H_{n,i})$ or $u(h_{n,i})$ $(n=1,...N_i)$, the original assessment, $S^i(e_i)$, can be transformed to an expectation equivalence of $S(e_i)$ as follows:

$S(e_i) = \{(H_j, \beta_{j,l}), \ j=1,...,N\}$

where,

$$\beta_{j,i} = \begin{cases} \sum_{n\in\pi_j} \gamma_{n,i}\tau_{j,n}, & for \ j=1 \\ \sum_{n\in\pi_j-1} \gamma_{n,i}(1-\tau_{j-1,n}) + \sum_{n\in\pi_j} \gamma_{n,i}\tau_{j,n}, & for \ 2 \le j \le N-1 \\ \sum_{n\in\pi_j-1} \gamma_{n,i}(1-\tau_{j-1,n}), & for \ j=N \end{cases} \tag{2.54}$$

For a qualitative attribute,

$$\tau_{j,n} = \frac{u(H_{j+1} - u(H_{n,i})}{u(H_{j+1}) - u(H_j)} \quad \text{Suppose } u(H_j) \le u(H_{n,i}) \le u(H_{j+1}),$$

For a quantitative attribute,

$$\tau_{j,n} = \frac{u(H_{j+1} - u(h_{n,i})}{u(H_{j+1}) - u(H_j)} \ \text{Suppose } u(H_j) \le u(h_{n,i}) \le u(H_{j+1}), \tag{2.55}$$

And

$$\pi_j = \begin{cases} \{n | u(H_j) \le u(H_{n,i}) < u(H_{j+1}), n=1,...,N_i\}, \ j=1,...,N-2, \\ \{n | u(H_j) \le u(H_{n,i}) \le u(H_{j+1}), n=1,...,N_i\}, \ j=N-1 \end{cases} \tag{2.56}$$

where,

$\pi_l \cap \pi_k = \phi(l,k=1,...,N; l \ne k)$ and $\bigcup_{j=1}^{N-1} \pi_j = \{1,2,..., N_i\}$

The equivalent matrix for a qualitative attribute e_i may be expressed as $\underline{b}_i = \underline{A}_i \times \underline{r}_i$ where $\underline{b}_i$ and $\underline{r}_i$ are defined in Equation (2.52) above and $\underline{A}_i$ is represented below as:

$$\underline{A}_i = \begin{array}{c c} & \begin{array}{ccc} H_{1,i} & H_{2,i\ldots} & H_{Ni,i} \end{array} \\ \begin{array}{c} H_1 \\ H_2 \\ \\ \\ \\ H_N \end{array} & \begin{bmatrix} \tau_{1,1} & \tau_{1,2\ldots} & \tau_{1,N_i} \\ \tau_{2,1} & \tau_{2,2\cdots} & \tau_{2N_i} \\ \cdot & & \\ \cdot & & \\ \cdot & & \\ \tau_{N,1} & \tau_{N,2\cdots} & \tau_{N,N_i} \end{bmatrix} \end{array}, \tag{2.57}$$

Note that $\tau_{j,n}$ can be derived from $\underline{b}_i = \underline{A}_i \times \underline{R}_i \underline{P}_i$.

$\underline{R}_i$ and $\underline{P}_i$ are defined in the expression below,

$$\underline{R}_i = \begin{array}{c c} & \begin{array}{ccc} h_{1,i} & h_{2,i\ldots} & h_{1,Mi,} \end{array} \\ \begin{array}{c} h_{11,i} \\ h_{2,i} \\ \\ \\ \\ h_{N,i} \end{array} & \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2\ldots} & \gamma_{1,M_i} \\ \gamma_{2,1} & \gamma_{2,2\cdots} & \gamma_{2M_i} \\ \cdot & & \\ \cdot & & \\ \cdot & & \\ \tau_{N,1} & \gamma_{N,2\cdots} & \gamma_{N,M_i} \end{bmatrix} \end{array}, \quad \underline{u}(h^i) = \begin{bmatrix} u(h_{1,i}) \\ u(h_{2,i}) \\ \cdot \\ \cdot \\ \cdot \\ u(h_{N,i}) \end{bmatrix}, \tag{2.58}$$

where, $\underline{P}_i$ is a probability of the vector and $\underline{R}_i$ is referred to as the data conversion matrix whose elements can be represented in the expression below.

$$\gamma_{n,j} = \frac{h_{n+1} - h_j}{h_{n+1,i} - h_{n,i}},\ \gamma_{n+1,j} = 1 - \gamma_{n,j}\ \text{if}\ h_{n,i} \le h_j \le h_{n+1,i} \tag{2.59}$$

and $\gamma_{k,j} = 0$ for $k = 1,\ldots,N, k \ne n, n+1$.

Therefore, the degrees of belief, $\beta_{j,i}$, can then be aggregated by applying the ER algorithm.

Summarily, information transformation could be conducted at three levels. If no preference information is available, it could be assumed that the utilities of evaluation grades for a qualitative criterion are equidistantly distributed in the normalised utility space and a linear utility function might be assumed for a quantitative criterion. At this basic level, there is no participation of the decision maker in information transformation. If the decision maker has sufficient expertise in analysing an assessment problem but is not confident in estimating utilities, the rule-based technique could be used for information transformation. If the decision maker is capable of estimating utilities, information transformation could be conducted through utility estimation.

2.10.4.6 Evidential reasoning (ER) algorithm

The main features of the ER algorithm and its approach to MCDM will be discussed in this subsection. ER is one of the many multiple-criteria decision-analysis (MCDA) methods; other MCDA methods include analytic hierarchy process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), ELimination and Choice Expressing Reality (ELECTRE), and Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE). Nevertheless, ER differs from other MCDA methods as it adopts a belief degree decision-making matrix and each element of the matrix is represented as a vector, whereas other MCDA methods are usually comprised of a single value. MCDA problems with multiple criteria-based belief degree matrix and D-S theory can be evaluated by the application of ER.

The ER algorithm is developed on the premise of multi-attribute evaluation framework and the evidence combination rule of the D–S theory (Huang and Yoon, 1981). The algorithm can be used to aggregate attributes of a multi-level structure (Sen and Yang, 2012). The rational aggregation approach satisfies certain common-sense or self-evident rules, referred to as synthesis axioms. This can be demonstrated in the ER approach to only satisfy the following synthesis axioms approximately. ER is applied to deal with MCDA problems for aggregating multiple criteria based on belief degree matrix (BDM) and D-S theory. Each criterion is assigned with belief degrees on several linguistic evaluation grades to assess the subjective uncertainties and ambiguities associated with both quantitative and qualitative criteria.

Assuming a MCDM problem has X alternatives $a_l (l = 1,...,X)$, an upper level criterion referred to as a general criterion, and L represents the lower-level measurable criteria also known as basic criteria $e_i (i = 1,...,L)$. Then, a decision-making matrix can be constructed by (a) assigning the weightings to the L basic criteria in order to express their relative importance as $W = \{w_i, i = 1,...,L\}$ and these weights are normalised as $\sum_{i=1}^{L} w_i = 1$, where $0 \leq w_i \leq 1$; (b) by assessing the alternatives on each basic criterion, and defining a set of mutually exclusive and collectively exhaustive evaluation grades as follows: $H = \{H_n, n = 1,...,N\}$.

Therefore, a MCDC case may be modelled using the following mathematical expression:

$$S(e_i(a_l)) = \{(H_n, \beta_{n,i}(a_l), n = 1,..., N\}, i = 1,..., L, l = 1,..., M,$$

(2.60)

whereas, the degree of belief is represented as $\beta_{n,i}(a_l) \geq 0$ and $\sum_{n=1}^{N} \beta_{n,i}(a_l) \leq 1$, where, $\beta_{n,i}(a_l)$ represents a degree of belief. This implies that an alternative l with respect to a criterion e_i can be assessed to an evaluation grade H_n with a degree of A belief $\beta_{n,i}(a_l)(n = 1,..., N)$. This is known as belief structure in the form of distributed assessment. An assessment is said to be incomplete unless $\sum_{n=1}^{N} \beta_{n,i}(a_l) = 1$. Similarly, $\sum_{n=1}^{N} \beta_{n,i}(a_l) = 0$ represents total ignorance of a_l on e_i.

In order to transform belief degrees into basic probabilities mass, they are multiplied by the relative weights. This allows the evidence to be combined during assessments. The following Equations can be applied for the transformation of degrees of belief:

$$m_{n,i} = m_i(H_n) = w_i \beta_{n,i}(a_l), n = 1,..., N, i = 1,..., L \tag{2.61}$$

$$m_{H,i} = m_i(H) = 1 - \sum_{n=1}^{N} m_{n,i} = 1 - w_i \sum_{n=1}^{N} \beta_{n,i}(a_l), i = 1,..., L \tag{2.62}$$

$$\overline{m}_{H,i} = \overline{m}_i(H) = 1 - w_l, i = 1,..., L \tag{2.63}$$

$$\tilde{m}_{H,i} = \tilde{m}_i(H) = w_i(1 - \sum_{n=1}^{N} \beta_{n,i}(a_l)), i = 1,..., L \tag{2.64}$$

where $m_{H,i} = \overline{m}_{H,i} + \tilde{m}_{H,i}$ and $\sum_{i=1}^{L} w_i = 1$ (2.65)

The probability mass of any individual evaluation grades is usually divided into two parts, which are represented as $\overline{m}_{H,i}$ and $\tilde{m}_{H,i}$, while the probability mass assigned to the whole set is represented by $H, m_{H,i}$, where $\overline{m}_{H,i}$ is created by the incompleteness of the assessment of the on e_i for a_l.

These basic probability masses generated from the above evaluation expressions are then aggregated into combined probability assignments with the D-S combination rule in a recursive fashion, as shown in the following expressions:

$$\{H_n\} : m_{n,I(i+1)} = K_{I(i+1)}[m_{n,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1} + m_{H,I(i)} m_{n,i} + 1], \tag{2.66}$$

$$m_{H,I(i)} = \overline{m}_{H,I(i)} + \widetilde{m}_{H,I(i),}\ n = 1,...,N, \tag{2.67}$$

$$\{H\}: \widetilde{m}_{H,I(i+1)} = K_{I(i+1)}[\widetilde{m}_{H,I(i)}\widetilde{m}_{H,i+1} + \widetilde{m}_{H,I(i)}\widetilde{m}_{H,i+1} + \overline{m}_{H,I(i)}\overline{m}_{H,i} + 1], \tag{2.68}$$

$$\{H\}: \overline{m}_{H,I(i+1)} = K_{I(i+1)}[\overline{m}_{H,I(i)}\overline{m}_{H,i+1}], \tag{2.69}$$

$$K_{I(i+1)} = [1 - \sum_{n=1}^{N}\sum_{\mathrm{t=1,t \neq n}}^{\mathrm{N}} m_{\mathrm{n,I(i)}} m_{t,i+1}]^{-1}, i = 1,..., L-1 \tag{2.70}$$

where, $m_{n,I(i)}$ represents the combined probability mass generated by aggregating the first i criterion. The assertion that the general criterion should be assessed by the evaluation grade H_n is validated by the expression $m_{n,I(i)}m_{n,i+1}$ by both the i criterion and the $(i+1)^{th}$ criterion, and the measures of the assertion for the hypothesis by the first aggregated i criteria only can be expressed as $m_{n,I(i)}m_{H,i+1}$. The relative support for the hypothesis by $(i+1)$ is measured by the expression $m_{H,I(i)}m_{n,i+1}$.

Therefore, assuming:

$$m_{n,I(1)} = m_{n,1}(n = 1,..., N), m_{H,I(1)} = m_{H,1}, \overline{m}_{H,I(1)} = \overline{m}_{H,1} \text{ and } \widetilde{m}_{H,I(1)} = \widetilde{m}_{H,1} \tag{2.71}$$

The process of aggregation is independent of the combination order of the evaluation criteria.

Normalisation of the combined probability masses into belief degrees on the general criterion is expressed as follows:

$$\{H_n\}: \beta_n = \frac{m_{n,I(L)}}{1 - \overline{m}_{H,I(L)}}, n = 1,...N, \tag{2.72}$$

Similarly,

$$\{H\}: \beta_H = \frac{\widetilde{m}_{H,I(L)}}{1 - \overline{m}_{H,I(L)}} \tag{2.73}$$

where, β_n and β_H denote the belief degree of the total aggregated basic probability masses that are assigned to the evaluation grades H_n and H. The combined assessments can be expressed as $S(y(a_l)) = \{(H_n, \beta_n(a_l)), n = 1,..., N\}$. According to Yang and Xu (2002a), $\sum_{n=1}^{N} \beta_n + \beta_H = 1$.

The ER Equations (2.67) and (2.70) represent direct application of the D-S combination rule in the belief decision matrix, process of weight normalisation and BPA of masses, as shown in Equations (2.61) to (2.64). The ER algorithms shown in Equations (2.72) and (2.73) are proposed to rationally handle conflicting evidence that satisfies common-sense rules for aggregation in MCDM (Yang and Xu, 2002a). Combined degrees of belief are largely dependent upon the assignment of the relative weights of any two pieces of evidence. This implies that various weights of evidence will result in various belief degrees. Obviously, the conclusions derived from the ER algorithm are evidently more sensible than those obtained from D-S theory (Wang *et al.,* 2006).

Evidential reasoning (ER) methodology is one of the various types of multi-criteria decision analysis (MCDA) techniques, and has attracted the interest of many risk analysts considering its ability to model qualitative and quantitative information in a unified way, aggregating probabilistic information rigorously and producing final distributed assessment results (Yang and Singh,1994). The ER methodology has been generally applied to a wide range of decision-making and risk analysis scenarios (Wang *et al*., 2013; Dymova and Sevastjanov, 2014). It is comprised of a generic conjunctive probabilistic reasoning process and combines multiple pieces of independent evidence conjunctively whilst taking into account both weights and reliabilities (Yang and Xu, 2013; Yang and Xu, 2014).

Conclusively, as the most recent development in the MCDM methodology indicates that the D-S theory was modified in the Evidential Reasoning (ER) approach in order to provide a rigorous reasoning process for aggregating conflicting information (Yang and Singh, 1994; Sen and Yang, 2012; Yang, 2001; Yang and Xu, 2002a, b), this is now considered to be a powerful alternative to overcome the above limitations of PT and D-S theory in dealing with uncertainty (Liu *et al*., 2002).

This section of the research will be aimed at developing a hierarchical risk assessment framework in combination with both qualitative and quantitative assessment statistics. Other aspects of this research will also include the introduction of basic key features of the ER rule with the following keys steps: (i) formulation of risk assessment hierarchy; (ii) representation of both qualitative and quantitative information; (ii) elicitation of attribute weights and information reliabilities; (iv) aggregation of assessment information using the ER rule; and (v) quantification and ranking of risks using utility-based transformation.

2.10.5 Bayesian network modelling

A Bayesian Network (BN) is a probabilistic graphical model (of statistical nature) or an artificial intelligence tool that is used to represent a set of random variables and their conditional dependencies through a directed acyclic graph (DAC). This simply means that the arrows that originate from a node should return to it through any path (Wang and Trbojevic, 2007). The networks are comprised of arcs and nodes, which represent causal relationships between variables and random variables respectively. The arcs are said to be directed by the 'parent' or 'causal node' to the 'child' or 'effect node'. In some cases, the nodes may possess neither parents nor children; such nodes are referred to as 'root nodes' (no parents) and 'leaf nodes' (no children).

The BNs modelling tool is used to model uncertainty in a domain or system (Nadkarni and Shenoy, 2001). Bayesian networks (BNs) are used to represent a network system of interactions between variables ranging from primary cause to outcome with all possible cause-effect assumptions made explicit. They are considered suitable for modelling systems requiring integration of multiple issues and are commonly applied in the investigation of trade-offs. BNs are also appropriate for handling data and knowledge from various sources as well as handling missing data. They can readily represent uncertain information that is propagated through to and expressed in the model outputs. BNs are relatively easy models to apply; hence, they are widely used in resource management (Voinov and Bousquet, 2010).

Furthermore, the variables in BNs are represented by nodes, which are linked by arcs that symbolise dependent relationships between variables. The strength of these dependent relationships specifies the belief degree, which is defined in the conditional probability tables (CPTs) associated with each node. The CPTs indicate that the node will be in a particular state, taking into consideration the state of the parent nodes (nodes directly associated with that particular node). In order for evidence to be entered in the BN, a priori beliefs of one or more nodes are substituted with observation or scenario values. A priori probabilities of the nodes are updated through belief propagation using Bayes' Theorem. Such belief propagation enables BNs to be used for diagnostic ('bottom-up' reasoning) or explanatory purposes ('top-down' reasoning) (Castelletti and Soncini-Sessa, 2007).

One of the advantages of the BNs is that the users are able to interrogate the rationale behind the model outputs, given that the interactions between variables are clearly demonstrated, which makes the system transparent and easy to operate. Other advantages include the fact that BN models allows new nodes to be added to the networks as well as accepting updates for previously added nodes when new information becomes available; an illustration of this can be seen in Figure 2.17 below (Pollino *et al.*, 2007a). The BNs are also useful in the prediction of states or events even when the data is uncertain (Newton, 2010); this obviously makes BNs unique compared to other traditional statistical models that rely on large amounts of empirical data to be built (Marcot *et al.*, 2006).

The Bayesian Belief Networks (BBNs) tool was first developed at Stanford University in the 1970s (McCabe *et al.*, 1988). The earliest publication on BBNs was written by Pearl (2014). Several authors have since extended the research in the subject area on more complex practical applications (Neapolitan, 1990; Oliver and Smith, 1990; Ottonello *et al.,* 1992; Szolovits and Pauker, 1994; Burnell and Horvits, 1995; Russell and Norvig, 1995; Jensen, 1996; Castillo, *et al.,* 1997; Kjaerulff and Madsen, 2008).

Other applications of the BNs include their scope for possible use in natural resources management including species or community models (Marcot *et al.*, 2001; Borsuk *et al.*, 2006); management models (Bromley *et al.* 2004; Lynam et al., 2010; Nash and Hannah, 2011); integrated models (Ticehurst *et al.*, 2007; Kragt *et al.*, 2011); social models (Ticehurst *et al.*, 2011); and risk assessment models (Pollino and Hart, 2005; Pollino *et al.*, 2007b). Chen and Pollino (2012) presented a case study of a spatial BN linked to a geographic information system (GIS) to model habitat suitability for an endangered species.

The limitations of BNs include their inability to readily represent feedback loops and dynamic relationships (Uusitalo, 2007). However, research into some software packages revealed that they could handle dynamic models by representing each time slice with a separate network (Kjærulff, 1995). Some progress has also been recorded in the development of spatial BNs (Smith *et al.,* 2007). Castelletti and Soncini-Sessa (2007) and Uusitalo (2007) revealed further details of the limitations of BNs in environmental modelling.

It is understandable that BNs may not be a suitable analytical tool where precise predictions are required; however, their predictions may be rather useful for comparison of alternative scenarios such as trade-off analysis. In order to ensure that the BN model is fit for purpose in any specific application, it is crucial to clearly define the fundamental objective of the model and its scope of functionality from the onset. This will be the key determinant of other features such as the model development process, the level of detail required, the scale to be considered, level of involvement and collaboration with domain experts or stakeholders, uncertainty management and the model evaluation process.

The rationale for development and application of Bayesian network models may include the following:

- Improving system understanding
- Participatory modelling
- Knowledge discovery
- Synthesising or encoding knowledge and data
- Prediction
- Exploratory and scenario analysis
- Trade-off analysis
- Informing and supporting management and decision-making
- Identifying knowledge and data gaps

These are not mutually exclusive and, as such, BNs can be developed for more than one application or purpose. The BNs modelling technique relies on the probabilistic inference in the network, i.e. observations are used to update the uncertainty of a parameter or node in a Bayesian model (Cowell, 1998). It relates to the conditional and marginal probabilities of two random events, calculating the posterior probabilities given observations of the two events. For example, if two events, X and Y, are considered where event X is the influenced node and event Y is the influencing node, Bayes' theorem as illustrated in Figure 2.17 below states that:

$$P(X \mid Y) = \frac{P(Y \mid X)P(X)}{P(Y)} \tag{2.74}$$

where:

$P(X)$ is the prior or marginal probability of X

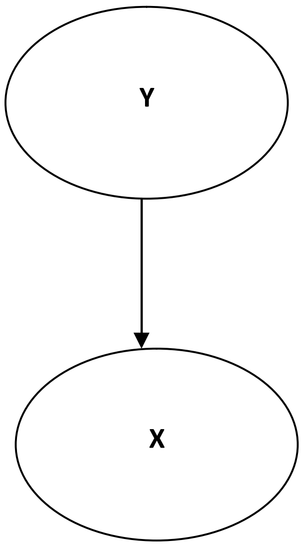
$P(X \mid Y)$ is the conditional probability of X given Y

$P(Y \mid X)$ is the conditional probability of Y given X

$P(Y)$ is the prior or marginal probability of Y

Source or 'Parent'

Target or 'Child'



y_1	$P(y_1)$
y_2	$P(y_2)$

	y_2	y_2
x_1	$P(x_1 \mid y_1)$	$P(x_1 \mid y_2)$
y_2	$P(x_2 \mid y_1)$	$P(x_2 \mid y_2)$

Figure 2.17 Basic Bayesian Network Model

As illustrated in Figure 2.17, the conditional probability table (CPT) for the event Y is comprised of two states, y_1 and y_2, and the probabilities $P(y_1)$, $P(y_2)$. Similarly, the CPT of event X is comprised of the states x_1 and x_2; however, the states are influenced by event Y. The states in a particular node may exhibit various conditions of the node; for instance, 'hot' and 'normal' for event Y and 'working' and 'failed' for event X. In this case, the probability for the event $X, P(x_1|x_1)$, is defined as the probability of x_1 given y_1, where the vertical symbol '$|$' means 'given that' or 'given'. As event Y has an effect on event X, event X represents conditional posterior probabilities $P(x_1|y_1)$, $P(x_1|y_2)$, $P(x_2|y_1)$, and $P(x_2|y_2)$. The number of parent nodes in the BNs model, the number of states in each parent node and the number of states in the child node determine the overall size of the CPT child node. A typical example of this will be a model of three nodes (2 parents and 1 child) consisting of two states each, which generates a CPT consisting of eight cells, four permutations and two parental distributions.

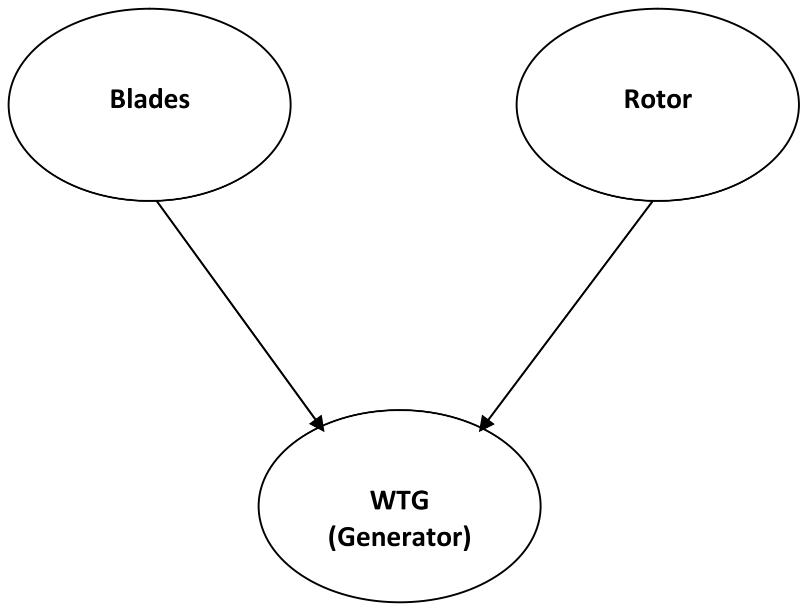


Figure 2.18 A simple Bayesian network model

The above model in Figure 2.18 shows key components of a wind turbine generator (WTG). The wind turbine generator requires the blade to trap the wind and rotate by the energy exerted on the blades; this will in turn rotate the rotor. This means the wind turbine generator will not work unless both the blades and the rotor are functional, as lack of either component will cause the WTG to fail. The influenced node in this instance is the WTG while the influencing nodes are the blades and the rotor. Therefore, the BN will have three nodes, i.e. blades, rotor and the WTG, with each node having two states. The two states of the blades are either 'fail or working', and the rotor has two states as well, which are either 'fail or working'. This illustration is known as the causal dependence between blades and engine and between rotor and engine. The probability of blade failure will influence the state or condition of the WTG. BNs do not support qualitative representation (visual representation of the relationship between various nodes or events), they also support quantitative representation of each node through CPT (Pollino *et al.*, 2007a). Nodes that have no predecessors (parent) are given a 'prior' probability distribution, while nodes that do have predecessors (child) are given 'posterior' probability distributions.

2.10.6 Fuzzy TOPSIS modelling

The technique for order preferences by similarity to ideal solution known as TOPSIS is one of the methodologies widely considered for use in multi-criteria decision-making (MCDM) challenges. TOPSIS was first proposed and developed by Hwang and Yoon (1981). The principle of TOPSIS is based on the evaluation of the alternatives by concurrently measuring their distances to the Positive Ideal Solution (PIS) and to the Negative Ideal Solution (NIS); this simply implies that the decision maker is more inclined to apply the alternatives that are closest to the PIS and farthest from the NIS (Sakthivel *et al.*, 2015). The PIS (most preferred solution) has the potential to maximise the benefit criteria and minimise the cost criteria, whilst the NIS (least preferred solution) has the potential to maximise the cost criteria and minimise the benefits. The order of preference is then decided in accordance with the relative closeness of the alternatives to PIS, which is a scalar criterion that combines these two distance measures. Generally, the TOPSIS methodology applies evaluation criteria, criteria weights, alternatives, well-defined resolution levels and a properly defined decision matrix filled with crisp data. The TOPSIS is classified into the systematic algorithms as shown below (Ishizaka and Nemery, 2013; Etghani *et al.*, 2013).

Hwang and Yoon (1981) first developed the TOPSIS in the early 1980s and it has since been broadly applied in various areas. Boran *et al.,* (2009) and Shiha *et al.,* (2007) revealed that TOPSIS has been successfully applied in the selection and evaluation of problems with finite a number of alternatives. In most cases, the decision maker is unable to assign crisp values for the judgements (Chan and Kumar, 2007; Shyur and Shih, 2006). Due to the challenges in the practical evaluation of weights of criteria and ratings of the alternatives being assessed by assignment of crisp numbers, fuzzy TOPSIS was proposed (Amiri, 2010; Wang and Elhag, 2006). The fuzzy TOPSIS approach utilises the linguistic variables represented by fuzzy numbers to resolve the imprecise nature that is inherent with the evaluation of complex and interdependent systems (Kuo *et al.,* 2007; Yang and Hung, 2007; Chen and Tsao, 2008; Ashtiani *et al.,* 2009; Ebrahimnejad *et al.*, 2009; Roghanian *et al.*, 2010; Aydogan, 2011; Jolai *et al.*, 2011; Awasthi *et al.*, 2011 and Yang *et al.*, 2011).

According to Mentes and Helvacioglu (2012), a fuzzy multiple-attribute decision support model can be applied for the selection of the most appropriate spread mooring system; this was developed by using fuzzy AHP and fuzzy TOPSIS methods and applied in the selection of the mooring system for gas companies situated near Yarimca on the Eastern Marmara Sea Region of Turkey. Lavasani *et al.,* (2012) developed a fuzzy multi-attribute decision-making (FMADM) method for ranking offshore well barriers' systems; the research uses fuzzy AHP and fuzzy TOPSIS for treating the well barriers as group decision-making problems in a fuzzy environment. Yang *et al.,* (2011) proposed an approximate TOPSIS for vessel selection under an uncertain environment; the research uses the concept of belief degrees to model the system and overcome some drawbacks encountered when using classical fuzzy TOPSIS methods to facilitate the development of a reliable vessel selection model under a fuzzy environment. Singh and Benyoucef (2011) proposed a fuzzy TOPSIS technique with a mechanism for determination of fuzzy linguistic value attributes using an entropy method to enumerate the weights of various attributes without involvement of decision makers, while Liaoand Kao (2011) proposed an integrated fuzzy TOPSIS and Multi-Choice Goal Programming (MCGP) approach to solve the supplier selection problem. According to Torlak *et al.,* (2011), fuzzy TOPSIS multi-methodology was applied in the facilitation of the selection process in the Turkish domestic airline industry.

Classification of TOPSIS algorithm steps

Step one:

Change of the decision-making matrix into a dimensionless matrix by the following formula:

$$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}} \quad (2.75)$$

Step two:

Creation of a weighted dimensionless matrix with W vector assumed as an input to the algorithm. This means:

$W = \{W_1, W_2, \ldots, W_n\}$ ≈(assumed from DM) where DM is decision maker.

Dimensionless weighted matrix

$$= V = N_D \times W_{n\times n} = \begin{bmatrix} V_{11} & \ldots V_{1j} & V_{1n} \\ & & \\ V_{m1} & V_{mj} \ldots & V_{mn} \end{bmatrix} \quad (2.76)$$

where N_D is the matrix with the rates of the dimensionless and comparable indices, $W_{n\times n}$ is a diagonal matrix in which only elements with its original diameter will not be zero.

Step three:

The positive ideal solution and the negative ideal solution are defined as follows:

$$PIS = \{(\max V_{ij} \mid j \in J), (\min V_{ij} \mid j \in J') \mid i = 1,2,\ldots m\} = \{V_1^+, V_2^+, \ldots V_j^+, \ldots, V_n^+\} \quad (2.74)$$

$$NIS = \{(\min V_{ij} \mid j \in J), (\max V_{ij} \mid j \in J') \mid i = 1,2,\ldots m\} = \{V_1^-, V_2^-, \ldots V_j^-, \ldots, V_n^-\} \quad (2.75)$$

Step four:

Here, the value of distance from PIS and NIS is calculated. The distance of the alternative from ideal solutions using the Euclidean method is as follows:

$$d_{i+} = \{\sum_{j=1}^{n} (V_{ij} - V_j^+)^2\}^{0.5};\ i = 1,2,\ldots m \quad (2.77)$$

$$d_{i-} = \{\sum_{j=1}^{n} (V_{ij} - V_j^-)^2\}^{0.5};\ i = 1,2,\ldots m \quad (2.78)$$

Step five:

Calculating the relative closeness to the ideal solution; this is defined as follows:

$$cI_{i+} = \frac{di-}{(di+)+(di-))}; 0 \le cI_{i+} \le 1; i=1,2,...,m$$

(2.79)

where $A_1 = PIS$, then $d_{i+} = 0$ and $cI_{i+} = 1$. Similarly, if $A_1 = NIS$, then $d_{i-} = 0$ and $cI_{i+} = 0$. Therefore, given that the size A_1 is closer to the PIS, the value of the cI_{i+} will be closer to 1.

Step six:

The available alternatives can be ranked based on the downside order of cI_{i+}. The entropy technique can be applied in multi-criteria decision-making problems, especially multi-index decision-making scenarios. This approach relies on the availability and knowledge of the relative weights of the existing indices as an effective step in the problem-solving process. Other techniques applied in determining the weights of indicators include the use of experts' opinions, least squares, the eigenvector technique, Shannon entropy, etc. (Ansarifar *et al.*, 2015; Sakthivel *et al.,* 2014).

Entropy in information theory is expressed as a measure of the uncertainty by a discrete probability distribution (P_i), where the value shown by the symbol E is calculated as shown in Equations (2.80) and (2.81):

$$E = -K\sum_{i=1}^{n}[P_i \times LnP_i] = \qquad (2.80)$$

$$E = -K\sum_{i=1}^{n}[P_i \times LnP_i] = -K\{(Ln\frac{1}{n})(\frac{n}{n})\} = kLn\frac{1}{n} \qquad (2.81)$$

where k is a positive constant and $1 > E > 0$ is possible from the probability distribution of P_i based on statistical calculations, and its value will be maximum in the case of $P_i s$. Hence, the entropy technique can be applied in this case in the decision-making matrix.

2.11 Conclusion

This chapter has presented an overview of the wind turbine generator, its historical development trends and status in recent times. The historic accidents and incidents in the wind farm industry have also been reviewed extensively, which justified the need for this research study in the subject area of a risk-based framework for assessment of wind turbine design, installations, operations and maintenance risks (Islam, *et al.,* 2013). Various risk assessment-modelling tools have also been reviewed and are applied in Chapters Three and Four to the problems of evaluating the risks associated with offshore wind farm development. A systematic process is also developed for identification and selection of best-case approach for management of the residual risks associated with the development of offshore wind farms.

CHAPTER THREE: RISK EVALUATION OF OFFSHORE WIND FARM DEVELOPMENT USING AN ANALYTIC HIERARCHY PROCESS AND EVIDENTIAL REASONING APPLICATION

Summary

This section of the research is a risk-based verification of offshore wind farm development by the application of Analytic Hierarchy Process (AHP) and evidential reasoning (ER). As elaborately explained in the previous chapter, subsection 2.10.3, FAHP is an established generic theoretical process of measurement used in deriving ratio scales from both discrete and continuous paired comparisons (Saaty and Vargas, 1981). The comparisons are taken from actual measurements or from the relative strength of preferences contained in the fundamental scale as shown in Table 3.1 (Saaty, 1980). The application of AHP in this research is to specifically evaluate the weighting of the risk parameters whilst the ER is applied to demonstrate a structured method that decision makers can employ to handle the multi-attribute decision-making (MADM) scenarios under uncertainties, as detailed in section 2.10.4 of the previous chapter.

3.1 Introduction

Wind energy has gradually developed into one of the most attractive renewable energy sources (RESs), and the global installed capacity has significantly increased in the past decade. For instance, the cumulative installed capacity of offshore wind farms in Europe (European Union) has increased from 532 MW in 2003 to 169GW in 2017, indicating a growth of 99.7% within 14 years (EWEA, 2017).

Decisions are consciously or unconsciously made in everyday life; therefore, it has become even more pertinent in certain professions to ensure decision making is systematically carried out using an established technique. Project Engineers and Business Managers collate information on particular subjects with a view to understand the full scope of the projects and their risk exposures in order to form good judgement to make informed and calculated decisions about the project execution (Putrus, 1990; Boucher and McStravic, 1991). Intuitively, it is easy to believe that all the information collated is useful judging by the general principle of 'the larger the quantity, the better'. However, this is not the case in practice as not all the information collated will be relevant to the subject matter, and thus some information may not aid the decision maker in their understanding and judgement of the situation (Saaty, 2008).

In order to make a justified decision, it is crucial to understand the problems associated with the particular circumstance, the criteria of the case, the sub-criteria, and the associated stakeholders. Therefore, it is important to determine the best alternative cases (priorities) for the alternatives in order to appropriately allocate the share of the resources (Saaty, 2008). In a professional environment, these decisions are made by experts who are fundamentally required to ensure the decisions are transparent and free from bias through the application of ranking processes of the decision alternatives by the mathematical evaluation of multiple criteria and sub-criteria of the case scenario (Roy, 2005).

Priorities are created for the alternatives with respect to the respective criteria and sub-criteria applied in the conditions for evaluation. Moreover, some criteria may be insignificant and as such cannot be measured for the purpose of ranking the alternatives (Roy, 2005). In that case, it becomes difficult to determine the priorities of the main criteria that are required to establish the priorities of the alternatives. If the priorities of the main criteria and sub-criteria are determined, the values are summed up in order to obtain the overall rank of the available alternatives.

The recognition of the challenges associated with the development of offshore wind farms and the fact that the industry is relatively new has sparked interest in conducting in-depth research into the risk estimation and risk assessment and to propose innovative methods of reducing, eliminating or managing the residual risks to as low as reasonably practical (ALARP) level. Risk assessment is an essential part of the project risk management process. Regrettably, the early days of the offshore wind farm construction industry had a poor record in risk assessment as the risk was either ignored or subjectively dealt with by building-in approximate contingency (Kangari and Riggs, 1989), which does not necessarily curb the risks. Various theories and methods to assess risk have been investigated, and different decision support systems (DSS) have been invented over the years to assist in the decision-making relating to construction risks in the offshore wind farm industry. However, the take-up of most of the proposed DSS is limited, which leaves industry practical experience and experts' judgements as the mainstream tool for analysing construction risks (Akintoye and MacLeod, 1997; Wood and Ellis, 2003; Lyons and Skitmore, 2004), hence the necessity to investigate and propose a novel approach that facilitates the closing of the gap between the theory and practice of risk evaluation in the construction industry.

This research presents a unique risk evaluation methodology that enables the risk impacts of a specific project risk elements to be analysed, weighted and compared against the impacts of other project risk elements. It utilises the industry experience data and experts' judgements to augment the lack of specific validated data through the combined application of the analytic hierarchy process (AHP), the Dempster–Shafer Theory of Evidence (DST) and the Evidential Reasoning (ER) approach innovatively to obtain the final risk impact for the case study (Xu, 2012).

3.2 Literature Review

Most decision-making exercises in engineering project management involve multiple attributes of both a quantitative and qualitative nature (Tah and Carr, 2001). This would normally require holistic consideration of all the attributes identified for evaluation (Belton and Stewart, 2002). The rational handling of qualitative attributes and uncertain or missing information causes complexity in multiple-attribute assessment. The growing need to develop theoretically sound methods and tools for dealing with multiple-attribute decision analysis (MADA) problems under uncertainty in a way that is rational, reliable, repeatable and transparent has resulted in various investigations associated with applications of ER. Over the past two decades, a considerable amount of research has been conducted on integrating techniques from artificial intelligence (AI) and operational research (OR) for dealing with uncertain conditions (Balestra and Tsoukias, 1990; Swartout, 1985; Cheng and Mon, 1994; Keeney and Raiffa, 1993; Yager, 1987).

Uncertainty may be defined as an unknown, unpredictable, and uncontrollable outcome of an event whereas risk constitutes the aspect of action taken in spite of uncertainty of such an even (NRC, 1996). A typical example is a scientific estimate of numbers of health effects of a particular medical innovation. The ranges in the outcome of such evaluation will be attributable to the variance and uncertainties in data and the uncertainties in the structure of any models applied in defining the relationships between exposure and adverse health effects. An uncertainty analysis is an important component of risk characterization and as such provides a quantitative estimate of value ranges for an outcome (Aven and Renn, 2009). The relationship between uncertainty and variability inherent in risk assessment models, the data, and the nature of the uncertainties likely to be experienced at each stage of the risk assessment process are identified EPA, 2004).

Huang and Yoon (1981) proposed methods and applications for multiple-attribute decision-making. Yang and Xu (2002) investigated the application of evidential reasoning algorithms for multi-attribute decision analysis under uncertainty. Yang *et al*., (2001) completed a study on 'nonlinear regression to estimate both weights and utilities via evidential reasoning for MADM'. Other studies of the evidential reasoning (ER) approach have been developed for MADA under uncertainty by Yang and Singh (1994), Sen and Yang, (2012), Yang (2001) and Yang and Xu (2002). In recent years, the ER approach has been applied to decision problems in engineering design, safety and risk assessment, organisational self-assessment and supplier assessment such as motorcycle assessment (Yang and Singh 1994), general cargo ship design (Sen and Yang 1995), marine system safety analysis and synthesis (Wang, 1995), software safety synthesis (Wang, 1997; Wang and Yang, 2001), retrofit ferry design (Yang and Sen, 1997), executive car assessment (Yang and Xu, 1998) and organisational self-assessment (Yang *et al.,* 2001).

Gates (1971), Spooner (1974), Carr (1977), Chapman and Cooper (1983), Diekmann (1983) and Beeston (1986) extensively deployed Probability Theory (PT) for analysing duration risk or cost risk in the construction industry. The PT-based assessment tools require objective probabilities (frequencies) that are not always attainable in the construction industry due to the fact that most construction projects are often one-off investments or enterprises (Flanagan and Norman, 1993). This is the main reason why research data relies on the industry experience and experts' judgements to carry out risk estimations.

The literature review presented in this thesis shows that the Fuzzy Sets Theory (FST) and the Analytic Hierarchy Process (AHP) technique have been extensively applied as analytical tools for various risk evaluations. FST was introduced as a viable alternative for handling subjectivity in construction risk assessment whereas the AHP was perceived to be an effective tool for modelling the increasing complexity in construction risk evaluations. However, both the FST and AHP have their limitations. Kangari and Riggs (1989) summarised the limitations of the FST as follows: (i) the challenges of assigning the membership values of a fuzzy set to represent a linguistic variable; (ii) the complexity in performing repetitive arithmetic operations; and (iii) the challenges with linking the final fuzzy set, after aggregating individual assessments, with a linguistic variable. Moreover, FST has a major limitation in aggregating risk assessments. Its aggregation rule and the fuzzy union operator produce an average assessment, which may not be suitable in all cases. Therefore, the effect of the influencing factors (Cox, 1999) is weakened. Similarly, AHP has a number of limitations including the number of judgements required to derive relative priorities (Mustafa and Al-Bahar, 1991).

Sen and Yang, (2012) also revealed that the large number of judgements required to complete such analysis often causes inconsistency. This will also make conducting sensitivity analysis very difficult and impractical (Belton and Stewart, 2002). Rank reversal is equally a major problem in AHP, and in certain situations the introduction of a new alternative, which does not change the range of outcomes on any criterion may lead to a change in the ranking of the other alternatives (Belton and Gear, 1983; Belton and Stewart, 2002). The limitations of FST and AHP do not undermine their usefulness. However, they inspire research innovations for approaches that can overcome these limitations.

Due to the lack of a common risk scale, it is difficult to foresee a comprehensive risk evaluation methodology that is capable of simultaneously analysing the risk impact of various construction project risks (Williams, 1995). Nonetheless, the most convenient common scale was proposed by Franke (1987) and Williams (1995) to be the risk cost. Franke (1987), Ben-David and Raz (2001), Fan and Yu (2004), Cagno *et al.,* (2007) and Cioffi and Khamooshi (2009) demonstrated the application of risk aggregation for measuring risk impact. However, none of them considered risk impact on different project objectives in order to obtain a comprehensive risk assessment. Obtaining comprehensive risk assessments is equally as important as aggregating individual risk assessments and as such forms the basis for reaching a realistic project risk level.

The averaging and the weighted sum are the most commonly used aggregation rules. Unfortunately, the averaging rules cannot generate a realistic project risk level in all cases, as was discussed earlier. Moreover, the weighted sum method also has a limitation of being over-simplistic due to the assumption of risk independence (Dikmen *et al.*, 2004), assuming risk independence is not a realistic assumption in most cases. Therefore, further research for a novel alternative for aggregating individual risk assessments is crucial for improving OWFD construction risk assessment.

According to Baker *et al.* (1998), the most successful qualitative and quantitative risk analysis tools in construction and oil & gas industries revealed that personal and corporate experience, and engineering judgement were the most frequently used qualitative risk assessment tools, and Expected Monetary Value (EMV), break-even analysis, scenario analysis and sensitivity analysis were the most widely used tools for quantitative risk assessment. Almost the same results were obtained in similar studies completed by Wood and Ellis (2003), Lyons and Skitmore (2004), Dikmen *et al.,* (2004) and Warszawski and Sacks (2004). These studies also noted that the frequently used quantitative risk assessment tools are not sophisticated, suggesting that the industry experts tend to use them for supporting their experience and judgements when assessing construction risks.

Actually, reflecting the real practice of risk analysis and appreciating the practitioners' experience is crucial for enhancing the usability of risk analysis tools, as Laryea and Hughes (2008) concluded. Hence, for any alternative tool to be successful, simplicity and facilitation of professional experience should be the key attributes.

3.3 A Risk Model of Offshore Wind Farm Development (OWFD)

Countries around the world are increasingly becoming dependent on OWF for renewable energy generation. In the same vein, the associated risk of OWFD is continually growing as the industry is pushing the boundaries in its efforts to reduce costs. Efforts to reduce costs of OWFD are counterproductive as the installation of the wind turbines extends further offshore into deep waters for some of the more complex projects. Generally speaking, the cost of offshore wind energy has been consistently reducing since 2009 (up till 2018), by 11%, and it is projected to come down to the target of £100/MWh by 2020 according to the agreement between the UK government and the industry (RenewableUK, 2015). By 2022, offshore wind energy will be significantly cheaper than energy generated from nuclear reactors. For instance, official data has revealed that the contracts for the offshore wind energy due to be generated in 2021 were awarded at £74.75 per megawatt hour and those expected to commence generation in 2022 received a subsidy of £57.50 per megawatt hour. These figures are much lower than the price of £92.50 per megawatt hour agreed with EDF in 2012 for energy generated from the Hinckley Point C nuclear reactor currently under construction (Cox, 2017).

These rapid changes in technology and advancements in innovations in such a relatively new industry and the quest to drive down the costs of the offshore wind energy are huge contributory factors to the dynamic nature of the inherent risks embedded in the activities of offshore wind development. These are evidenced in the complex natures and categories of reported accidents and incidents discussed in the literature review. The uncertainties and the interdependencies of the risk parameters further increase the complexities of the overall effects of the risks associated with the

OWFD. These risks are grouped into the following main classifications (Handler-Scchlar and Navare, 2010):

- External risk factors
- Engineering risk factors
- Financial risk factors
- Organisational risk factors

3.3.1 External risk factors

The sub-criteria of the external risk factors considered are as follows:

- Vandalism/Sabotage risk
- Political risk
- Environmental risk

It is increasingly expected that the development and operations of offshore facilities will be prone to external uncertainties such as sabotage, political influences, environmental challenges, etc. (Brian, 1988; Tørhaug, 2006; Baev, 2006).
The risk of sabotage may be divided into two categories, i.e. low level and high level. Low-level sabotage encompasses potential vandalism or other calculated actions to temporarily disrupt or disable a facility or simply to impose a financial cost on a corporation; whereas high-level sabotage involves actions intended to destroy a facility, with intent to possibly endanger human lives (Brian, 2001; Bunn and Bunn, 2001; Thomas, 1984). Low-level sabotage/vandalism is mostly perpetrated by disgruntled employees or members of social groups, predominantly during labour disputes, and seldom involves the use of classified weapons such as explosives. On the other hand, organised crime, terror-related incidents or surrogate warfare usually involve high-level sabotage by one nation against another. The motivation for high-level sabotage may simply be to take temporary control of the facility and this may be surreptitiously carried out by placing explosives underwater, or by an overt assault on the facility (Thomas, 1984; Bunn and Bunn, 2001).

Although there are currently no known recorded or reported incidents of sabotage/vandalism or terrorism attacks on offshore wind farm facilities, research has revealed overwhelming concerns about terrorism moving beyond society to technical and industrial attacks (Charm, 1983; Jacobs *et al.,* 1984; POST, 2004). Therefore, attention should be focused on the probable sabotage/vandalism attack on an offshore wind facility, as this could easily become a soft target for perpetrators wishing to disrupt the power supply or inflict harm on people (Snyder, 2015; Parfomak and Frittelli, 2007). However, it is possible that the industry considers the likelihood of an attack on an offshore wind farm facility as very low compare to the high security attention being generated from government and construction companies over nuclear reactor facilities (Åshild and Brynjar, 2001; Luft and Korin, 2009).

Another considerable risk element relating to the external risk factors capable of affecting the offshore wind farm development (OWFD) is the political risk, which is often considered as a component part of a country's risk factor (Satyanand, 2011); Fitzpatrick, 1983; EDC, 2015; Braun, and Fischer, 2018). Political risk consists of potential associated uncertainties encountered by investors, corporations and governments that are induced by certain political decisions, events or conditions capable of significantly affecting the profitability of a business or the expected value of a particular economic action (Simon, 1984; Cosset and Suret, 1995; Sottilotta, 2013). Although political risk assessments have been widely practised by multinational companies, this is currently non-existent in the OWFD.

The prevailing internal and foreign policies of any host country determine if the country will have an enabling business and investor-driven environment (Nigh, 1986). Governmental actions and policies involving a parent country, a host country and overall international relationships are seen as factors that can lead to political risk in business environments (Nigh, 1986; Ekpeyong *et al*., 2010; Sottilotta, 2013). The political risks are often classified into two categories, namely the micro-risks and macro-risks, depending on whether the risk factors affect selected or multifaceted industries (Simpson, 2007; Kobrak *et al*., 2004; Robock and Simmonds, 1983).

Micro-risks consist of the risks resulting from political changes that only affect a selected field of business activity or foreign enterprises, whereas macro-risks are comprised of the risks resulting from political changes that influence business activities. This classification methodically improves the fundamental framework for identification of political risk factors (Friedmann and Kim, 1988; Howell, 2007).

Tsai and Su (2005) conducted political environmental evaluations on the seaport development for five East Asian countries, namely Hong Kong, Singapore, Busan in South Korea, Kaohsiung in Taiwan and Shanghai in China. They concluded that low political risk was a strong indicator for the business environments of the host ports. Although this proposal is not directly related to OWFD, it highlights the impact of political risk in the broader perspective of country risk. Many risk-rating agencies apply various techniques in the verification of country risk ratings by combining a wide range of qualitative and quantitative data in respect of alternative measures of economic, financial and political risks into associated composite risk ratings (Hoti *et al.,* 2004; Jensen, 2008).

According to AON's (2017) political risk map, approximately a 50% increase in supply chain disruption is due to government embargoes, interference and strikes, riots and civil unrest. The risk map applies a combination of market experience, innovative analytical tools and tailored risk transfer schemes in effectively minimising and managing risk exposure. Emerging markets are particularly attractive to businesses seeking alternative locations for growth potential but these locations are usually prone to political risks (Jarvis, 2008; Erb *et al*., 1996). However, developed countries may also face similar challenges due to their foreign policies or international relationships with other countries. For instance, the relationship of the Russian Federation with most European countries may pose trade and investment barriers.

Environmental challenges also constitute a risk in the OWFD in such areas as weather conditions, vessel collision at sea, impact on marine life in the seabed, collision with birds, noise pollution, etc. (SDC, 2005, Farfán *et al*., 2009; Band *et al.,* 2007, Walker *et al.,* 2005). Some of the environmental loading conditions with the potential to adversely impact the OWFD include loads from wind, wave, ice, currents and earthquakes and hurricanes. These loading conditions are time dependent (anything between fractions of a second and several hours) with a greater degree of uncertainty associated with them.

In recent years, research and reports have focused on the health, safety and environmental (HSE) impacts of the offshore wind farm on humans and marine lives but little or nothing is being undertaken on a commercial scale about the environmental impact on the OWF and the HSE risks to the personnel working in the offshore wind energy industry; this may be an avenue for future researches. The offshore wind farm developers are currently implementing the occupational health and safety culture transferred from the offshore oil & gas industry in their individual capacities as corporate organisations and not necessarily as a properly regulated industry. Concerns in the offshore wind farm industry such as construction and operational safety, electromagnetic radiation, noise, vibroacoustic disease and wind turbine syndrome have been widely documented and studied in order to determine health and safety risks on populations living in the vicinity of wind turbines; however, evidence of the impact that these same issues could have on workers is not available (EU-OSHA, 2013b).

3.3.2 Engineering risk factors

Some of the engineering risk factors considered in the risk model are:

- Design risk
- Construction risk
- Operational risk

The design process involves an initial site selection followed by an assessment of external conditions, selection of wind turbine size, subsurface investigation, assessment of geo-hazards, foundation and support structure selection, developing design load cases, and performing geotechnical and structural analyses (Malhotra, 2009). The site selection process considered as part of the design risk also accounts for potential environmental challenges such as the level of existing wind conditions, water depth, currents, tides, wave conditions and ice loading, the site geology and associated geo-hazards, such as seabed mudslides, scour and other seismic hazards.

Other potential risk factors designed out at the early stage of wind turbine development include (Henderson and Zaaijer, 2004):

- Design loads – mainly characterised by the wind as the source of dominant load.
- Permanent loads – comprising total mass of the structure or equipment in air and hydrostatic forces on the various members below the waterline.
- Variable loads – personnel, crane operational loads, ship impacts from service vessels, loads from fenders, access ladders and actuation loads. Actuation loading may result from the operation of the wind turbine generator itself. This loading is generated from the generator torque control, yaw and pitch actuator loads, and mechanical braking loads. In addition to the above operating loads, gravity loads on the rotor blades, centrifugal and Coriolis forces, and gyroscopic forces due to yawing must be considered in the turbine design process (Henderson and Zaaijer, 2004).

Aside from constructing the offshore wind farm (OWF) in favourable wind conditions, there are other factors affecting the selection of a wind farm site, which are taken into consideration at the design stage. These include site availability, distance from shore, proximity to power demand sites, proximity to local electricity distribution companies, potential impact on existing shipping routes and dredged channels, interference with other utility facilities (e.g. telecom installations, buried undersea cables and gas lines), distance from local airports to avoid potential interference with aircraft flight paths and interference with bird flight paths (Band *et al.*, 2005).

The above concerns are best addressed at the initial conceptual design stage of the OWF as they become integrated risk factors during the construction and operational phases of the OWF. If such potential issues are not considered at the design stage, they often result in disruptions in construction or operational processes, accidents, incidents and turbine availability challenges (EU-OSHA, 2013b).

The risks perceived during both the construction and operational phase of the OWFD are similar in nature. Some of the risks faced include challenging inclement weather conditions (wind speeds, wave height, tidal currents, wind directions, tidal current directions), falling due to working at height or aloft risk, dropped object, heavy loads handling during lifting operations, finger trapping during rigging, crushing, sea sickness of personnel, trips, slips and falls, construction vessel collision with asset, vessel-to-vessel collision, DP run-offs especially when attached to fixed structures or during lifting operations, jack-up barge punch through, risk of explosion from unexploded ordinances (UXO) during subsea operations using remotely operated vehicle interventions, survey towfish, transponders, etc.

3.3.3 Financial risk factors

The following risk parameters are considered significant in the financial risk factors:

- Accounting risk
- FOREX risk
- Inflation risk

Accounting risk is a measure of the degree to which the financial statements of a corporate entity are affected by the uncertainty of the exchange rate. This is also regarded as a translation risk or accounting risk exposure (Chorafas, 2007; Gallagher, 1956; Woods and Dowd, 2008).
Some of the factors that influence exchange rate include (Collier *et al.,* 2006; Spicer, 1978):

- Interest rate
- Inflation rate
- Trade balance
- Political stability
- Internal harmony
- High degree of transparency in government and public offices
- Economic status of the country
- Quality of the governance

Although there is no unanimously accepted quantification of accounting risk, Lorie and Hamilton (1973) proposed a general concept that the risk is inherently related to the degree of unpredictability of future returns.

Madura (1989) defines exchange rate risk as the effect of unexpected exchange rate changes on the value of a company or business. Foreign exchange (FOREX or FX) risk is also referred to as exchange rate risk or currency risk. It is the uncertainty that exists when a financial transaction is carried out in a currency other than the business currency of domicile (Hoti *et al.,* 2004). Lam (2003) investigated the importance attached to financial risk management by corporate financial institutions, which revealed a systematic approach for estimation of financial risk and its mitigation strategy.

Exchange rate risk has a potential direct loss to the organisation's cash flows, assets, liabilities, net profit, returns and stock market value. Multinational companies usually manage these inherent risks by taking certain decisions such as determining the current risk exposure of the FX, the hedging strategy and the instruments available for dealing with the currency risks (Papaioannoul, 2006). It is important to evaluate the implied value-at-risk (VaR) if the organisation runs the risk of trading in a foreign currency by identifying the type of risk it may be exposed to and the amount of risk encountered (Hakala and Wystup, 2002; White *et al.,* 2010).

The three main types of exchange rate risks are as follows (Shapiro, 1996; Madura, 1989, Arun *et al.,* 1991):

i. Transaction risk – this is a cash flow risk and it is concerned with the exchange rate movements on translational account exposure in respect of receivable (export contracts), payable (import contracts) or repatriation of dividends.
ii. Translation risk – comprises the balance sheet exchange rate risk in respect of exchange rate movements to the valuation of a foreign subsidiary, which is further consolidated to the parent company's balance sheet. This is normally measured by the exposure of net assets (assets less liabilities) to potential exchange rate fluctuations.
iii. Economic risk – reflects the financial risk to an organisation's current value of future operating cash flows from exchange rate fluctuations. The financial risk applies to the effect of exchange rate fluctuations on domestic sales and exports (revenues) and cost of domestic inputs and imports (operating expenses).

Inflation is the purchasing power risk, and it is the uncertainty that an investment may not be worth its original value in the future because of variation in the currency purchasing power caused by inflation. Considering the uncertainty in the financial world, inflation risk remains one of the most important aspects of financial risks confronted by consumers and investors alike. Inflation can have serious adverse effects on an individual's savings for retirement if not properly risk assessed and protected. In the same vein, inflation can also destroy corporate organisations, financial institutions and governments if not adequately risk assessed (Bekaert, and Wang, 2010). The uncertainty associated with the inflation risk premium equally means that there is uncertainty in the critical inputs to any strategic asset allocation, such as the real returns on cash and bonds (Grishchenko and Huang, 2013).

3.3.4 Organisational risk factors

The following risk parameters are considered significant in the organisational risk factors:

- Lack of functional procedures risk
- Staff unreliability risk
- Lack of coordination/communication risk

Organisational risk factors are largely characterised by human behaviours. The behaviours and responses of staff members towards some activities may give rise to uncertainties that expose an organisation to potential risks (Britain, 2002). Wagenaar *et al.,* (1990) identified that organisational failures such as poor or bad management, incompatible goals, lack of communication, poor procedures and lack of training are some of the attributes of system failures due to the human error element. Although most of the organisational risk factors may eventually lead to unsafe situations, they may not be termed unsafe acts on their own (Cooper, 2010; Anderson, 2011); Woodward, 2004). Despite the awareness of the effects of organisational risks, most organisations today are still ignorant of the imbalances and imperfection of their organisational structures (van Vuuren and Van der Schaaf, 1995; Epstein and Buhovac, 2006; Harwood *et al.,* 2009). It is therefore crucial to identify the underlying potential organisational risks, as these would have extended effects on the safety performance of the organisation and its profitability (van Vuuren, 1998; Epstein, and Rejc, 2005; Harvey, 2012).

Kambiz (2011) reviewed studies carried out by the Office of Government Commerce, UK (OGC) in 2002 (Britain, 2002) and proposed the following prompts for estimation of underlying risk factors in any organisation:

- Lack of clarity over roles and responsibilities
- Management incompetence
- Poor leadership
- Key personnel having inadequate authority to fulfil their roles
- Inadequate corporate policies
- Lack of support to business processes
- Inadequate and inappropriate operational procedures
- Inadequate or inaccurate information
- Poor staff selection procedure
- Indecision or inappropriate decision-making
- Professional negligence
- Performance failure (people or equipment)

In addition to the above attributes, other areas of staff unreliability may include unauthorised leave of absence, sick leave, etc.

Having identified the potential risk attributes obtainable in offshore wind farm development, a systematic methodology for evaluating those risks attributes using specific models is developed in this research.

3.4 Methodology

In order to evaluate the weights of the risk elements in this study, some logical steps are taken to generate priorities as follows:

i. Determine clearly the overall object of the problem and identify the criteria that most influence the overall objective.
ii. The risk hierarchy is structured from the top with the identified goal of the decision, the objectives are identified from a broad perspective through the

intermediate levels (criteria on which subsequent elements depend) to the lowest level (which usually is a set of the alternatives) if applicable.

iii. Starting at the first level of the hierarchy:

- Construct a set of pairwise comparison matrices of all elements in the first and second levels.
- Calculate the priorities by normalising the vector in each column of the matrix of judgements and compute the average of the rows of the resulting matrix and obtain the priority vector (PV).
- Compute the consistency ratio (CR) of the matrix of judgements in order to ensure the overall evaluation remains consistent.

iv. The priorities obtained from the comparisons are used to weigh the priorities in the level immediately below, and the process is repeated for every element. Then, the weighted values in the levels below are added up in order to obtain the overall global priorities.

v. Repeat the process of evaluation in step 3 for all elements in the succeeding level and with respect to each criterion in the preceding level.

vi. Synthesise the local priorities over the hierarchy in order to obtain an overall priority for each alternative.

The expert opinion is gathered through a survey by the application of paired comparison. Suppose the expert is of the opinion that the Engineering risk is more important than the External risk; it is also important to make a relative scale to measure how much more important the Engineering risk is compared to the External risk. Therefore, Figure 3.1 below denotes that the expert states that the Engineering risk is strongly more important than the External risk (reciprocal value).

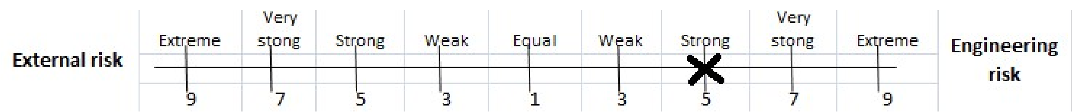


Figure 3.1 Example of pairwise comparison between two criteria (reciprocal)

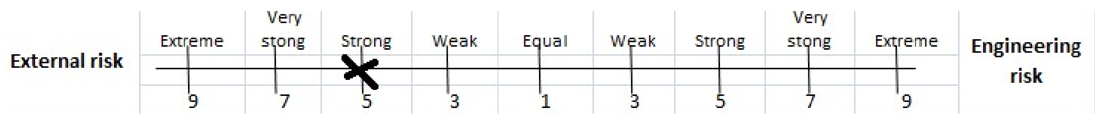


Figure 3.2 Example of pairwise comparison between two criteria (positive)

Conversely, if the expert is of the opinion that External risk is strongly more important than the Engineering risk then the pairwise comparison will be as shown in Figure 3.2 (positive value). In other words, selection made between 1 and 9 to the left is positive and between 1 and 9 to the right will have a reciprocal value.

The chronological steps taken in the proposed methodology for the risk evaluation of OFWD are shown in the event chart provided in Figure 3.3.

The proposed methodical framework in Figure 3.3 is actualised by the following systematic steps (adapted from Yang and Xu, 2002):

i. Identification of risk attributes presented in a hierarchical model
ii. Assignment of assessment grades to the risk evaluation criteria
iii. Evaluation of weights of each criterion in the hierarchical model using the AHP approach
iv. Transformation of quantitative data in the hierarchy structure
v. Modelling the risk hierarchy data through the conversion of the lower-level criteria to the upper-level criteria using a fuzzy rule-based approach
vi. Application of the Evidential Reasoning (ER) algorithm in order to synthesise the risk evaluation results
vii. Determination of the crisp result of the synthesised risk
viii. Performing of sensitivity analysis
ix. Decision-making strategy

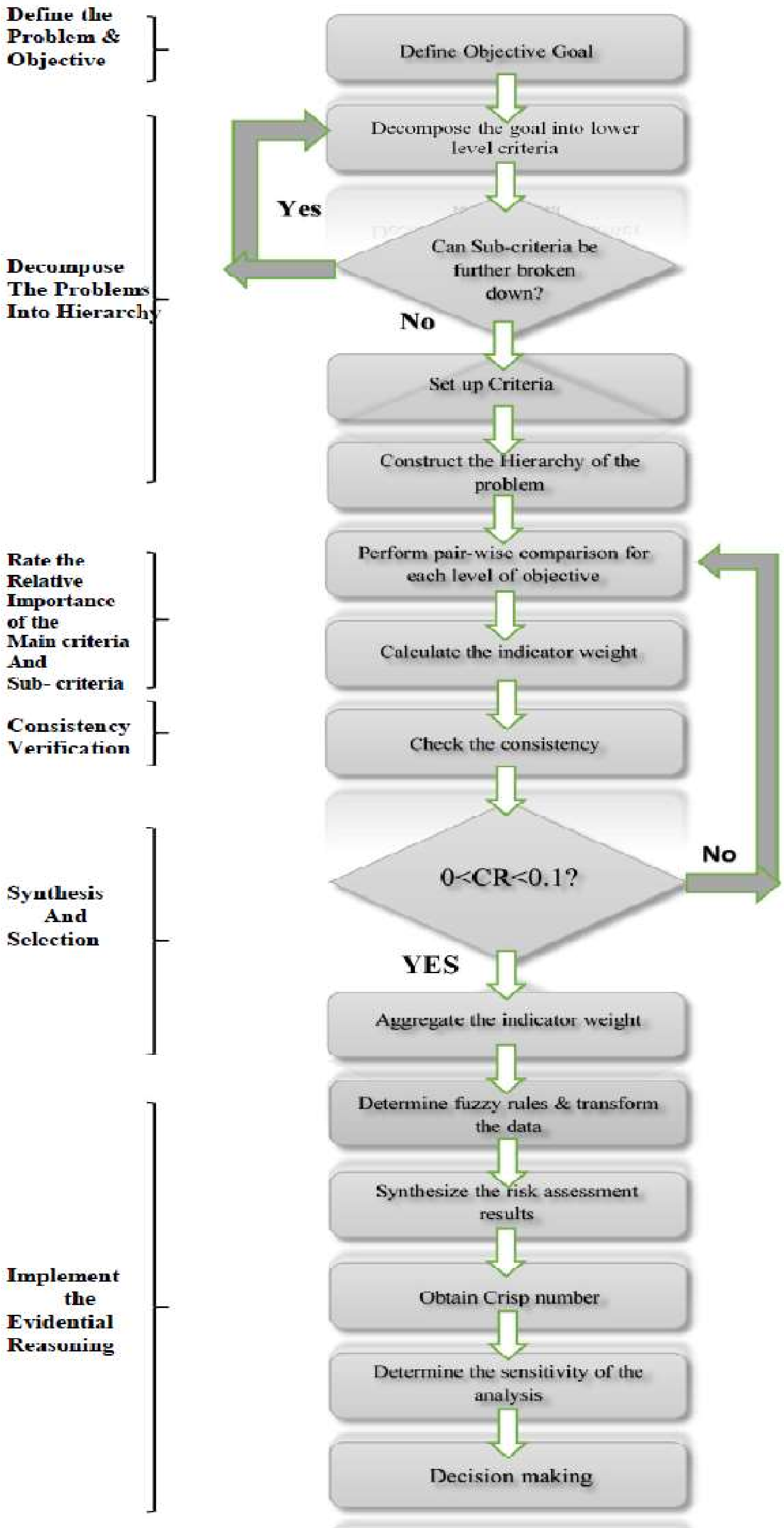


Figure 3.3 The proposed methodology

3.5 Generic Model for Risk-Based Verification of Offshore Wind Farm Development

The generic model is a crucial part of this research as it forms the holistic framework for evaluation of risks associated with OWFD in its complex characteristics. The risk parameters considered in this research work are essentially represented in a structured order of hierarchy as shown in Figure 3.4.

The generic model (see Figure 3.4) is comprised of the upper level representing the goal. The upper level of the model is followed by the main risk criteria that contribute to the assessment and measurement of the goal. The remaining levels include the sub-criteria that are used to measure the main criteria and these are broken down into sub-sub-criteria. Each level of these criteria forms the bases of measurements for the preceding level in the hierarchy, which enable the decision maker to make an informed decision.

This generic model is formulated based on a review of previous studies completed in various applications in the diverse offshore oil & gas and marine construction industries. The studies include those proposed by Mokhtari *et al.,* (2011), Mokhtari *et al.,* (2012), Kroger and Probst (2010), Handley-Schachler and Navare (2010), Di Zhang *et al.,* (2016), Bichou et., (2013), Bichou (2008), Hallikas *et al.,* (2004), Charif *et al.,* (2013), Dorofee *et al.,* (1996) and Mabrouki *et al.,* (2013a,b). Due to the complexity of the system generic model (Figure 3.4), it is necessary to scale down the model and only consider the most significant risk parameters in a more specific modelling structure (see Figure 3.8) in order to concentrate the assessments on more relevant risk factors.

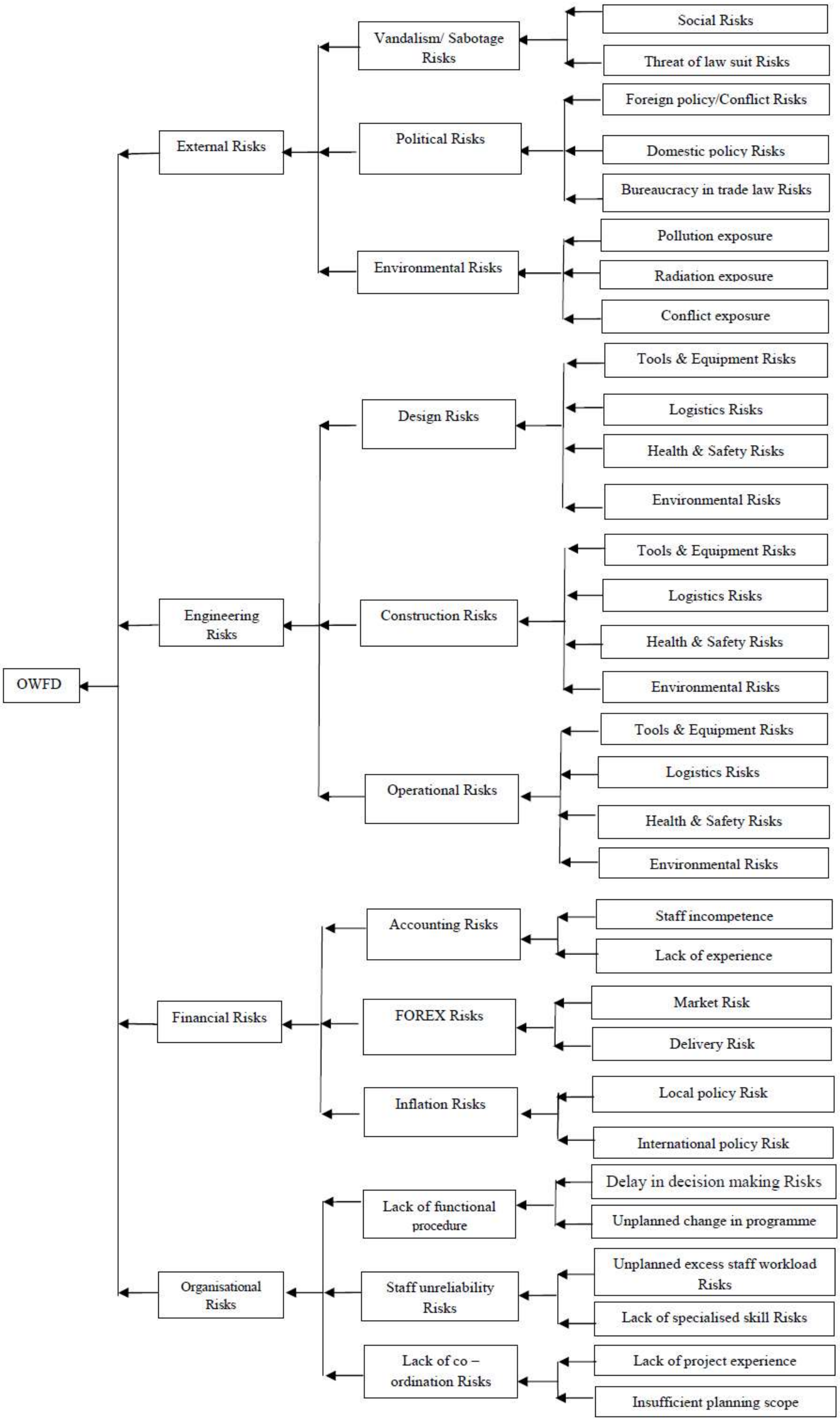


Figure 3.4 A generic model for risk-based verification of OWFD

3.5.1 Quantitative data transformation

Some of the data collated for analysis may be available in quantitative or qualitative formats, in which case data transformation may be required to validate the data in the required format. This can be achieved by the application of membership functions of continuous fuzzy sets in order to obtain rational synthesis. There are various shapes of membership functions such as triangular type, trapezoidal, Gaussian curves, pie curves and s-curves (Yen and Langari, 1999). Attention will be paid to only the triangular and trapezoidal shapes (see Figures 3.5 and 3.6) for the purpose of this research due to their simplicity in calculation. The choice of the membership function to be used is dependent on the decision makers' perception of the linguistic variables used. The fuzzy members in a triangular (TFN) and trapezoidal (ZFN) membership shape represent the linguistics variables (qualitative descriptors).

3.5.1.1 Triangular fuzzy membership functions

Based on the detailed review of the fuzzy set modelling (FSM) in subsection 2.10.1 of the previous chapter, fuzzy sets (denoted by $\widetilde{A}$) have an infinite number of memberships to represent the required situation (Zedah, 1965). The typical fuzzy set notation can be reiterated as in Equation 3.1 below:

$$\mu\widetilde{A}(u) \in [0,1] \qquad (3.1)$$

Where $\mu\widetilde{A}(u)$ represents the degree of membership of element u in a fuzzy set $\widetilde{A}$; therefore, $\mu\widetilde{A}(u)$ is equal to the degree to which $u \in \widetilde{A}$ and $\in$ denotes an element of or a member of.

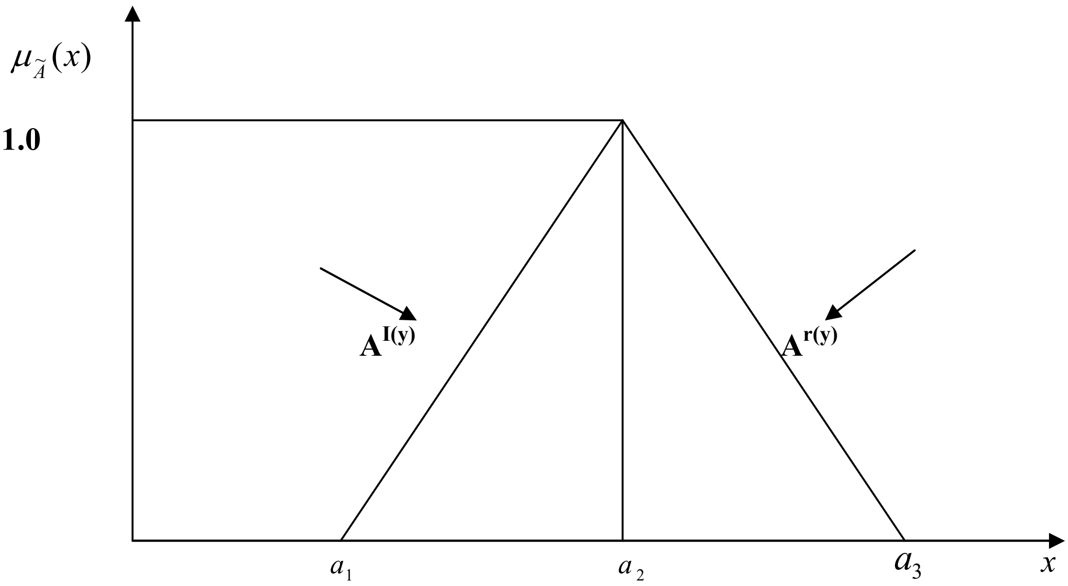


Figure 3.5 Triangular membership function

Considering Figure 3.5 above, a triplet can define a triangular fuzzy number and may be mathematically represented as shown in Equation (2.3) of Chapter Two.

3.5.1.2 Trapezoidal fuzzy membership functions

Considering the information represented in Figure 3.6 below, trapezoidal fuzzy membership can be mathematically represented as shown in Equation (2.10) of Chapter Two.

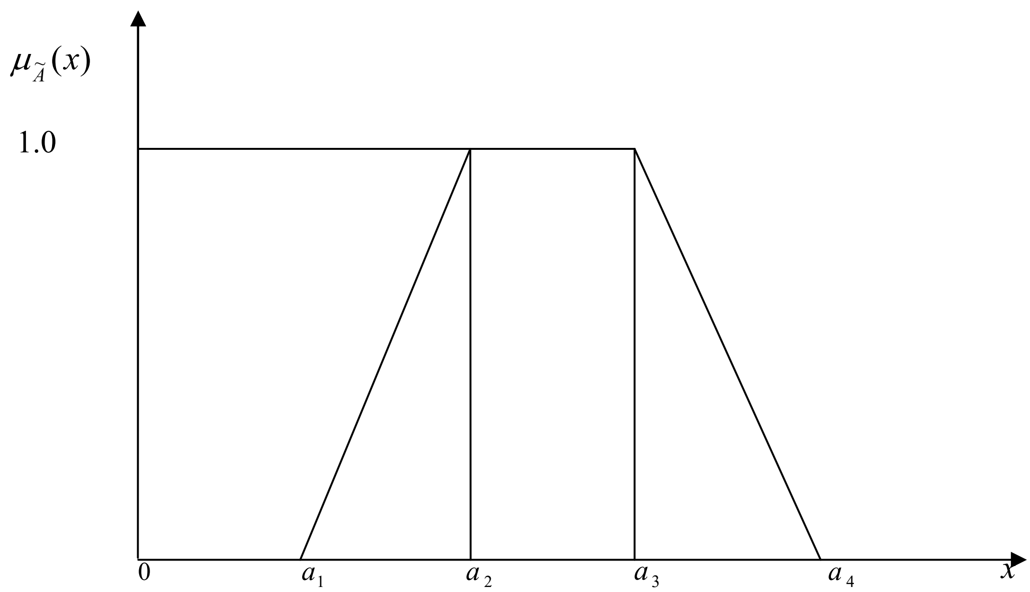


Figure 3.6 Trapezoidal membership function

3.6 Conducting Mapping for the Transformation Process

Some of the data is presented in quantitative formats; therefore, data transformation will be required in order to validate it for Evidential Reasoning (ER) application (Yang and Xu, 2002). This can be achieved through a mapping process, which is implemented by the Fuzzy Rule-Base (FRB) approach as detailed in subsection 2.10.2 of the previous chapter (Yang, 2006 and Sii *et al*., 2001). Further details of the ER theory, Belief Structure and various transformation techniques can be referred to in subsection 2.10.4 of Chapter Two. The assessment grades assigned to the main criteria differ from those assigned to the sub-criteria of the elements considered in the specific model, hence the need to ensure that all data used for the assessments is uniformly transformed on the basis of common fuzzy rules.

A typical example of the mapping process is illustrated as follows:

Let "I" represent the lower level of the qualitative criterion and "U" represent the upper level of the qualitative criterion. Also, let "L_1" be the evaluation grades of the particular lower level of the linguistic variable and "L_n" for the highest level of the linguistic variable. For instance, "L_1" represents 'very low', "L_2" represents 'low', … "L_n" represents the highest grade (see Figure 3.7). And "L^j" represents the input data of "L_i". Similarly, "U_j" represents the evaluation grades of a particular upper level linguistic variable (i.e. "U_1" represents 'extremely low', "U_2" represents 'fairlylow', … "U_n" represents 'extremelyhigh') and "u^j" denoted the output data as shown in Figure 3.7.

The relationship between the input and the output data is mathematically given as:

$$\sum_{j=1}^{4}\beta_1^j = 1, \sum_{j=1}^{4}\beta_2^j = 1, \sum_{j=1}^{4}\beta_3^j = 1, \sum_{j=1}^{4}\beta_4^j = 1, \ldots \sum_{j=1}^{n}\beta_n^j = 1 \qquad (3.2)$$

$$u^j = \sum_{i=1}^{4} L^i \beta_i^j \qquad (3.3)$$

$$\sum_{i=1}^{4} L^i \leq 1 \qquad (3.4)$$

where $\sum_{i=1}^{4} L^i \beta_i^j$ the belief degree of an attribute given a certain evaluation grade.

The mapping process indicates the relative combination of the evaluation grades between two distinct levels of hierarchy, i.e. the main criteria and the sub-criteria levels, as can be seen in Figure 3.7 below. In this case, the input data is aggregated in order to transform the lower-level criteria into the corresponding upper-level criterion. In accordance with experts' opinions, the belief degrees (β_i^j) are typically distributed in the format shown in Figure 3.7. The sum of the belief degrees from one linguistic variable is always equal to '1', as shown in Equation 3.4 above.

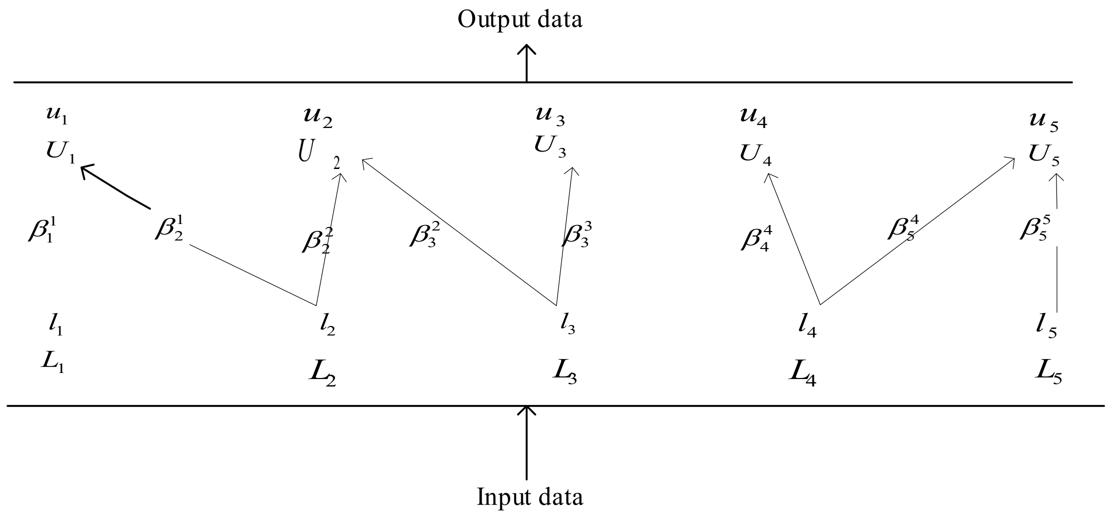


Figure 3.7 A mapping of lower-level criteria into upper-level criterion

The hierarchy structure may be extended beyond the current two levels shown in Figure 3.7. However, there will be no significant advantage in adding another level of sub-sub-criteria to the structure as the model has been careful constructed with the influencing variables in the sub-sub-criteria represented in the sub-criteria level. Therefore, aggregation of the weights sub-sub-criteria level will make little or no impact to the sub-criteria. Secondly, the extension to three levels will introduce a complex mathematical computation.

3.7 Risk Evaluation Using the Fuzzy Analytic Hierarchy Process

The Fuzzy Analytic Hierarchy Process (FAHP) is employed in order to obtain the weights of the risk factors. This is achieved by constructing pairwise comparisons of sub-criteria with respect to their corresponding main criterion (refer to subsection 2.10.3 of Chapter Two).

In order to determine the n^{th} ratio of the risk components, an evaluation of the main risk criteria and the sub-criteria is required. This can be achieved by the application of the relevant AHP procedure, which includes developing weights for the criteria. The weights for the risk criteria can be determined by developing a single pairwise comparison matrix for the criteria. The values in each row are multiplied to calculate the n^{th} root of the said product. The n^{th} root of the products is then normalised in order to obtain the relevant weights after which the Consistency Ratio (CR) is calculated and verified. Some sample calculation illustrations can be found in Tables 3.9, 3.10 and 3.11.

The CR enables the decision maker to determine how consistent the pairwise comparisons are. The four steps of calculating the CR are as follows:

i. Add up the pairwise values in each column (the sum values) and each sum value in the column is multiplied by the corresponding weight (from the priority vector column)

ii. Add up the values shown in the row of ‘ $Sum \times PV$ ’, the total value is represented as (λ_{Max}) know as Lamda Max,

where $$PV = \frac{n^{th} root}{Sum\, of\, n^{th} root} \tag{3.5}$$

Priority Vectors is represented by PV and

$$(\lambda_{\max}) = \sum (\text{sum of individual pairwise comparison} \times \text{PV}) \tag{3.6}$$

where Lambda Max is represented by $(\lambda_{\max})$.

iii. Then, calculate the Consistency Index (CI)

iv. Determine the CR by dividing the CI by the Random Index (RI). The RI is obtained from the standard lookup table represented in table 3.1; it is determined by the number of criteria, n. In the case of this study, $n = 4$ corresponding to 0.9 (Saaty, 1980)

Finally, the consistency ratio is calculated in order to measure the accuracy and the consistency of the decision makers. This is done by applying Equation (3.7).

$$CI = (\lambda_{Max} - 1)/(n-1) \tag{3.7}$$

where $n = n^{th}\ term$ (number of experts considered).

Table 3.1 Random index (Saaty, 1990)

n	1	2	3	4	5	6	7	8	9
Random Index (RI)	0	0	0.58	0.9	1.12	1.24	1.3	1.4	1.5

Table 3.1 above is a standard random index table proposed by Saaty and it is used to determine whether or not the pairwise comparison is consistent. Therefore, Consistency Ratio (CR) = Consistency index (CI)/Random Index (RI)

$$CR = \frac{CI}{RI} \tag{3.8}$$

In the case of this study, $n = 4$, which corresponds to the random index value of '0.90'.

If the $CR \leq 0.10$, it indicates that the decision maker's pairwise comparisons are relatively consistent and no corrective action is required. Where the CR is > 0.10, it implies that the pairwise comparisons are inconsistent and the source of the inconsistency must be identified and corrected. The higher the CR values, the more inconsistent the decision maker's pairwise comparisons. And the lower the CR, the more consistent the pairwise comparisons are (Saaty, 1980).

Table 3.2 Fundamental scale of absolute numbers and ratio scales for pairwise comparison (importance or unimportance)

Intensity of importance	Description	Explanation
1	Equal Importance	Two activities contribute to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgement slightly favour one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favour one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
8	Very very strong	The evidence favouring one activity over another is of the highest possible order of affirmation
9	Extreme importance	
Reciprocals of above	If activity i has one of the above non-zero numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i	A reasonable assumption
1, 1-1.9	If the activities are very close	Maybe difficult to assign the best value but when compared with other contrasting activities the size of the small numbers would not be too noticeable, yet they can still indicate the relative importance of the activities.

Table 3.2 above shows the pairwise comparisons scale that ranges from equally important to extremely important. The reciprocal relationships are also known as the integer n and it is equal to $1/n$. The pairwise comparisons are used to establish the relative priority of each criterion against another criterion as well as the relative priority of each sub-criterion against another sub-criterion.

3.7.1 Estimation procedure of the fuzzy analytic hierarchy process

Chen *et al*., (2011) applied a fuzzy number scale and An *et al*., (2007) applied the qualitative variables in the evaluation approach of the weighting of the risk parameters (see Table 3.3 below). For instance, when two events are equally important, it is deduced from the scale as (1,1,2). Similarly, when an event is weakly important compared to another, it is represented as (2,3,4).

Table 3.3 Membership Function Estimation Scheme

Grade/Level of importance	Strength of importance in linguistic scales or qualitative descriptors	Scales of triangular fuzzy members
1	Equally important	(1,1,2)
3	Weakly important	(2,3,4)
5	Strongly important	(4,5,6)
7	Very strongly important	(6,7,8)
9	Extremely important	(8,9,9)

The triangular fuzzy number (TFN) has a relative variable used to construct pairwise comparisons of the experts' judgements. This is used in obtaining the weight factors in accordance with the risk estimation scheme presented in Table 3.4.

Table 3.4 Risk Estimation Scheme

Level of importance in qualitative descriptor	Description	Triangular Fuzzy Numbers (TFNs)
Equal importance	Two attributes contribute equally to the OWFD risks	(1,1,2)
Between equal and weak importance	When compromise is needed	(1,2,3)
Weak importance	The subjective judgement and experience of experts slightly favour one attribute group over another	(2,3,4)
Between weak and strong importance	When compromise is needed	(3,4,5)
Strong importance	The subjective judgement and experience of experts slightly favour one attribute group over another	(4,5,6)
Between strong and very strong importance	When compromise is needed	(5,6,7)
Very strong importance	A given attribute is favoured very strongly over another	(6,7,8)
Between very strong and absolute importance	When compromise is needed	(7,8,9)
Absolute importance	The evidence of favouring one attribute group over another is of the highest possible order	(8,9,9)

3.7.2 Fuzzy judgement using a pairwise comparison matrix

The construction of the pairwise comparisons using expert judgements is one of the critical paths of the AHP approach that is employed in this study. An illustration assumes two events, a and b, are of 'weak importance' (i.e. a is weakly more important than b); then a fuzzy number of (2,3,4) is assigned to the pairwise comparison of ab. Similarly, the fuzzy number of $(\frac{1}{3},\frac{1}{2},\frac{1}{1})$ is assigned to the pairwise comparisons of ba. Further details of the operational rules of TFN can be found in subsections 2.10.1 and 2.10.3 of the previous chapter.

Assuming the experts (decision makers) n have equal weights to assess a given fuzzy condition, the elements in the fuzzy pairwise comparisons can be mathematically evaluated as:

$$\tilde{a}_{i,j} = \left(\frac{1}{n}\right) \otimes \left(e^{1}{}_{i,j} \oplus e^{2}{}_{i,j} \oplus ..., e^{k}{}_{i,j} ... \oplus e^{m}{}_{i,j}\right) \tag{3.9}$$

$$\tilde{a}_{j,i} = \frac{1}{\tilde{a}_{i,j}} \tag{3.10}$$

where $\tilde{a}_{i,j}$ represents the relative importance of comparing event i and j; $e^{k}{}_{i,j}$ represents the k^{th} experts' judgements in the TFN presentation.

For $n \times n$ (i.e. 2×2, 3×3, 4×4, etc.), let $\tilde{A}$ represent the fuzzy pairwise comparison matrix as follows:

$$\tilde{A} = \begin{pmatrix} \tilde{a}_{1,1} & \tilde{a}_{1,2} & ... & \tilde{a}_{1,n} \\ \tilde{a}_{2,1} & \tilde{a}_{2,2} & ... & \tilde{a}_{2,n} \\ \vdots & \vdots & \tilde{a}_{i,j} & \vdots \\ \tilde{a}_{n,1} & \tilde{a}_{n,2} & \cdots & \tilde{a}_{n,n} \end{pmatrix} \tag{3.11}$$

3.7.3 Calculation of weighting factor

According to Bukcley (1985), weight factors can be computed by the application of mean geometry for each element in the model considered. This can be achieved mathematically as follows:

$$\tilde{r}_i = \left(\tilde{a}_{i,1} \otimes \tilde{a}_{i,2} \otimes \cdots \otimes \tilde{a}_{i,n}\right)^{1/n} \tag{3.12}$$

$$\tilde{w}_i = \tilde{r}_i \otimes \left(r_1 \otimes \cdots \otimes \tilde{r}_n\right)^{-1} \tag{3.13}$$

where $\tilde{a}_{i,n}$ is the comparison value of i to the criterion n, while the $\tilde{r}$ represents the mean geometry of the i^{th} row in the construction of the fuzzy pairwise comparison matrix and $\tilde{w}_i$ represents the fuzzy weight of the i^{th} criterion of the TFN denoted by $\widetilde{w}_i = (l\widetilde{w}_i, m\widetilde{w}_i\, u\widetilde{w}_i)$. Meanwhile, $l\widetilde{w}_i$, $m\widetilde{w}_i$ and $u\widetilde{w}_i$ represent the lower, the middle and the upper values of the fuzzy weight of the i^{th} criterion.

3.7.4 Defuzzification process

Tang *et al.* (2000) proposed a methodology for converting the mean geometry derived from TFN into the matching weight factors of the crisp numbers. For instance, assuming a TFN weight factor is $(y^l{}_i, y^m{}_i, y^u{}_i)$, the crisp weight factor will be represented as:

$$DF_{\widetilde{w}_i} = \frac{(y^u{}_{i,} - y^l{}_{i,}) + (y^m{}_{i,} - y^l{}_{i,})}{3 + y^l{}_i} \quad (3.14)$$

Therefore, the normalised weight factor is obtained as:

$$\widetilde{w}_1 = \frac{DF_{\widetilde{w}_i}}{\sum DF_{\widetilde{w}_i}} \quad (3.15)$$

3.8 Application of the Expected Utility Modelling Approach

The expected utility method is used to determine the crisp number for the main risk criteria, which defines the level of the associated risk in the system (Yang, 2001).

Assume a utility value of an assessment grade H_n is represented as $u(H_n)$ where $u(H_{n+1}) > u(H_n)$ when H_{n+1} is preferred to H_n, where H_n is the n^{th} evaluation grade (Yang, 2001). The utility value of the linguistic term is denoted by $u(H_n)$. In cases where there is no available information, the utilities of the assessment grades will be assumed to be equidistantly distributed in the normalised utility space. This scenario is represented as follows:

$$u(H_n) = \frac{T_n - T_{\min}}{T_{\max} - T_{\min}} \quad (3.16)$$

where T_n represents the ranking value of the linguistic term H_n, $T_{\max}$ represents the ranking value of the most preferred term H_N and $T_{\min}$ denotes the ranking value of the least preferred term H_1. The expected utility determines the overall associated risks of the system, which may be represented as $(U(E))$.

The following belief degree intervals $\beta_n, (\beta_n + \beta_H)$ indicate that $(U(E))$ may be assessed to H_n, where $\beta_H \neq 0$. When $\beta_H \neq 0$, then the evaluation is not complete; hence, $\beta_H = 1 - \sum_{n=1}^{N} \beta_n$, where β_H denotes the belief degree that is unassigned to any individual evaluation grade after all of the basic attributes have been properly assessed. This indicates a degree of incompleteness in the assessment (Liu *et al.*, 2004).

Similarly, when $\beta_H \neq 0$, the minimum utilities, maximum utilities and average utilities of $(U(E))$ remain constant. This relationship is expressed as:

$$u(U(E)) = \sum_{n=1}^{N} \beta_n u(H_n) \tag{3.17}$$

The minimum, maximum, and average utilities of $(U(E))$ as proposed by Yang (2001) are mathematically represented as shown in Equations (2.44), (2.45) and (2.46) respectively.

3.9 Performing Sensitivity Analysis

Sensitivity analysis will be applied to verify the level of uncertainty in the output of a model and the potential sources of the uncertainties in its inputs. The analysis is aimed at further understanding the relationships between input and output variables in a model. Sensitivity analysis is a method used to determine the potential impact of various values of an independent variable on a particular dependent variable under a given set of assumptions (Sadiq *et al.*, 2007). It is applied within specific boundaries, which is dependent on one or more input variables; for example, consider the impact that changes in interest rate may have on bond prices. Sensitivity analysis is also known as 'what if' analysis and it is widely used in many applications.

3.9.1 Steps of sensitivity analysis measurement

i. Step one entails defining the base case output. For example, determine the NPV at a given base case input value (V_1) for which the sensitivity is to be measured. All the other inputs of the model are kept constant.
ii. Step two defines the calculation of the output value at a new value of the input (V_2), while keeping other inputs constant.
iii. Step three involves calculating the percentage change in the output and the percentage change in the input.
iv. Step four entails dividing the percentage change in output by the percentage change in input in order to determine the sensitivity of the model

The above process of analysing the sensitivity of any particular input while keeping the rest of the inputs constant is repeated until the sensitivity figure for each of the inputs is obtained. The higher the sensitivity value, the more sensitive the output will be to any change in that input and vice versa.

3.9.2 Axiom of sensitivity analysis for decision making

The sensitivity analysis must conform to certain axioms if the inference of the evidential reasoning applied is logical (Yang *et al.*, 2009). These axioms include the following:

Axiom 1: Slight increment/decrement of degrees of beliefs (DoBs) associated with a risk-oriented linguistic variable of the lowest criteria will certainly result in the decrement/increment of the safety preference degree of the model output.

Axiom 2: If the degrees of belief associated with the highest preference linguistic term of a lowest-level criterion are decreased by p and q simultaneously, the degrees of belief associated with its lowest preference linguistic term are increased by p and q $(1 > q > p)$. In addition, the utility value of the model's output is assessed as U_p and U_q respectively. Therefore, U_p should be greater than U_q.

Axiom 3: If x and y criteria from all the lowest-level criteria are selected, and the degree of belief associated with the highest preference linguistic terms of such x and y criteria is decreased by the same amount where $(y < x)$. Simultaneously, the degrees of belief associated with the lowest preference linguistic variables of such criteria are increased accordingly by the same amount, the utility value of the model's output will be assessed as U_x and U_y where $U_x > U_y$ in this regard.

3.10 Test Case

The test case demonstrates the risk-based verification of an OWFD by application of the proposed methodology. The previous chapter contains referenced details of the methodologies proposed for this research work. The AHP is employed to enable the structuring of the complexity in construction risk assessment. The ER algorithm is applied in order to improve the original Dempster's rule of evidence combination. The full details of the AHP, ER and ER algorithm can be found in Chapter Two of this study.

3.10.1 Determine the goal objective and decompose goal into lower-level criteria

3.10.1.1 OWFD specific modelling

The specific model presented in Figure 3.8 is designed to capture the most relevant risks associated with OWFD. Due to limitations in the scope of this research and the unavailability of data for some of the risk elements shown in the generic model presented in Figure 3.4, the specific model has been carefully reviewed to incorporate only the most significant and relevant risk elements to OWFD. Due to the complexity of the system generic model (Figure 3.4), it is necessary to scale down the model and only consider the most significant risk parameters in a more specific modelling structure (see Figure 3.8) in order to concentrate the assessments on more relevant risk factors. Moreover, the risk variables in each level of the structure in the hierarchy (from lowest) are aggregated to determine the impact on the next level (to upper level) of the structure. In effect, the influences of risk variables in the sub-sub-criteria level are also accommodated to be reflected sub-criteria level.

The risk parameters in the specific model will be assessed by the application of both qualitative and quantitative approaches. The evaluation will consider a minimum of five and maximum of seven linguistic variables where possible. The qualitative data presented in linguistic terms following expert opinions will be transformed into numerical values in order to obtain conclusive assessment for making an informed decision. The decision maker will formulate functional assessment grades to support the linguistic variable as shown in tables 3.5, 3.6 and 3.7. These will be used to evaluate the risk factors presented in the specific model as shown in Figure 3.8.

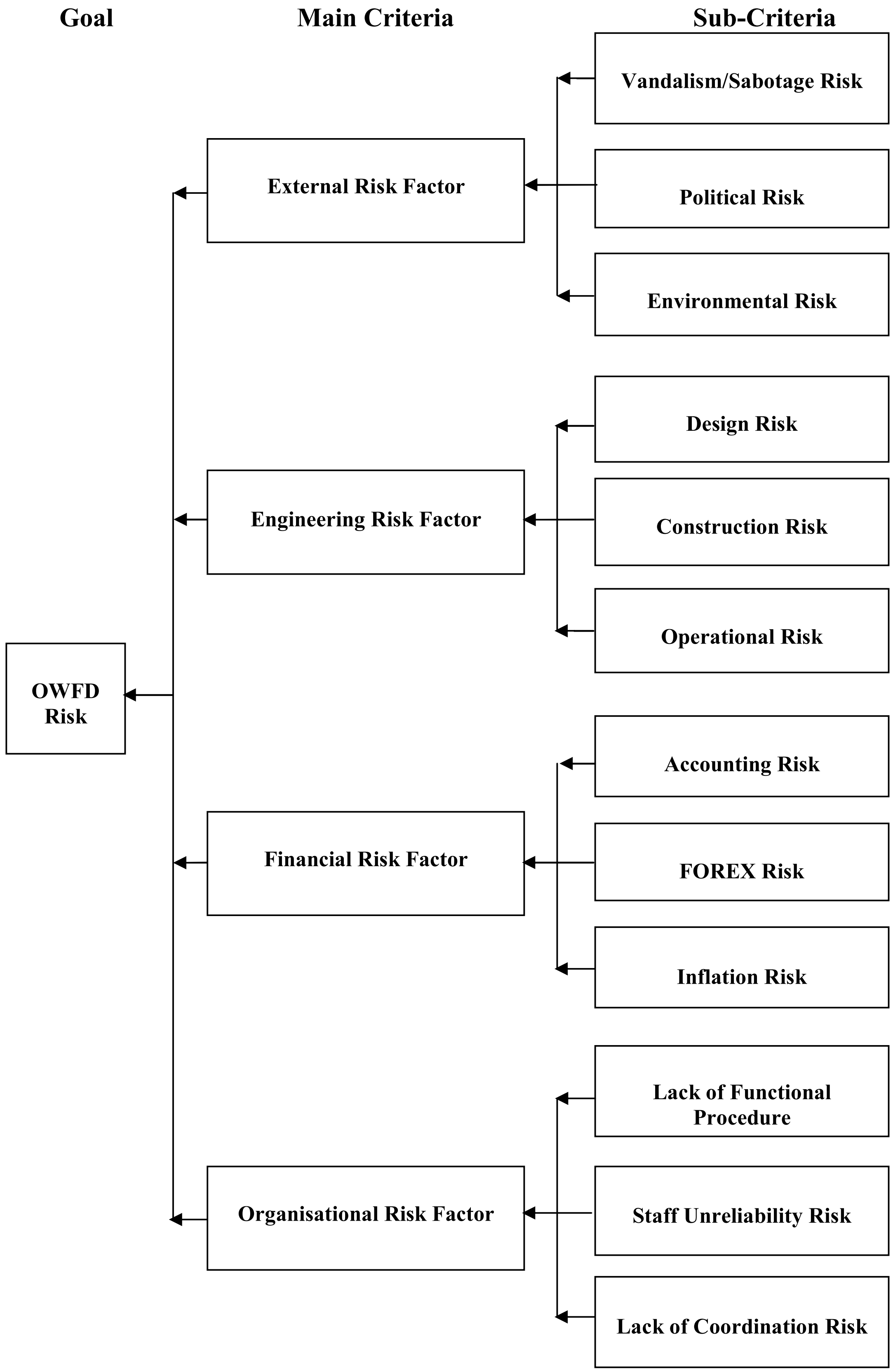


Figure 3.8 Specific model of a risk-based framework for an offshore wind farm

3.10.2 Setup the criteria for assessment

Table 3.5 Assessment grade for the Goal

Goal	Assessment Grade				
OWFD Risks	Very Low	Low	Medium	High	Very High

Table 3.5 presents the linguistic variables applied to the research goal, which are used in the assessment of the risk associated with offshore wind farm development. The linguistic terms consist of five variables between 'Very Low' and 'Very High'. For instance, if the expert believes the risks associated with the OFWD are Very Low, it indicates that the risk of that particular criterion is low. Similarly, if the belief degree of the risk is 'Very High', it indicates that the risks associated with the OFWD are high.

Table 3.6 Assessment grades for the main criteria

Main Criteria	Assessment Grades				
External risk	Extremely Low	Fairly Low	Medium	Fairly High	Extremely High
Engineering risk	Extremely Low	Fairly Low	Medium	Fairly High	Extremely High
Financial risk	Extremely Low	Fairly Low	Medium	Fairly High	Extremely High
Organisational risk	Extremely Low	Fairly Low	Medium	Fairly High	Extremely High

Table 3.6 represents the five linguistic variables applied to the main criteria of the model. The linguistic terms consist of five variables between 'Extremely Low' and 'Extremely High'. For instance, if the expert believes the risk of any of the criteria considered is 'Extremely Low', it indicates that the risk of that particular criterion is the lowest it can be. Similarly, if the risk of the belief degree of any particular criterion is 'Extremely High', it indicates that the risk of that criterion is the highest it can be.

Table 3.7 Assessment grades for the sub-criteria

Sub-criteria	Assessment Grades				
Vandalism/Sabotage risk	Very High	High	Moderate	Low	Very low
Political risk	Very High	High	Moderate	Low	Very low
Environmental risk	Very High	High	Moderate	Low	Very low
Design risk	Very High	High	Moderate	Low	Very low
Construction risk	Very High	High	Moderate	Low	Very low
Operational risk	Very High	High	Moderate	Low	Very low
Accounting risk	Very High	High	Moderate	Low	Very low
FOREX risk	Very High	High	Moderate	Low	Very low
Inflation risk	Very High	High	Moderate	Low	Very low
Lack of functional procedure	Very High	High	Moderate	Low	Very low
Staff unreliability	Very High	High	Moderate	Low	Very low
Lack of coordination/communication risk	Very High	High	Moderate	Low	Very low

The assessment grades shown in Table 3.7 represent the five linguistic variables (between 'Very High and 'VeryLow') for the assessment of the sub-criteria risk elements considered in the OWFD. The belief degree of the expert opinion determines the extent of the assessed risk with respect to the corresponding main criterion.

3.10.3 Apply the AHP methodology

3.10.3.1 Weight assignment to risk parameters

It is important here to develop priorities for the main criteria and sub-criteria of the risk factors presented in Figure 3.8. This will be achieved by understanding the rationale and the judgements of the decision makers through the application of AHP. The priorities set by the experts are determined by the pairwise assessments of individual judgements. The weighting process is finally applied in order to obtain the overall priorities for the sub-criteria and the contributions towards achieving the goal.

For the purpose of this research, the participating experts are assigned equal weights in order to eliminate bias. The pairwise comparison is constructed by the application of the linguistic variables shown in tables 3.3 and 3.4.

The Participant Experts are of the following backgrounds:

- A Construction Manager in Offshore Wind Farm development with a total offshore construction experience of about 35 years spanning marine subsea construction, offshore oil & gas development and the renewable energy industry.
- A senior Offshore Installation Manager in offshore wind farm development with a total offshore installation experience of about 35 years.
- A senior Safety Advisor in offshore wind farm development with a total offshore safety management experience of about 18years.
- A senior Offshore Wind Farm Package Manager and Marine Engineer with shipboard practical experience with a total offshore construction experience (including oil & gas) of 20 years.

3.10.3.2 An evaluation of the judgements of expert 1's survey feedback by modelling of the hierarchy to obtain the weights of risk parameters using the AHP approach

In order to determine the n^{th} ratio of the risk components, an evaluation of the main risk criteria and the sub-criteria is required. This can be achieved by the application of the relevant AHP procedure, which includes developing weights for the criteria. (Reference can be made to Appendix 1 for full expert judgements).

The weights for the risk criteria can be determined by constructing a single pairwise comparison matrix for the criteria based on the expert judgements (see Appendix 1), multiplying the values in each row together and calculating the n^{th} root of the said product, normalising the n^{th} root of the product in order to obtain the relevant weights and by calculating and verifying the Consistency Ratio (CR).

<u>Sample calculation from expert of judgment of just one expert:</u>

Using the expert opinion (refer to Appendix 1) to form the risk evaluation matrix in Table 3.8; the following rules are observed:

- If the judgement value is on the left side of '1', the actual judgement value is recorded.

- If the judgement value is on the right side of '1', the reciprocal value will be recorded.

In comparing the four main criteria as shown in Table 3.8, the expert has determined that:

- External risk is 'moderately more important' than engineering risk (4)
- Financial risk is 'strongly important' over external risk (5)
- Financial risk is 'strongly plus important' over engineering risk (6)
- Financial risk is 'weakly or slightly' more important than organisational risk (2)
- Organisational risk is 'strongly important' over external risk (5)
- Organisational risk is 'strongly important' over engineering risk (6)

The values obtained from the above pairwise comparison established by the expert are used to construct the pairwise comparison matrix and thereafter compute the weights of the main risk criteria (external, engineering, financial and organisational risks) as shown in Table 3.8.

3.10.4 Perform pairwise comparison for each level of objective (sample calculation using one expert judgement only)

Table 3.8 Pairwise comparison matrix of the main risk criteria

OWFT	External Risk	Engineering Risk	Financial Risk	Organisational Risk
External Risk	1	4	1/5	1/5
Engineering Risk	1/4	1	1/6	1/6
Financial Risk	5	6	1	2
Organisational Risk	5	6	1/2	1

Table 3.8 shows 4 x 4 matrix that contains all possible pairwise comparisons for the main risk criteria. The equally important comparisons shown in the matrix table indicate the comparison of each criterion to itself; this is represented by diagonal values of '1'. The rest of the values shown in Table 3.8 represent the reciprocal pairwise comparisons of relationships. The reciprocal comparisons specifically indicate that:

- External risk is ‘strongly more unimportant’ than the financial risk (1/5 or 0.200)
- External risk is ‘strongly more unimportant’ than the organisational risk (1/5 or 0.200)
- Engineering risk is ‘moderately plus more unimportant’ than the external risk (1/4 or 0.250)
- Engineering risk is ‘moderately plus more unimportant’ than the financial risk (1/6 or 0.167)
- Engineering risk is ‘moderately plus more unimportant’ than the organisational risk (1/6 or 0.167)

Having constructed a single pairwise comparison matrix for the main risk criteria as shown above, now multiply the values together and obtain the n^{th} root of the risk components and present answers in three decimal places (see table 3.9). Then, normalise the n^{th} root in order to obtain the appropriate weights. The Consistency Ratio (CR) can then be calculated and checked. The n^{th} root in this study is ‘4’, given that there are four main risk criteria being considered.

<u>Calculation procedures as represented in the above table are as follows (sample calculation using one expert judgement only):</u>

External Risk: $(1.000 \times 4.000 \times 0.200 \times 0.200)^{(1/4)} = (0.160)^{(0.25)} = 0.632$

Engineering Risk: $(0.250 \times 1.000 \times 0.167 \times 0.167)^{(1/4)} = (0.112)^{(0.25)} = 0.289$

Financial Risk: $(5.000 \times 6.000 \times 1.000 \times 2.000)^{(1/4)} = (60)^{(0.25)} = 2.783$

Organisational Risk: $(5.000 \times 6.000 \times 0.500 \times 1.000)^{(1/4)} = (15)^{(0.25)} = 1.968$

Table 3.9 Pairwise comparison matrix of the main risk criteria in order to obtain n^{th} root (4^{th} root)

OWFT	External Risk	Engineering Risk	Financial Risk	Organisational Risk	4^{th} Root
External Risk	1.000	4.000	0.200	0.200	0.632
Engineering Risk	0.250	1.000	0.167	0.167	0.289
Financial Risk	5.000	6.000	1.000	2.000	2.783
Organisational Risk	5.000	6.000	0.500	1.000	1.968
					5.672

In order to obtain the respective weights of the risk components, normalise the n^{th} root. This is done by dividing the n^{th} root by the total sum of the n^{th} root (4^{th} root in this case). The weights of the risk criteria, which are the priority vector values, must be equal to 1 when summed up together, as shown in Table 3.10 below. See calculations showing the detailed process below.

Risk Criteria: (n^{th} Root /Sum of n^{th} Root)

External Risk: (0.632 / 5.672) = 0.111

Engineering Risk: (0.289 /5.672) =0.051

Financial Risk: (2.783/5.672) = 0.491

Organisational Risk: (1.968 / 5.672) = 0.347

Table 3.10 Pairwise comparison matrix of the main risk criteria in order to obtain the Priority Vector

OWFT	External Risk	Engineering Risk	Financial Risk	Organisational Risk	4^{th} Root	Priority Vector
External Risk	1.000	4.000	0.200	0.200	0.632	0.111
Engineering Risk	0.250	1.000	0.167	0.167	0.289	0.051
Financial Risk	5.000	6.000	1.000	2.000	2.783	0.491
Organisational Risk	5.000	6.000	0.500	1.000	1.968	0.347
					5.672	1.000

The Consistency Ratio (CR) enables the decision maker to determine how consistent the pairwise comparisons are. Therefore, in order to determine the CR, apply Equations (3.5), (3.6), (3.7) and (3.8) and follow the steps described in section 3.7. The pairwise values in each column (the sum values) are added up as shown in Table 3.11 and each sum value in the column is multiplied by the corresponding weight (from the priority vector column); see Table 3.11 below.

<u>**Calculation details for obtaining the consistency ratio (CR):**</u>

<u>**(sample calculation using one expert judgement only)**</u>

External Risk: (1.000 + 0.250 + 5.000 + 5.000) x 0.111 = 1.249

Engineering Risk: (0.125+ 1.000 + 5.000 + 7.000) x 0.051 = 0.867

Financial Risk: (0.200+ 0.167 + 1.000 + 0.500) x 0.491 = 0.912

Organisational Risk: (0.200 + 0.167 + 2.000 + 1.000) x 0.347 = 1.168

Therefore, (λ_{Max}) = (1.249 + 0.867 + 0.912 +1.168) = 4.196

3.10.5 Determine the consistency ratio and the relative risks (sample calculation using one expert judgement only)

Table 3.11 Evaluation of relative risk of the main criteria in order to obtain the Lambda Max (λ_{Max})

OWFT	External Risk	Engineering Risk	Financial Risk	Organisational Risk	4^{th} Root	Priority Vector
External Risk	1.000	4.000	0.200	0.200	0.632	0.111
Engineering Risk	0.250	1.000	0.167	0.167	0.289	0.051
Financial Risk	5.000	6.000	1.000	2.000	2.783	0.491
Organisational Risk	5.000	6.000	0.500	1.000	1.968	0.347
Sum up	11.250	17.000	1.867	3.367	5.672	1.000
Sum up x PV	1.254	0.865	0.916	1.168	**4.203**	

From Table 3.11, the derived scale (PV) based on the judgement of the expert is shown as 0.111, 0.051, 0.491, 0.347.

Based on Equation 3.9 above, Consistency Index (CI),

$$CI = (\lambda_{Max} - 1)/(n-1)$$

Where $n = 4$ (4 main risk criteria in this case)

Hence, CI = (4.203– 4) / (4 – 1)

CI = 0.203 / 3 = 0.068

Therefore, Consistency Ratio (CR) = Consistency Index (CI)/ Random Index (RI) in line with Equation 3.10:

$$CR = \frac{CI}{RI}$$

In this case, $n = 4$

From the above RI table (see Table 3.1), $n = 4 = 0.9$

Hence, $CR = \frac{CI}{RI} = \frac{0.068}{0.90}$

$CR = 0.076$

If the $CR \leq 0.10$, it indicates that the decision maker's pairwise comparisons are relatively consistent and no corrective action is required. Given that CR in this case is 0.076, which is less than 0.10, it indicates that the pairwise comparisons are consistent. Hence, no corrective action is necessary.

Assuming the CR is > 0.10, it implies that the pairwise comparisons are inconsistent and the source of the inconsistency must be identified and corrected. The higher the CR values, the more inconsistent the decision maker's pairwise comparisons. The lower the CR, the more consistent the pairwise comparisons are. Further details can be found in the Appendices.

3.10.6 Develop the ratings for each sub-criterion (Sample calculation using one expert judgement only)

The ratings for each decision alternative of each individual criterion will be developed by generating the pairwise comparison matrix for each criterion and each of the matrices will contain the pairwise comparisons of the performance of the decision alternatives of each criterion; the n^{th} root of the main risk criteria will be calculated by multiplying through the values in each row; the n^{th} root of the main criteria is then normalised in order to obtain the ratings of the risk criteria. The ratings for each decision alternative will be determined for every criterion considered, and a pairwise comparison in each matrix will rate each sub-criterion relative to other sub-criteria.

In the case of this study, there are four main risk criteria identified for offshore wind farm development, namely the external risk factors, the engineering risk factors, the financial risk factors and the organisational risk factors. Four matrices will be constructed for these main risk criteria, each representing main risk criteria. A pairwise comparison will be developed for each of the sub-criteria against other sub-criteria relative to the specific main risk criteria. Given that there are three sub-criteria being considered for evaluation, each of the matrixes constructed must be of size 3x3, as shown in Table 3.12.

Similarly, the sub-criteria risk attributes can be evaluated with respect to each particular main criterion in order to obtain the priority vector, the $\lambda_{\max}$ and consistency ratio as previously demonstrated in the case of the main risk Priority Vector (PV).

3.10.7 Aggregation of pairwise comparison of the four experts for main criteria with respect to the Goal

The calculations of the aggregated pairwise comparisons are the main evaluation process of the case study as they are comprised of the expert judgements of the four participants. This is where the full assessments begin and the methodologies of the sample calculations are applied.

Let the four experts be represented as x_1, x_2, x_3 and x_4.

<u>**Computing the judgements of the experts for each criterion (see Appendix 1):**</u>

$$Combined pair-wise comparison = (x_1 \times x_2 \times x_3 \times x_4)^{1/4}$$

$$ExtR - EngR = (4 \times \frac{1}{7} \times \frac{1}{5} \times \frac{1}{5})^{1/4} = 0.389$$

$$ExtR - FinR = (\frac{1}{5} \times \frac{1}{3} \times 3 \times 1)^{1/4} = 0.669$$

$$ExtR - OrgR = (\frac{1}{5} \times 2 \times \frac{1}{5} \times 4)^{1/4} = 0.752$$

$$EngR - FinR = (\frac{1}{6} \times 5 \times 7 \times 2)^{1/4} = 1.848$$

$$EngR - OrgR = (\frac{1}{6} \times 7 \times 4 \times 5)^{1/4} = 2.198$$

$$FinR - OrgR = (2 \times 5 \times \frac{1}{4} \times 4)^{1/4} = 1.778$$

Where $FinR$ represents Financial Risks, $ExtR$ represents External Risks, $EngR$ represents Engineering Risks and $OrgR$ represents Organisational Risks.

Construct pairwise comparison matrices from the values derived from the above calculations.
First Step - use the Expert feedback from the 4 experts and aggregate the values of the pairwise comparisons. Then, the figures obtained in this table will be used to construct pairwise matrices of the main criteria.

Table 3.12 Aggregated values derived from the pairwise comparisons of the main risk criteria.

Pairwise	x_1 (Expert 1)	x_2 (Expert 2)	x_3 (Expert 3)	x_4 (Expert 4)	4th Root
ExtR-EngR	4.00	$\frac{1}{7}$=0.143	$\frac{1}{5}$=0.200	$\frac{1}{5}$=0.200	$(4x0.143x0.200x0.200)^{1/4}$ = 0.389
ExtR-FinR	$\frac{1}{5}$=0.200	$\frac{1}{3}$=0.200	3.00	1.00	$(0.200x0.333x3x1)^{1/4}$ = 0.669
ExtR-OrgR	$\frac{1}{5}$=0.200	2.000	$\frac{1}{5}$=0.200	4.000	$(0.200x2x0.200x4)^{1/4}$ = 0.752
EngR-FinR	$\frac{1}{6}$=0.167	5.00	7.000	2.000	$(0.167x5.0x7.0x2)^{1/4}$ = 1.848
EngR-OrgR	$\frac{1}{6}$=0.167	7	4	5	$(0.167x7x4x5)^{1/4}$ = 2.198
FinR-OrgR	2	5	$\frac{1}{4}$=0.250	4	$2x5x0.250x4)^{1/4}$ = 1.778

Table 3.12 shows the aggregated values derived from the pairwise comparisons of the main risk criteria. Similarly, the aggregated pairwise comparisons for the sub-criteria with respect to the corresponding main criterion from the four experts can be calculated using the same methodology. Full details of the calculations can be found in Appendix 1.

3.10.8 Synthesising the judgements of the four experts

The global weights of the sub-criteria can be obtained from the aggregation of the weights of the overall priorities of the sub-criteria in the entire hierarchy. The overall priorities of the elements at the highest and the lowest level of the hierarchy are computed by multiplying through with the local priorities of the alternatives with the priorities of the main criteria as shown in Table 3.13.

Table 3.13 Representation of risk parameters

Main Criteria	Representation	Sub-Criteria	Representation
External Risk	C1	Vandalism/Sabotage risk Political risk Environmental risk	C11 C12 C13
Engineering Risk	C2	Design risk Construction risk Operational risk	C21 C22 C23
Financial Risk	C3	Accounting risk FOREX risk Inflation risk	C31 C32 C33
Organisational Risk	C4	Lack of functional procedure Staff unreliability risk Lack of coordination/communication risk	C41 C42 C43

Table 3.13 above shows the details of the risk parameter connotations assigned by the decision maker to ease data presentation. Therefore, these will be used to present the risk parameter and corresponding data in the analytical report of this thesis.

Table 3.14 Aggregated pairwise comparison of the main criteria from the four experts' judgements

OWFD	C_1	C_2	C_3	C_4	4th Root	Priority vector
C_1	1.000	0.389	0.669	0.752	0.665	0.154
C_2	2.572	1.000	1.848	2.198	1.798	0.416
C_3	1.495	0.541	1.000	1.778	1.095	0.253
C_4	1.330	0.455	0.562	1.000	0.764	0.177
Sum up	6.397	2.385	4.079	5.728	4.322	1.000
Sum up x PV	0.984	0.992	1.034	1.012	**4.022**	

CI = 0.007
CR = 0.008

The pairwise comparisons of the main criteria (see Table 3.14) indicate that the engineering risk factor has the highest normalised principal eigenvector (priority vector) at 42%, which shows that it contributes more significant risks to the development of an offshore wind farm. This is followed by the financial risk factor with 25% risk contribution to the OWFD.

Table 3.15 Global ranking of the main and sub-criteria

Main criteria	Main criteria weights	Sub-criteria	Sub-criteria weights	Global weight	Global Ranking
C1	0.154	C11	0.149	0.023	12
		C12	0.495	0.076	5
		C13	0.355	0.055	8
C2	0.416	C21	0.293	0.122	3
		C22	0.551	0.229	1
		C23	0.156	0.065	7
C3	0.253	C31	0.180	0.045	10
		C32	0.542	0.137	2
		C33	0.278	0.071	6
C4	0.177	C41	0.180	0.032	11
		C42	0.542	0.096	4
		C43	0.278	0.049	9
				1.000	

The global ranking of the entire risk parameters associated with the OWFD presented in Table 3.15 indicates that the construction risk is the most significant risk in the lower hierarchy level with a global weight of 0.208 in the upper hierarchy with respect to the engineering risk factor. In the engineering risk category, the construction risk has been considered more significant risk than the design risk, with a global weight of 0.137, and the operational risk, with a global weight of 0.076. It is not surprising that participants consider construction risk to be more important than design risk and operational risk, because construction barriers have a high impact and are more difficult to solve than design or operational issues.

Another reason why the expert judgements have remained consistent in choosing the construction risk over the rest of the risk parameters in the same engineering risk factor category may be the fact that the experts are all from an offshore wind farm construction background and have first-hand experience of the potential impact and severity of the construction risk. Moreover, the construction risk is more likely to have long-term damage and fewer remedial opportunities.

3.10.9 Weights obtained through hierarchical modelling

The final weights of the aggregated pairwise comparisons of all the risk parameters computed are shown in Table 3.16. This also shows the consistency ratios of the individual risk parameters obtained from the overall assessments of the hierarchy.

Table 3.16 A summary of the weights and the consistency ratios of associated influencing risks factors of OWFD

Risk Parameters	Representation of Risk Parameters	weights (Priority Vector)	Consistency Ratios (CR)
Vandalism/Sabotage risk	C11	0.149	
Political risk	C12	0.495	0.097
Environmental risk	C13	0.355	
Design risk	C21	0.293	
Construction risk	C22	0.551	0.063
Operational risk	C23	0.156	
Accounting risk	C31	0.180	
FOREX risk	C32	0.542	0.029
Inflation risk	C33	0.278	
Lack of functional procedure	C41	0.180	
Staff unreliability risk	C42	0.542	0.011
Lack of coordination/communication risk	C43	0.278	
External Risk	C1	0.154	
Engineering Risk	C2	0.416	0.008
Financial Risk	C3	0.253	
Organisational Risk	C4	0.177	

The details of the calculations for the aggregation of the sub-criteria input, determination of their priority vectors and verifications of consistency ratios can be found in Appendix 1.

3.10.10 Determine the fuzzy rules and transfer of data

3.10.10.1 Implementation of the mapping process

As explained in section 3.6, a mapping process is employed to transform data presented in the form of linguistic terms into common utility space prior to the application of the ER approach. Therefore, a fuzzy rule base (FRB) is required and will be developed on the basis of the professional judgements formed by the experts on the subject matter.

Vandalism/sabotage risk

The following fuzzy rules are developed on the grounds of the expert judgements from vandalism/sabotage to external risk factors presented in Figure 3.8:

- If the vandalism/sabotage risk is very low, then the external risk factors impacting on the offshore wind farm development are 100% extremely low.
- If the vandalism/sabotage risk is low, then the external risk factors impacting on the offshore wind farm development are 50% fairly low, 50% extremely low.
- If the vandalism/sabotage risk is moderate, then the external risk factors impacting on the offshore wind farm development are 70% medium, 30% fairly low.
- If the vandalism/sabotage risk is high, then the external risk factors impacting on the offshore wind farm development are 90% fairly high, 10% medium.
- If the vandalism/sabotage risk is very high, then the external risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_{VS} = \{(VeryLow, 0), (Low, 0.5), (Moderate, 0.5), (High, 0), (VeryHigh, 0)\}$$

The fuzzy rules developed by the experts are transformed into quantitative values by application of the mapping process from vandalism/sabotage risk to external risk factor, as shown in Figure 3.9.

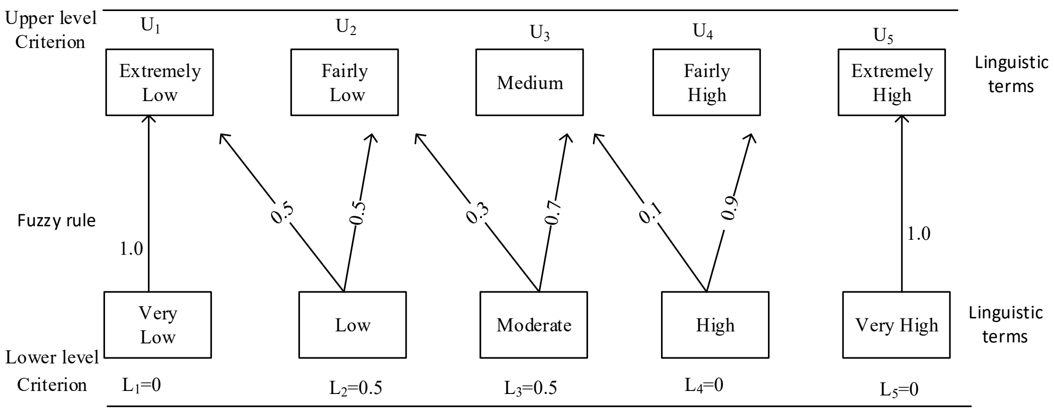


Figure 3.9 Mapping vandalism/sabotage risk to external risk factor

Using Equations 3.4, 3.5 and 3.6, the associated belief degrees of the linguistic terms of the upper-level criterion (external risk factor) are transformed from the lower-level criterion (vandalism/sabotage risk) into numerical quantities.
Hence,

$$U_1 = \{(0\times 1.0)+(0.5\times 0.5),\ U_2 = (0.5\times 0.5)+(0.5\times 0.3),\ U_3 = (0.5\times 0.7)+(0\times 0.9)\}$$
$$= 0.25, \qquad = 0.40, \qquad = 0.35,$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{VS} = \{(Extremely Low, 0.25), (Fairly\ Low, 0.40), (Medium, 0.35),$$
$$(Fairly\ \ High\ , 0), (Extremely\ \ High\ , 0)\}$$

Similarly, the rest of the criteria (political risk and environmental risk) can be transformed from their lower level to the upper level of the hierarchical structure. The derived fuzzy set output results are presented in Table 3.17 below. However, the details of the mapping process can be found in Appendix 1 for reference purposes.

Table 3.17 Aggregation of the sub-criteria with respect to external risk factors

External Risk	**Extremely Low**	**Fairly Low**	**Medium**	**Fairly High**	**Extremely High**
$\widetilde{M}_{VS}$	0.25	0.40	0.35	0	0
$\widetilde{M}_P$	0	0.12	0.18	0.70	0
$\widetilde{M}_E$	0	0	0.4	0.6	0
Result from Aggregation	0.0142	0.0353	0.3614	0.5892	0.0000

The rest of the calculations and details of the data transformation processes for $\widetilde{M}_P$ and $\widetilde{M}_E$ can be found Appendix 2. As previously explained, this process is used to transform the qualitative data into quantitative data to be applied in the risk evaluations.

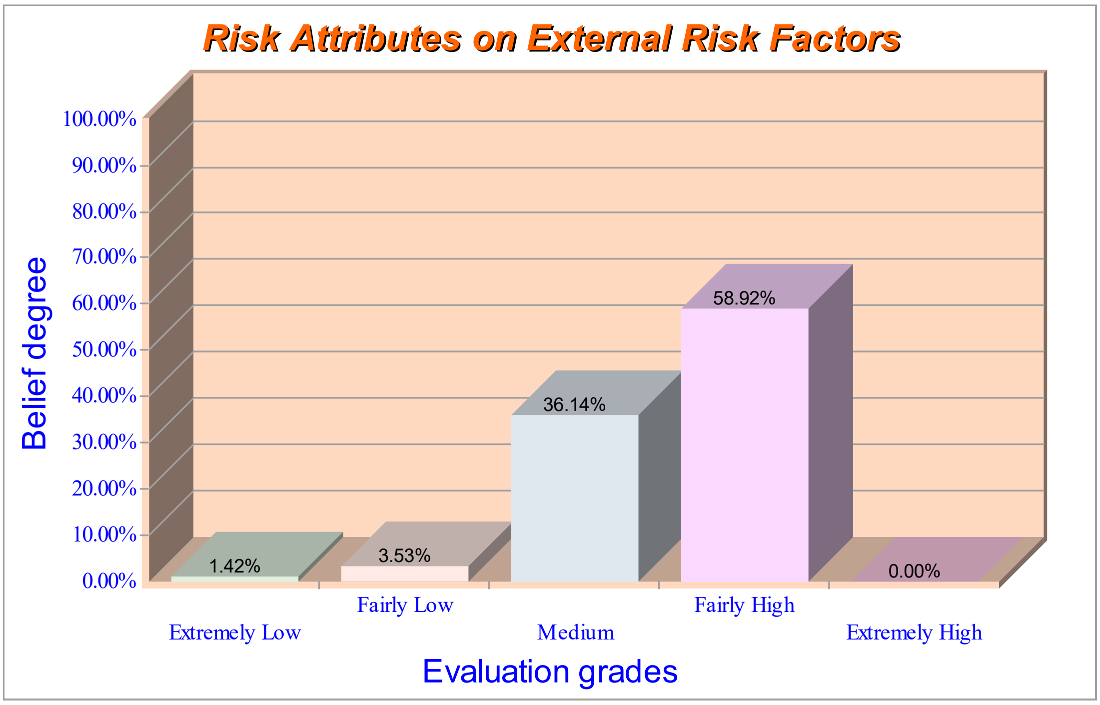


Figure 3.10 external risk factors aggregation result chart

The result of the aggregation of the sub-criteria with respect to the external risk factor is represented the chart shown in Figure 3.10 above.

<u>Mapping from external risk factors to the Goal</u>

In order to evaluate the potential external risk factors affecting the offshore wind farm development (OWFD), the external risk factors will be transformed to the 'goal' using a mapping process. Therefore, the fuzzy set input for mapping the external risk factors to the goals is as follows:

$$\widetilde{M}_{OWF} = \{(Extremely Low, 0.0142), (Fairly Low, 0.0353), (Medium, 0.3614), \\ (Fairly\ High, 0.5892), (Extremely\ High, 0)\}.$$

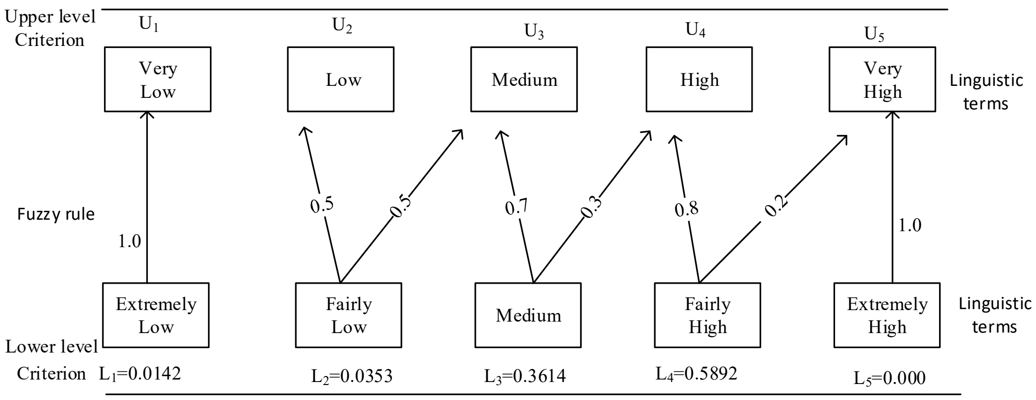


Figure 3.11 Mapping from external risk factors to the goal

From the above mapping process in Figure 3.11, the output values are as follows:

$U_1 = \{(0.0142 \times 1.0),\ \ U_2 = (0.0353 \times 0.5),\ \ U_3 = (0.0353 \times 0.5) + (0.3614 \times 0.7$

$U_4 = (0.3614 \times 0.3) + (0.5892 \times 0.8),\ \ U_5 = (0.5892 \times 0.2) + (0.000 \times 1.0)\}$

$U_1 = 0.0142, \quad U_2 = 0.0177, \quad U_3 = 0.2706, \quad U_4 = 0.5798, \quad U_5 = 0.1178$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{EXO} = \{(VeryLow, 0.0142), (Low, 0.0177), (Medium, 0.2706),$$
$$(High, 0.5798), (VeryHigh, 0.1178)\}.$$

In a similar way, the rest of the main criteria in the hierarchy are transformed to the goal in order to derive the individual fuzzy output sets and the overall risk estimation, the results of which are presented in Table 3.18. Further details of the calculations and transformation processes of the rest of the risk factors are in Appendix 1.

3.10.11Calculating the crisp value for the main risk associated with OWFD

Using the utility values obtained from the aggregated assessments (see Table 3.19), the crisp value for informed decision-making in respect of the OWFD risk is determined. This can be achieved by computation of the weights of the main criteria as shown in Table 3.18 and the aggregated values in Table 3.19 in IDS software. The result of the computation is presented in the pictorial chart of Figure 3.12 as alternative risk factors for offshore wind farm development.

Table 3.18 Aggregated values of main risk criteria transformed to the goal through the mapping process

OWFD Risk	Very Low	Low	Medium	High	Very High
$\widetilde{M}_{ExtR}$	0.0142	0.0177	0.2706	0.5798	0.1178
$\widetilde{M}_{EngR}$	0.2293	0.0219	0.0569	0.5566	0.1354
$\widetilde{M}_{FinR}$	0.2192	0.2374	0.4269	0.0891	0.0255
$\widetilde{M}_{OrgR}$	0.2971	0.3314	0.2069	0.1082	0.0564
Result from Aggregation	0.1841	0.1282	0.2302	0.3739	0.0836

Further details of the computations for the determination of the rest of aggregated risk factors i.e. $\widetilde{M}_{EngR}$, $\widetilde{M}_{FinR}$ and $\widetilde{M}_{OrgR}$ of the main criteria can be found in Appendix 1. The values are used as the input data for IDS software in order to evaluation chart results shown in the Figure 3.12 below. The same process is applicable for the rest of the criteria shown in Appendix 1.

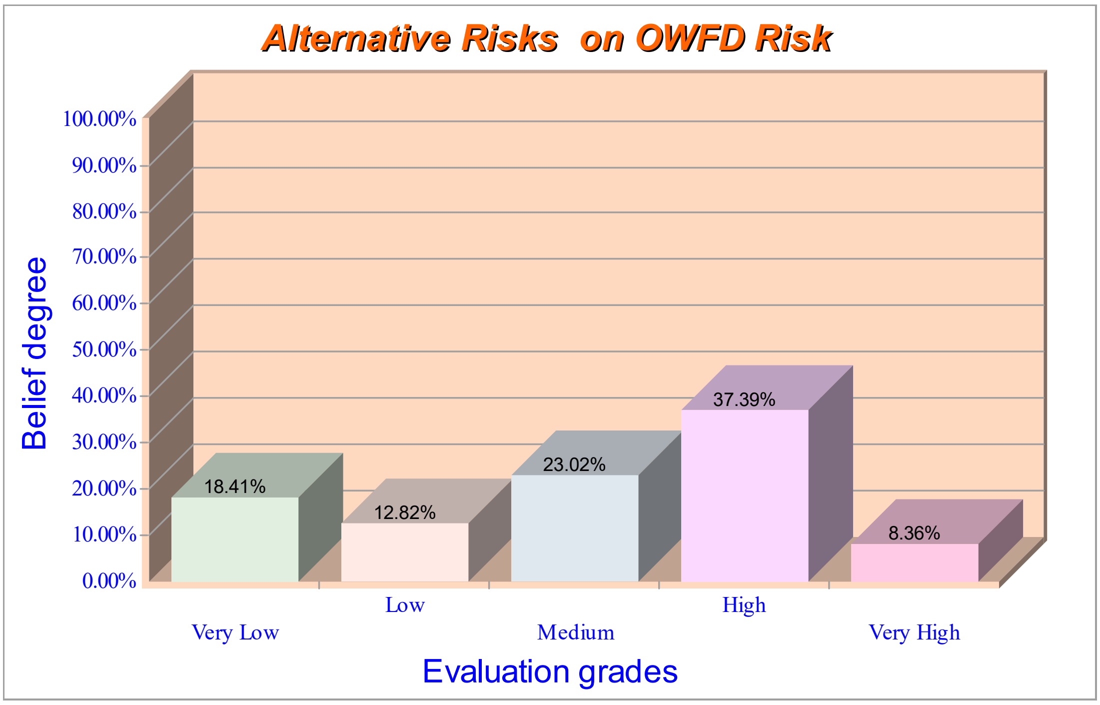


Figure 3.12 Main risk criteria aggregation of alternative on OWFD

From the information presented in Table 3.18, the fuzzy output set is:

$$\tilde{M}_{OWFR} = \{(Very Low, 0.1841), (Low, 0.1282), (Medium, 00.2302), (High, 0.3739), (Very\ High, 0.0836)\}$$

From the above fuzzy set, the lowest linguistic preference is Very High at 37.39% and the highest linguistic preference is High at 8.36%. The values obtained in the fuzzy set output values (utility values) of the main criteria are then used to calculate the utility value of the goal (OWFD Risk); see Table 3.19.

Let the utility value of OWFD Risk be represented by M_{OWFR}.

See table 3.19 below for indicating how the crisp value of OWFD is determined by application of linguistic variable assessment.

Table 3.19 Obtaining the crisp value

H_n	Very Low	Low	Medium	High	Very High
V_n	1	2	3	4	5
$u(H_n)$	$\frac{1-1}{5-1}=0$	$\frac{2-1}{5-1}=0.25$	$\frac{3-1}{5-1}=0.5$	$\frac{4-1}{5-1}=0.75$	$\frac{5-1}{5-1}=0.75$
β_n	0.1841	0.1282	0.2302	0.3739	0.0836
$\beta_n \times u(H_n)$	0	0.0321	0.1151	0.2804	0.0836

$$\sum_{n-1}^{N} \beta_n = 0 + 0.0321 + 0.1151 + 0.2804 + 0.0836 = 1 \rightarrow \beta_H = 0$$

$$M_{OWFR} = \sum_{n-1}^{N} \beta_n \times u(H_n) = 0.5112$$

Associated risk level to OWFD is approximately = 0.51

3.10.12 Determining the sensitivity of the analysis

Sensitivity analysis is applied to determine how much variation in the input values for each given independent variable impacts on the results of the dependent variable through application of a mathematical model under a set of uncertainty or assumptions. Full details of the principles of the sensitivity analysis and its application can be found in section 3.9 of this thesis. This is also supported by the axioms as described in subsection 3.9.3.

The sensitivity analysis is performed by varying (decrement) of the input data associated with highest preference linguistic values of all the lower-level criteria by 10%, 20% and 30% and simultaneously increasing the input data of the lowest preference linguistic values of each of the criteria at the lower level. This means that, by decreasing the input data of the highest preference linguistic value (β_H) of a given criterion by a factor of (x), the input data of the lowest preference linguistic value will be increased by the same factor. If (β_H) is less than (x), the remaining belief degree ($x-\beta_H$) can be obtained from the next linguistic value until (x) is completely exhausted in a systematic manner.

The utility values obtained from the sensitivity studies are presented in Table 3.21 with the sensitivity chart shown in Figure 3.13. The results of this chart comply with Axioms 1 and 2. However, Axiom 3 illustrates that this is logical and reflects reality. The preference degrees of the risk attributes at the lower levels of the hierarchy in connection with y factors (evidence) will be smaller than the one from $y-z(z \in y)$ factors (sub-evidence). This can be achieved by comparison of the preference degree of the risk attributes using analytical modelling.

Table 3.20 Risk attributes and the derived fuzzy input sets

Risk Attributes	Derived fuzzy input sets
Vandalism / Sabotage	{(Very Low, 0), (Low, 0.5), (Moderate, 0.5), (High, 0), (Very High, 0)}
Political risk	{(Very Low, 0), (Low, 0), (Moderate, 0.3), (High, 0.7), (Very High, 0)}
Environmental risk	{(Very Low, 0), (Low, 0), (Moderate, 1.0), (High, 0), (Very High, 0)}
Design risk	{(Very Low, 0.6), (Low, 0.4), (Moderate, 0), (High, 0), (Very High, 0)}
Construction risk	{(Very Low, 0), (Low, 0.4), (Moderate, 0), (High, 1.0), (Very High, 0)}
Operational risk	{(Very Low, 0), (Low, 0), (Moderate, 0.2), (High, 0.8), (Very High, 0)}
Accounting risk	{(Very Low, 0), (Low, 0), (Moderate, 0), (High, 0.3), (Very High, 0.7)}
FOREX risk	{(Very Low, 0.5), (Low, 0.5), (Moderate, 0), (High, 0), (Very High, 0)}
Inflation risk	{(Very Low, 0), (Low, 0.4), (Moderate, 0.6), (High, 0), (Very High, 0)}
Lack of functional procedure	{(Very Low, 0), (Low, 1.0), (Moderate, 0), (High, 0), (Very High, 0)}
Staff Unreliability	{(Very Low, 0), (Low, 0.3), (Moderate, 0.7), (High, 0), (Very High, 0)}
Lack of communication / Coordination	{(Very Low, 0), (Low, 0), (Moderate, 0), (High, 0.4), (Very High, 0.6)}

The derived fuzzy input sets of the risk attributes of the OWFD model are presented in Table 3.20. Table 3.21 below shows the increment of the input data of the risk attributes with the lowest preference linguistic terms and decrement of the input data with the highest preference linguistic terms. The derived fuzzy set inputs may also be referred to as the assigned input values as indicated in page 128 (see subsection 3.10.9.1) and full details can be found in Appendix 1.

Table 3.21 Decrement and Increment of all the input data of the risk attributes

Risk Attributes	Key	Utility value (10%)	Utility value (20%)	Utility value (30%)
Vandalism/Sabotage Risk	C11	0.325	0.275	0.225
Political Risk	C12	0.6	0.525	0.45
Environmental Risk	C13	0.45	0.4	0.4
Design Risk	C21	0.2	0.3	0.3
Construction Risk	C22	0.675	0.6	0.525
Operational Risk	C23	0.625	0.55	0.475
Accounting Risk	C31	0.825	0.725	0.625
FOREX Risk	C32	0.225	0.325	0.425
Inflation Risk	C33	0.35	0.3	0.25
Lack of Functional Procedures	C41	0.125	0.2	0.175
Staff Unreliability	C42	0.3225	0.325	0.275
Lack of Coordination/Communication	C43	0.92	0.7	0.6

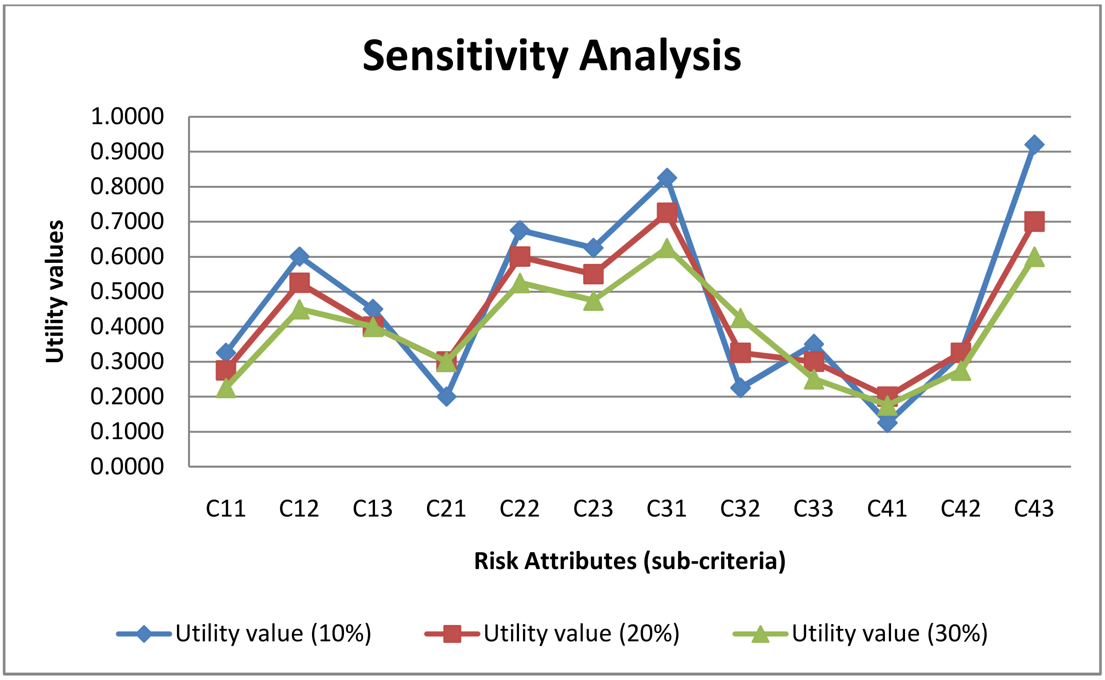


Figure 3.13 Graph of the sensitivity of the model risks to the variation of each risk attribute (sub-criterion)

3.11 Results and Discussions

The data represented in Table 3.18 indicates that the belief degree of the assessed risk factors is 'High' linguistic variable at 37.39% whereas the belief degree is 'Low' linguistic variable at 12.82%. The aggregated results of the computation also show that the Engineering Risk factor has the highest score of 13.54% of the belief degree whereas the Financial Risk factor has the lowest score of 2.55% of the belief degree as evident in Table 3.18.

The overall risk impact of the offshore wind farm development (OWFD) obtained from the analytical model is 0.51. This figure is subject to change due to other variable conditions and potential uncertainties associated with the OWFD in given geotechnical, geophysical conditions and the overwhelming supply chain challenges. On completion of 36 computational analyses of the sensitivity of the risk alternatives using the IDS software, the results obtained are presented in Table 3.21 and Figure 3.13, which indicate that the analytical model is most sensitive to 'Lack of coordination/Communication' and least sensitive to 'Lack of Functional Procedures'. Accounting risk has an 'equally significant' response to the sensitivity analysis. These attributes play important roles in the influencing parameters affecting the OWFD.

The results of this analytical model indicate that it can be useful to decision makers in the offshore wind farm industry. This model has thoroughly established the weight of the each influencing factor in the OWFD and the impact of each of the overall factors. This knowledge is crucial to decision makers in the subsea construction and offshore renewable industry.

3.12 Conclusion

In order to aggregate the individual risk factors, the evidential reasoning (ER) algorithm has been applied (the full details of the ER methodology can be found in Chapter Two of this study, subsection 2.10.4). The aggregation methodology is ideal for the purpose of generating an overall risk assessment at any level in the risk hierarchy. The aggregation process is continued until the project risk has been assessed on every objective, and ultimately the project risk level is obtained. The aggregation results are presented in distributed formats; yet, they can be easily consolidated into percentages of the project risk attributes by summing up the multiplications of the assessment grades and the associated degrees of belief.

The sensitivity studies were useful tools to the decision makers as they provide a more in-depth idea about how sensitive the selected optimum solution is to any changes in the input values of one or more parameters, under uncertainties.
This chapter has presented a novel methodology for assessing risks associated with the offshore wind farm industry in an attempt to fill a gap in the literature, which is compounded by the sheer lack of data and unwillingness of the investors and energy operators to share some of the potential innovative concepts, accidents, incidents, near hits and lessons learned. An analytic hierarchy process (AHP) is applied to determine the pairwise comparisons of the influencing variables by employing the experiences and personal judgements of risk analysts, and belief structures are used to assess the risk impact using the available evidence obtained through subjective reasoning. This allows for transparent expression of ignorance that is used to generate upper and lower boundaries of the analysis results. The ER algorithm is applied in order to aggregate individual risk factors without averaging them or compromising their transparent nature. Aside from measuring the belief degrees in the various assessment grades, the results measure the degree of belief in risk effect materialisation, which is critical for justifying any decision or action.

The proposed combination of application of AHP and ER is complex but practical and produced effective result analyses despite the incompleteness of the data. This incompleteness of data is acceptable as it allows decision makers to express their experience in order to provide realistic and unbiased assessments based on the pool of knowledge and expertise of the industry experts. It is concluded that the AHP and the ER approach provide a viable alternative for aiding risk analysis and decision-making in OWFD. Additionally, the direct contribution to knowledge obtained from the industry experts remains a valuable asset in bridging the gap between the theory and practice of subsea construction and offshore wind farm risk assessment.

Although the application of the combined modelling approach using AHP and ER is flexible and practical, the results obtained from the risk evaluations do not necessarily provide a high degree of confidence in dealing with the dependencies of the risk criteria. Therefore, it is imperative to develop a fuzzy Bayesian modelling tool that is capable of handling this shortfall using a systematic approach. The detailed application of this Bayesian modelling tool is demonstrated in the next chapter.

CHAPTER FOUR: A BAYESIAN NETWORK APPROACH TO OFFSHORE WIND FARM (OWF) DEVELOPMENT RISK ANALYSIS

Summary

In the previous chapters, all the risk factors identified via a risk-based hierarchy specific model were evaluated, prioritised and ranked. Then, the same model was implemented on a real case study for offshore wind farm development based on expert judgements of the associated risk factors. At the same time, the model was tested by applying a sensitivity analysis in order to confirm that it was suitable in analysing the weights of the risk factors.

In this chapter, a symmetrical Bayesian Networks (BNs) technique is used to assign prior probability to the risk variables affecting Offshore Wind Farm Development (OWFD) under high uncertainties (EU-OSHA, 2013a). The application of this technique is unique in its flexible feature to accommodate re-emerging variable/new evidence, which allows the model to be updated. These variables are classified into categories of: i) target node/goal, ii) intermediate node, and iii) starting node as described in section 2.10.5.

4.1 Introduction

The growing concerns in the private and public sector regarding the threat of risks associated with offshore wind farm development and their impacts on personnel, assets and the environment have sparked investigations of several major accidents. The outcomes of most of the investigations completed into offshore marine operations revealed that most accidents could have been avoided through the application of an effective risk management regime (Wang, 2004). Therefore, robust risk analysis and a risk management programme are important in order to prevent accidents and recurring accidents in similar areas of the industry such as the Offshore Wind Farm Development (OWFD).

Offshore installations are complex and expensive engineering processes comprised of various integral component structural members; the system is usually unique with its own design, installation and operations threatened with a high degree of uncertainty grouped into randomness, vagueness and ignorance characteristics (Wang and Ruxton 1997). Vagueness mainly results from imprecise or hazy concepts in a study or the inaccuracy and poor reliability of instruments used to carry out the study. Ignorance results from weak inference, which occurs when an expert is unable to establish a strong correlation between a premise and a conclusion. Offshore installations need to constantly adopt new approaches, new technologies, *etc*., each of which brings a new hazard in one form or another. Therefore, it is crucial to reduce the occurrence likelihood of accidents, both at the design stage of new facilities and during normal operations, in order to optimise technical and operational solutions.

There are few analytical tools currently in existence; however, a Bayesian Network (BN) approach is employed in this study to determine the probability of occurrence of each of the risk variables considered in the Bayesian Networks (BNs) model whilst taking into consideration the potential fuzziness and incompleteness of the data. In most cases, it may be difficult or even impossible to precisely determine the parameters of a probability distribution for a given event due to a lack of evidence or due to the inability of the safety/risk engineer to make accurate evaluations. The occurrence likelihood of an event may be described in terms of vague and imprecise descriptors such as “very likely to happen” or “unlikely to happen”. These judgements are fuzzy and probabilistic; therefore, a novel technique capable of handling such judgements and modelling the safety of OWFD is developed.

4.2 Literature Review

The Department of Trade and Industry (DTI) in conjunction with British Maritime Technology (BMT) Renewables Ltd developed a methodology for assessing the marine navigational safety risks of offshore wind farms (OWF) and other offshore renewable energy installations (OREIs) in 2005 (MCA, 2008).

Some of the established probability theory-based tools for evaluating randomness uncertainties include Fault Tree Analysis (FTA), Decision Table Method (DTM) and Failure Mode & Effects Analysis (FMEA) (Wang *et al.,* 1995). Zhou *et al.,* (2011) proposed a concise representation of BN analysis, which proved to be a success. Riahi *et al.,* (2014) also proposed a decision-making model for evaluating a container's security score; John *et al.,* (2014), Khakzad *et al.,* (2013) and Salleh *et al.,* (2014) proposed decision-making solutions using the BNs technique.

Bayesian Networks modelling is commonly used in establishing the causal relationships amongst risk elements and estimating the occurrence likelihood of each risk element. BNs applications can also replicate the relevant structures of conceptual reasoning in a consistent, efficient and mathematical manner. It has the ability to accommodate new or additional variables in the event that new evidence becomes available (Pearl, 2014). Following the development of its new algorithms, BNs modelling has been widely applied in various industries and has proven successful in many applications in recent years (Lauritzen and Spiegelhalter, 1988; Zhang *et al.,* 2004).

Hayes (1998) successfully applied BNs to ecological risk assessment. Kang and Golay (1999) proposed BNs for fault diagnosis in complex nuclear power systems. The BNs theory has also been applied to failure rate, consequence severity and failure consequence probability to determine uncertainties in offshore risk analysis (Ren *et al.,* 2005a; Sii *et al.,* 2002; Wang *et al.,* 1995).

4.3 Bayesian Networks Theory (BNT)

4.3.1 General graphical model of Bayesian networks

The general graphical model (GGM) is a basic tool used for visual illustration of conditional independencies of variables in a given problem (Whittaker, 1990). When two variables are conditionally independent, they have no direct impact on each other's value. For instance, if A is conditionally independent of C given B then $P(A \mid B,C) = P(A \mid B)$ (Cowell *et al.*, 2006). This graphical model is presented such that it also shows any intermediary variables that separate two conditionally independent variables. The intermediary variables are the connecting component characteristics of any two conditionally independent variables.

The graph representation normally comprises a set of nodes (representing variables) and a set of edges. Each edge is connected to two nodes, with the potential for optional directions assigned to it. The direction of the edge is normally from parent X_p to child X_c. For any given direction between variables X_1 and X_2, the edge will be directional from the cause variable to the effect variable assuming there is a causal relationship between the variables. Similarly, the edge will be undirected if there is only a mere correlation between the two variables (Cowell *et al.*, 2006). For example, assuming two conditionally independent variables, A and C, exist, and are both directly related to another variable, B, an edge can be drawn between the nodes of the variables that are directly related, i.e. between A and B and between B and C. Also, assuming the relationships between A and B and between B and C each work equally in two directions, and both edges are undirected, Figure 4.1 illustrates the dependency of both A and C upon the variable B but there is no edge between A and C. Therefore, variables A and C are conditionally independent given variable B. This does not imply that A and C are totally independent; it simply means that variable B encodes any information from variable A, which may impact C and vice versa.

Although each variable has a probability distribution function that may either be continuous or discrete and depends on edges leading into the variable, this study is restricted to dealing with the discrete functions. For instance, the probability distribution for B depends on both variables A and C whereas the probability distribution for variable A depends solely on the value of variable B (see Figure 4.1). Therefore, a graphical model may be mathematically expressed as follows: Let the variables (nodes) be $K = \{1,2,\ldots,k\}$ within a set E of dependencies (edge) between the variables of A, B, C and a set of probability distribution functions of each variable.

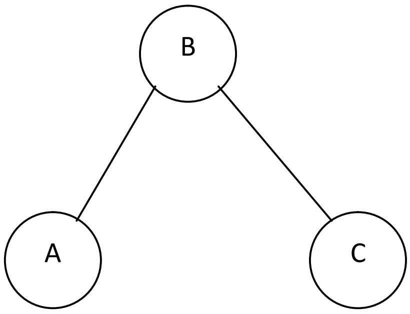


Figure 4.1 A graphical model illustrating conditional independence (Cowell *et al.,* 2006)

The variables A and C are said to be conditionally independent given the variable B (probabilities are omitted).

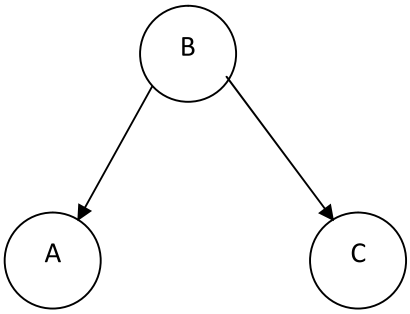


Figure 4.2 A Bayesian network (probabilities are omitted)

There are various types of graphical models that are similar to Bayesian networks; they include belief networks, causal networks, probabilistic independent networks, probabilistic networks and Markov fields. However, this study will focus only on the application of the BNs approaches. The Figures 4.1 and 4.2 shows the features of directed (Figure 4.1) and undirected (Figure 4.2) graphical representations. The arrows are used to indicate the direction of influence of the edges connecting the nodes.

4.3.2 Bayesian network model

A Bayesian network model is a type of graphical model defined as a directed acyclic graph (DAG). This means that all the edges in the graph are directed (pointing in a particular direction) whereas no cycles exist (meaning the direction of the edges travelling along any particular direction cannot return in the correct direction at the same starting node) (Neapolitan, 1990).

The Bayesian network represented in Figure 4.2 shows the set of edges $E = \{(B, A), (B, C)\}$. It is composed of a DAG given that: a) there are no undirected edges, i.e. no edges travelling in both directions between any vertices, and b) there are no cycles, i.e. there are no means of cycling back to the original vertex once travelling in a particular direction of edges. Therefore, given that A and C are conditionally independent, $P(A \mid B, C) = P(A \mid B)$ as the probability of A is conditioned on B and the value of variable C is not relevant to the probability. The factorisation of the joint distribution of this Bayesian network can be represented as follows:

$$P(A, B, C) = P(A \mid B).P(B).P(C \mid B) \tag{4.1}$$

Assuming the nodes are $X = X_1, ..., X_n$, the joint probability function for any Bayesian network is represented as follows:

$$P(X) = \prod_{i=1}^{n} P(X_i \mid parents(X_i)) \tag{4.2}$$

The joint probability of all the variables is the product of each individual variable's probabilities given its parents' values. Where each parent node causes an effect on its children, the edges in the Bayesian networks are referred to as causal connections. Considering the Bayesian rule in Equation (4.1), the joint probability is represented as (see Figure 4.3):

$$P(A \mid B).P(B).P(C \mid B) = \frac{P(B \mid A).P(A)}{P(B)}.P(B).P(C \mid B) = P(A).\, P(B \mid A).P(C \mid B) \tag{4.3}$$

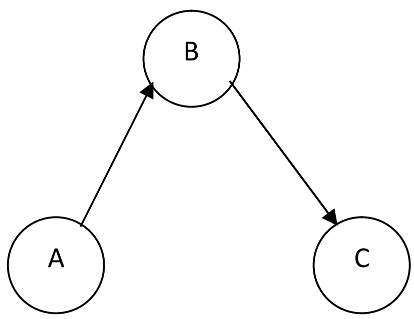


Figure 4.3 A Bayesian network representing joint probability

4.3.3 Bayesian network features

BNs are strongly linked to a combination of probability and graph theories that provides a platform for reasoning under high uncertainties (Weidl, 2002). A BN is a knowledge base of problems that model the underlying structure of the domain, and expresses its dependency by cause-effect relationships of the domain variables. The causal relationships are stochastic and not deterministic, and are expressed as conditional probabilities. In general, BNs incorporate the prior knowledge on the domain and it is used for calculating/updating the probability distributions of the unobserved variables, given the observed variable. A BN is therefore represented in two parts as follows: i) the qualitative part representing the causal structure and ii) the quantitative representing the probabilistic relationship.

A BN has the following features:

- It has the ability to incorporate new observations in the network and to predict the influence of possible future observations on the results obtained (Heckerman and Breese, 1996).
- It does not only allow users to easily observe the relationships among variables, but also gives an understandable semantic interpretation to all the parameters in a BN (Myllymaki, 2010). This allows users to construct a BN model directly using domain expert knowledge. Furthermore, a BN has both causal and probabilistic semantics, and thus it provides an ideal representation scheme for combining prior knowledge (which often comes in a causal form) and the historical data.
- It can handle missing and/or incomplete data. This is because the model has the ability to evaluate the relationships amongst its nodes and to encode dependencies among all variables in the system, as detailed in section 4.4 (Heckerman, 1997).
- It can conduct inference inversely.

4.3.4 Dynamic Bayesian Networks (DBNs)

A DBN determines how Bayesian networks change with reference to time. On the other hand, static Bayesian networks determine how Bayesian networks change with no reference to time; typical illustrations of this are evident in figures 4.2 and 4.3.

Both prior network and transition network are to be clearly defined (Friedman *et al.*, 1998). An example of a possible prior network representing the variable when the time = 0 is illustrated in Figure 4.4 below. Similarly, Figure 4.5 represents the transition network of the same dynamic Bayesian network at the time $t = 1,\ldots n$ (Zweig, 1998). On the other hand, those BNs that have no reference to time are referred to as static Bayesian networks (see Figure 4.2).

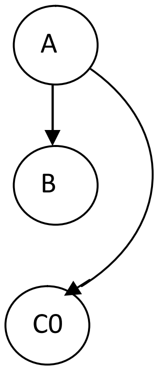


Figure 4.4 A prior Network for a Bayesian Network with three variables, A, B and C.

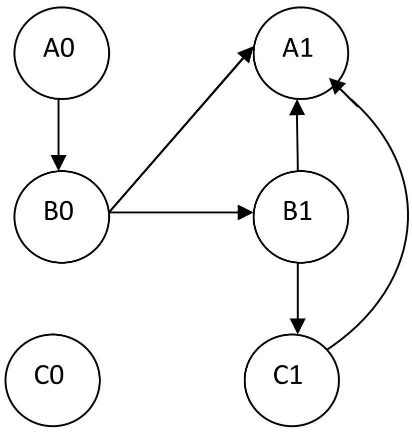


Figure 4.5 A Transition network for a Bayesian network with three variables, A, B and C

4.4 Bayesian network (BN) semantics

The semantics of BNs may be expressed in the following ways, i.e. 1) joint probability distribution (JPD) representation and 2) encoding of the conditional independence statements. These two expressions of BNs are similar and equivalent; however, the JPD is useful in the understanding of the network's construction whereas the encoding of the conditional independence statements is useful in designing BN inference procedures. This study will pay more attention to the utilisation of the JPD technique.

4.4.1 Representing the joint probability distribution

All Bayesian networks provide a complete description of the domain with a Joint Probability Distribution (JPD) (Bohlin *et al.,* 2000). This is mathematically expressed as:

$$P(X_1,\cdots,X_n)=\prod_{i=1}^{n}\mathrm{P}(\mathrm{X_i}\mid Parents(X_i)) \tag{4.4}$$

where $parents(X_i)$ represents the values of $Parents(X_i)$ in a given set $X_1,\cdots,X_n$, X_i represents the state of the child node.

Assume a JDP contains a set of random variables $X_1,X_2,\cdots,X_n$ represented as $P(X_1,X_2,\cdots,X_n)$ for all X values and suppose each random variable n is a binary value, the complete distribution of joint probabilities requires that 2^{n-1} numbers be specified. Therefore, the exponential computation of X will be based on chain rule from probability theory.

JPD can be computed by the application of the following mathematical expressions:

$$P(X_1,X_2,\cdots,X_n)=P(X_1\mid X_2,\cdots,X_n)\times P(X_2,\cdots,X_n) \tag{4.5}$$

$$=P(X_1\mid X_2,\cdots,X_n)\times P(X_2\mid X_3,\cdots,X_n)\times P(X_3,\cdots,X_n)$$

$$=P(X_1\mid X_2,\cdots,X_n)\times P(X_2\mid X_3,\cdots,X_n)\times P(X_{n-1}\mid X_n)P(X_n)$$

Suppose a BN contains variables $X=(X_1,X_2,X_3,X_4)$ that are dependent on one another (where n=4), Equation (4.5) or Equation (4.8) maybe applied. Hence, the JPD can be evaluated mathematically as:

$$P(X_{1,}X_2,X_3,X_4)=P(X_4\mid X_1,X_2,X_3)\times P(X_1,X_2,X_3)$$

$$=P(X_4\mid X_1,X_2,X_3)\times P(X_3\mid X_1,X_2)\times P(X_1,X_2)$$

$$=P(X_4\mid X_1,X_2,X_3)\times P(X_3\mid X_1,X_2)\times P(X_2\mid X_1)\times P(X_1) \tag{4.6}$$

4.5 A Method for Constructing Bayesian Networks

According to Equation (4.5), joint terms can be represented by the definition of conditional probability in the following way:

$$P(X_1,\cdots,X_n)=P(X_n\mid X_{n-1},\cdots,X_1)P(X_{n-1}\mid X_{n-2},\cdots,X_1),\cdots,P(X_2\mid X_1)P(X_1)$$

$$= \prod_{i=1}^{n} P(X_i \mid X_{i\text{-}1}, \cdots, X_1) \quad (4.7)$$

Therefore, in the event that n = 2,

$$P(X_1, \cdots, X_2) = P(X_n \mid X_{n-1}) \cdot P(X_{n-1}),$$

The above equation may vary depending on the value of 'n'

For example, in the event that n = 3,

$$P(X_1, \cdots, X_3) = P(X_n \mid X_{n-1}, X_{n-2}) \cdot P(X_{n-1} \mid X_{n-2}) \cdot P(X_{n-2})$$

hence,

$$P(X_1, X_2, X_3) = P(X_3 \mid X_2, X_1) \cdot P(X_2 \mid X_1) \cdot P(X_1)$$

In the event that n = 4,

$$P(X_1, \cdots, X_4) = P(X_n \mid X_{n-1}, X_{n-2}, X_{n-3}) \cdot P(X_{n-1} \mid X_{n-2}, X_3) \cdot P(X_{n-2} \mid X_{n-3}) \cdot P(X_{n-3})$$

hence,

$$P(X_1, X_2, X_3, X_4) = P(X_4 \mid X_3, X_2, X_1) \cdot P(X_3 \mid X_2, X_1) \cdot P(X_2 \mid X_1) \cdot P(X_1)$$

If $X_{n-i} \neq 0$ in the above equations, where $i < n$ (let i *represents states* $1, 2, \cdots n$). In orders words, $X_{n-i} \neq 0$, $X_{n-2} \neq 0$ and so on.

Generalising the product rule in Equation (4.7) leads to the application of the chain rule. This is demonstrated as follows:

$$P\left(\bigcap_{k=1}^{n} X_k\right) = \prod_{k=1}^{n} P\left(X_k \mid \bigcap_{j=1}^{k-1} X_j\right) \quad (4.8)$$

This expression (Equation 4.8) is only applicable to cases of more than two variables in order to determine the value of the member of the joint distribution, assuming an indexed collection of random variables is considered. The example of such a scenario is expressed in Equation 4.6 in section 4.4.1 where the number of variables is four.

Comparison of Equations (4.4) and (4.9) shows that the specification of joint probability distribution is equivalent to the general assertion that:

$$P(X_i \mid X_{i-1},...,X_1) = P(X_i \mid Parents(X_i)) \qquad (4.9)$$

Providing the $Parents(X_i) \subseteq \{X_{i-1},\cdots,X_1\}$. Then, the Bayesian network is a true representation of the domain only if each node is conditionally independent of its predecessors in the node ordering, given its parents. Therefore, in order to construct BNs with the correct domain, the parents for each node must be selected such that Equation (4.9) applies. This requires that the parents of nodes X_i should contain all those nodes in $X_1,\ldots,X_{i-1}$ that directly influence X_i.

Russell and Norvig (1995) proposed a procedure for incremental BNs construction, which guarantees the network is acyclic by the following steps:

i. Select the set significant variables X_i that best describe the domain.
ii. Select the relevant ordering for variables.
iii. If there are other remaining variables, then:
  - Take a variable X_i and add a node to the network for it.
  - Set parent (X_i) to minimal set of nodes already in the net in a way that the conditional independence is satisfied.
  - Define the conditional probability table (CPT) for X_i.

Bayesian network can be more compact than full joint distribution even though it is considered as a complete and non-redundant representation of the domain. This characteristic gives it the flexibility of handling domains with multiple variables. The Bayesian network's compactness represents the general feature of a locally structured (also known as sparse) system. Each subcomponent interacts directly with only a bounded number of other components in a locally or sparse system irrespective of the total number of components. In the case of BNs, it is assumed that each random variable is directly influenced by at most k, where k (the number of parent nodes) is constant in most domains. Considering the logical concept of BNs theory (assuming n Boolean variable), then the level of data required to specify each CPT for a node will at most be 2^k numbers and the complete BNs will be specified by $n2^k$ numbers, where n is the number of states in the child. On the other hand, the joint distribution contains 2^n. For instance, suppose the BN structure has 14 nodes $n = 14$ and each node has three parents $k = 3$. Then, the BN will require $n2^k = 14 \times 2^3 = 112$ numbers. However, the full joint distribution will require over a million numbers.

4.6 Representation of Conditional Probability Tables (CPTs)

The parameters of the graph are to be defined; then, the conditional probabilities for each node are established. Given that each node is dependent on its immediate parent node, the $P(v \mid u_v)$ can be estimated for each node where v is the variable (node) and the u_v represents the set of parent nodes. The probability is estimated by using the frequency with which each configuration of the variables is found in the dataset.

The management of probability outcomes can be challenging due to the large volume of values. For instance, a discreet Boolean variable with four parents will require 32 values in order to complete the CPT. There is usually a potential risk that certain combinations of variables will provide unreliable estimates. Therefore, this has to be taken into consideration when constructing the CPT tables. The analytical model known as Noisy-OR has been found to avoid the risk of error (Bohlin *et al.*, 2000). The Noisy-OR model can be described as a parameterised conditional probability table for the effect variable of a causal mechanism with multiple cause variables. Such a model requires a restricted number of parameter probabilities, from which the values for the other probabilities in the table are readily calculated.

The symmetrical model is used to analyse the relationship amongst the variables and it focuses on the causal factors of the parent nodes in a normalised space to the associated child nodes. Assuming the conditional probability of a child node variable, A, on a parent node variable, X_r $where\ r = (1,2,3,\ldots,n)$ with the assigned normalised weights ($\xi_1, \xi_2 \ldots\ldots, \xi_n$), the following approach may be applied to estimate the probability (Riahi *et al.,* 2012; Salleh *et al.*, 2014):
Based on the influence of each parent node, the conditional probability of a binary child node A in the normalised space, given each binary parent node, X_r where $r = 1, 2, \cdots, n$ can be estimated as:

$$P(A = present \mid X_1 = present) = \xi_1$$
$$P(A = present \mid X_2 = present) = \xi_2$$
$$\vdots$$
$$P(A = present \mid X_n = present) = \xi_n \tag{4.10}$$

$$\sum_{r=1}^{n} \xi_r = 1$$

By application of the symmetry approach using Equation (4.10) (normalised space), the probability of a binary child node A conditional upon n binary parent node variable X_r; where $r = 1,2,3,\cdots,n$ can be determined by:

$$P(A \mid X_1, X_2, \cdots X_n) = \sum_{r=1}^{n} \tilde{\xi}_r \tag{4.11}$$

$\tilde{\xi}_r = \xi_r$: If the state of the r^{th} parent node variable is identical to the state of its associated child node variable, and

$\tilde{\xi} = 0$: If the state of the r^{th} parent node variable is not identical to the state of its associated child node variable.

Therefore, a CPT for each child node can be qualified by the application of symmetrical model based on Equation (4.11).

4.7 Representation of Unconditional Probability Tables (UCPTs)

The key influential variables identified from the previous chapter form the basis for consideration of the unconditional probabilities of the mirror image of the derived variables (Fenton *et al*., 2007). These derived variables are comprised of nine parent nodes of relative weights and they serve as the input values for each parameter in order to determine the actual prior probabilities. These nodes are specified and assigned to underlying unit intervals [0,1]. In order to construct a UCPT of parent node, the assigned weights are to be normalised as follows:

$$P(X_r, S) = P(S \mid X_r) \prod_{r=1}^{n} P(X_r) \tag{4.12}$$

where, X_r denotes the parent node, assuming $r = 1,2,3,\ldots,n$

S denotes the ranked variable for the value of parent node X at specific normalised weight Nw.

4.8 Determining the Marginal Probability

In order to determine the marginal probability for a consequence node, the JPD in the CPT will be assessed and aggregated. The BN inference may be drawn when the structure and the parameters have been evaluated. Hence, the marginal probability for the consequence node is calculated using the marginalisation rule as follows:

$$P(a_m) = \sum_{r=1}^{n} P(a_m \mid b_r) P(b_r) \tag{4.13}$$

where n is the number of states in the node. Given that each variable A and B have two states, $A = a_2$ and $B = b_2$, the following can be stated:

$$P(a_1) = \sum_{r=1}^{2} P(a_1 \mid b_r) P(b_r) = P(a_1 \mid b_1) P(b_1) + P(a_1 \mid b_2) P(b_2) \tag{4.14}$$

$$P(a_2) = \sum_{r=1}^{2} P(a_2 \mid b_r) P(b_r) = P(a_2 \mid b_1) P(b_1) + P(a_2 \mid b_2) P(b_2)$$

4.9 Conditional Independence Relationship in BNs

The links between variables in BNs mainly represent direct causal relationships. For example, Figure 4.6 below shows that A has no direct influence on variable C (similar to the illustration in Figure 4.2). However, if the properties of variable C are altered, the prerequisite of A changes, which implies that the variables are dependent. This sort of relationship is not caused by direct influence, but instead transferred by common node B. The information contained in BED is transmitted through nodes in the opposite directions of the links.

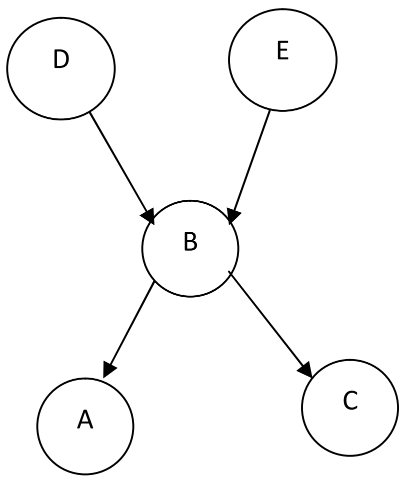


Figure 4.6 Bayesian Network showing dependency and independency.

In order for a Bayesian network to model a probability distribution, the following must be true by definition: each variable is conditionally independent of all non-descendants in the graph given the value of all its parents.

Conditional independence can be mathematically expressed as:

$$P(X_1, X_2 ..., X_n) = \prod_{i=1}^{n} P(X_i \mid parents(X_i)) \qquad (4.15)$$

4.9.1 Linear topologies

Consider the illustration in Figure 4.7: assuming variable B is unknown, the probability of B will be determined from the status of A. Given that variable C is determined from variable B, variable C can be said to be dependent on variable A.

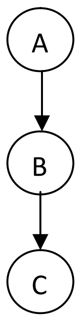


Figure 4.7 BNs Linear Network Connections

Similarly, if variable B is known to be in a state of b_1 (variable A does not influence it), the probability of C can then be computed directly from its probability table $P(C \mid b_1)$; hence, it is conditionally independent of A.

4.9.2 Diverging

Consider the illustration in Figure 4.8, which generally indicates that the nodes with common parents such as A and B are dependent unless there is evidence in C that blocks the path from A to B. This is similar to the illustration demonstrated in Figure 4.6.

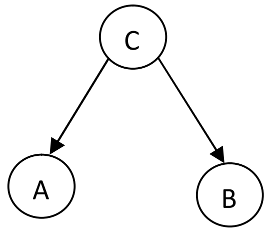


Figure 4.8 BNs Divergent Network Connections

Assume X_1 and X_2 are the two child nodes representing A and B experiencing the effects of the single parent node X_3 representing C (see Figure 4.8). Based on Equation (4.15), the JPD for diverging connections can be calculated as (John *et al.*, 2014):

$$P(X_1, X_2, X_3) = P(X_1 \mid X_3)P(X_2 \mid X_3)P(X_3)$$

4.9.3 Converging

Consider the illustration in Figure 4.9, which indicates a scenario where two or more variables have the same influence: unless there is other evidence of the special characteristics of D, the parent nodes A and B will be classed as independent. This implies that the converging node D blocks the path between its parents unless evidence is identified in D or any of its descendants.

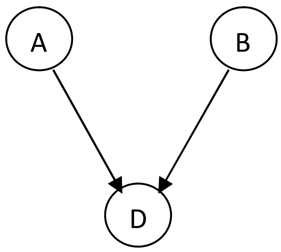


Figure 4.9 BNs Convergent Network Connections

Assume X_1 and X_2 are the two parent nodes representing A and B experiencing the effects of the single child node X_3 representing D (see Figure 4.9). Based on Equation (4.15), the JPD for converging connections can be calculated as (John *et al.,* 2014):

$$P(X_1, X_2, X_3) = P(X_1)P(X_2)P(X_3 \mid X_1, X_2)$$

4.9.4 D-Separation

Conditional independence is a major consideration for designing the inference algorithm. It is important to determine whether or not a given BN with a set of nodes X is independent of another set of nodes, Y, considering a set of evidence nodes Z (Russell and Norvig, 1995). Russell and Norvig (1995) proposed that this approach is provided by the notion direction-dependent separation or d-separation. The understanding of d-separation is critically important in determining an effective inference algorithm for BNs. For instance, any two nodes, A and B, in a BNs are considered d-separated; hence, conditionally independent if every path between A and B is blocked by an intermediate node, i.e. $P \notin \{A, B\}$. P will be considered to be blocking the nodes if: i) the BNs structure is linear or divergent and the P is known; and ii) the structure is converging and neither P nor any of its descendants are known.

4.10 Modelling Concept and Theory

The application of the BN model in this study is specifically designed to evaluate the associated risk elements of OWFD in order to improve construction and operational safety by eradicating the risks or reducing and managing the residual risks. The list of risk factors influencing the OWFD (see Table 4.1) is categorised into four different groups, i.e. i) the Decision node, ii) Target nodes (or decision node), iii) Intermediate nodes and iv) Starting nodes (Bayraktar and Hastak, 2009; Riahi *et al.*, 2012). According to the BN model presented in Figure 4.10, the decision node provides a clear definition of the problem under study and it is usually dependent on other nodes in the network, whereas the target nodes have parent and child and represent the performance of the network. Starting nodes are simply the input nodes; they have no parents and are not easily modified during the modelling process. The starting nodes represent prior probabilities as may be provided by experts or historical data. Intermediate nodes have both parent and child nodes; they are responsible for conveying the conditional probabilities from the decision and starting nodes to the target nodes. The nodes in the proposed BNs with at least one parent node are only conditionally dependent upon their parent nodes.

In order to ease computational difficulties and provide flexibility in the modelling process, the following assumptions are acceptable for BNs (Russell and Norvig, 2010):

A_1: If two or more nodes known as child nodes have at least one parent node, they will directly be influenced by the parent node; such nodes (variables) in this type of structure are said to be conditionally dependent. On the other hand, if two variables are independent given the state of the third variable; then they are said to be conditionally independent (Stich, 2004).

A_2: If the nodes have no child, they represent marginally independent relationship. This means that the occurrences of the nodes are independent of the outcome of each other or any other variables.

A_3: The child node provides the mutual exclusivity of the node crucial to the analytical process; this is generally useful during the application of certain probability distributions at the analytical stage. These assumptions are expected to be applied in this study.

4.11 BNs Model for OWFD

The BNs approach is applied to the OWFD in order to determine the probabilities of the occurrences of the associated risk factors of OWFD under high uncertainties. The identified risk factors in the previous chapter are adapted to develop the BNs model in this study; see the graphical representation in Figure 4.10. The resultant weighting of the assessment of the risk factors considered from the previous chapter forms the basis of the dynamic BNs of the OWFD; this mainly focuses on the variables with most significant weights in the analytical model. A mapping process will be considered in order to transform the quantitative variables into deterministic weight vectors. A symmetric model is adopted in order to evaluate the conditional probabilities of the variables in the BNs model (Riahi *et al.,* 2014; Salleh *et al.,* 2014). The symmetric model approach allows expert opinions to be distributed by the relative importance of the parent node to its child node in an orderly manner; hence, the parent node's normalised weight determines the strength of each parent node to its corresponding child node.

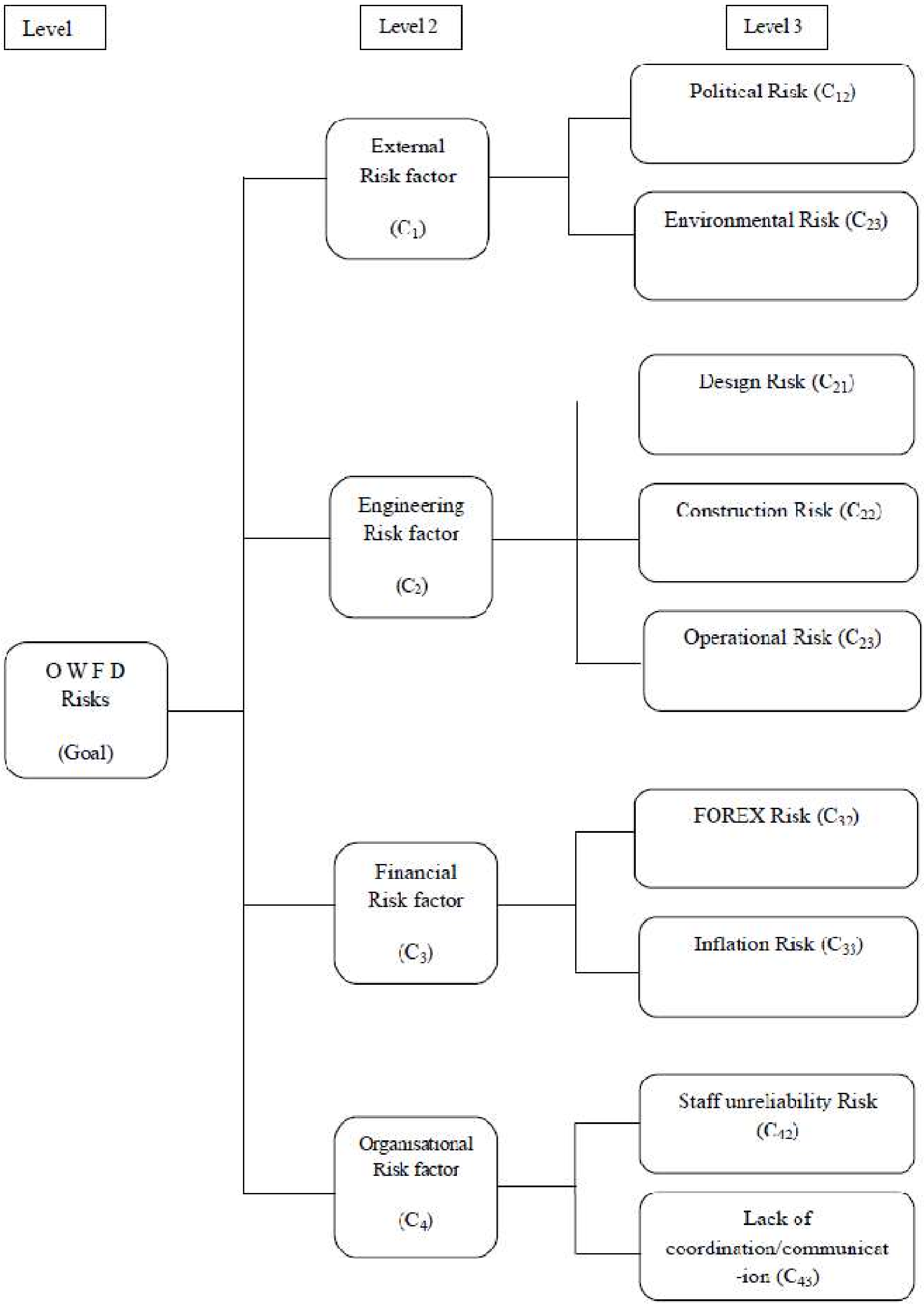


Figure 4.10 A proposed BNs structure of the variables with the significant relative weights

The BNs variables and the corresponding states represent the quantitative data in the form of a CPT while the graphical presentation of the variables indicates the qualitative data in the form of a structural network. The application of this BNs modelling benefits from the Bayes theorem, which allows risk propagation to be updated when new information becomes available. Due to the high level of uncertainty in the OWFD, new information is likely to be available for the construction and/or operational process. The BNs model evaluation determines the possible combination of which parent nodes and child nodes have the highest probability that can lead to system failure in the OWFD.

4.11.1 Identification of interrelationships between critical risk factors

Based on the weights of the risk variables obtained in the evaluation of the *AHiP-Evi* modelling in subsection 3.10.5 of the previous chapter as shown in Table 3.16, the significant weights of the variables that are most critical to the failure of the OWFD system have been selected to form the BNs structure represented in Figure 4.10. The relative importance of each of the parent (root) node to its associated child node is considered in the BNs structure. An evaluation of the likelihood of occurrence of each root node with respect to the associated child node determines its potential level of impact on the overall system under high uncertainty. This can be proactively used to assess the vulnerability of the OWFD due to the existence of each variable or a combination of certain variables.

Table 4.1 List of risk factors influencing OWFD systems

Node description	Representation	Type of Node
Political Risk	C12	Starting node
Environmental Risk	C13	Starting node
Design Risk	C21	Starting node
Construction Risk	C22	Starting node
Operational Risk	C23	Starting node
FOREX Risk	C32	Starting node
Inflation Risk	C33	Starting node
Staff Unreliability	C42	Starting node
Lack of coordination/Communication	C43	Starting node
External Risk	C1	Intermediate node
Engineering Risk	C2	Intermediate node
Financial Risk	C3	Intermediate node
Organisational Risk	C4	Intermediate node
Decision	OWFD	Target node (decision node)

From the above BNs model (see Figure 4.10) showing the conditional dependencies of the most significant variables, the assessment grades are assigned by the experts (with same background as detailed in section 3.10.3) in order to establish the correctness and completeness of the proposed BNs model. The values of the weights of these significant variables are transformed into the same universe for equitable distributions. Only the significant weighted variables that are capable of influencing the system are considered in the DAG representation.

4.12 Methodology

The proposed BNs model presented in Figure 4.10 (specific model) is implemented to support the decision-making process through the assessment of the critical risk variables of the OWFD under high uncertainties. The model development process is comprised of two major steps: i) the identification of influencing variables and their causal networks and ii) the quantification of the significant relationships among the critical influencing variables.

Considering the shortcomings of the *AHiP-Evi* modelling system applied in the previous chapter where the dependency of the critical risk elements was not considered in the hierarchical process evaluation, a Bayesian Network Sensitivity Analysis Technique (BN-SAT) is proposed. This is achieved by application of a Bayesian reasoning mechanism to perform the analysis taking into account the difficulties encountered in the previous chapter of this study (Chapter Three). Therefore, the most important aspect of this approach is the ability to transform experts' opinions into subjective conditional probabilities in Bayesian networks.

Consequently, when assessing a group of variables, the relative importance of these variables is also taken into consideration in order to allow for their quantitative analysis. The proposed methodology is summarised into the following logical approach:

Step one: Identify the key risk factors and their interrelationships. A list of key risk factors is identified from the previous chapter; these are divided into four main variables.

Step two: Customise the BNs modelling of the OWFD by defining the critical variables (nodes) from the list of identified risk factors. The starting nodes are known as influencing nodes and are directly associated with the root causes (main criteria) known as the intermediate nodes. The identified starting nodes at the i^{th} stage and the associated intermediate node at the $(i+1)^{th}$ stage indicate the hierarchical order, which is maintained until the variables are all linked in the graph.

Step three: Specification of variable state and assignment of specific nodes.

- Establish the BN model
- Update the values of all the variables
- Graphical representation of the relationship between nodes
- Specify the states and assign inputs for CPT of each variable

Step four: Evaluation of assessment and results obtained

- Model analysis
- Elicitation of the CPT for the child nodes in the BNs using the symmetric model
- Marginal probability for the root nodes

Step five: Sensitivity Analysis of the model

- Model validation

Sensitivity analysis is a methodical approach used in exploring the responses of complex models to change. It provides for the observation of variations and uncertainties in the output of a model and the distribution criteria of the variables to different sources of variations in the input of that model. Sensitivity analysis is performed by altering the parameters of the nodes of the input variables and observing the relative corresponding changes in the probabilities of the nodes of the output variable. Realistically, an increment/decrement in the rate or probability at which any of the input variables occurs will result in a relative corresponding increment/decrement in the rate or probability of occurrence of the output node. The sensitivity analysis in this study is carried out in order to ascertain the sensitivity of the BN-SAT model in responding to the slightest variation to any input data.

Assuming the applied methodology for the construction of the BN-SAT model is logical and functional; then its sensitivity analysis must conform to the following axioms:

Axiom 1: An increment/decrement in the rate or probability at which any of the input variables occurs will result in a relative corresponding increment/decrement in the rate or probability of occurrence of the output node.

Axiom 2: If the rate or the probability of occurrence of an input variable is decreased by "K%" and "L%" where $(L < K)$, and accordingly the rate or probability of occurrence of the model output is evaluated as A_K and A_L respectively, in the same way A_K should be greater than A_L.

Axiom 3: If B and C where $(C < B)$ input variables from all the input variables are selected and the rate or probability of occurrence of each B and C and input variable is decreased by the same percentage and accordingly the rate or probability of occurrence of the model output is evaluated as A_C and and A_B respectively, in light of the above, A_C should be greater than A_B.

Axiom 4: If the target node input value is increased to 100%, the probability of the likelihood of occurrence will increase and the unlikelihood of occurrence will decrease by equal amount. Conversely, the probability of the likelihood of occurrence will decrease and the unlikelihood of occurrence will increase by equal amount if the target node value is decreased by 100%.

4.13 A Test Case Illustrating Applicability of the BN Model

The proposed methodology as detailed in section 4.12 above is a further investigation of the relative importance of the OWFD risks as established in the previous chapter (using the Analytic Hierarchy Process & Evidential Reasoning Modelling System, *AHiP-Evi*) in order to demonstrate its applicability in estimating the degree of influence of each variable on the decision node or goal of the problem. The proposed methodology, known as the Bayesian Network Sensitivity Analysis Technique (*BN-SAT*), is formed by mapping the outcome of the *AHiP-Evi* into the BNs structure.

4.13.1 Identification of the key influencing risk factors (step 1)

The key risk factors were identified in the previous chapter of this study and were used to form the basis of the generic modelling system for hierarchical analysis (see Figure 3.6). However, this section will only be concerned with the customisation of the belief network, which involves selection of the most significant influencing factors amongst the risk factors based on the result of the evaluation completed by the application of AHP modelling presented in Table 3.16 of the previous chapter (see Table 4.1). Customisation includes modification of certain relationships between the variables and/or redefinition of the states of some variables to provide a premise for easy modelling of the test case. As a result, a dependency-specific BN model is developed for the risks associated with OWFD as represented in Figure 4.11.

Table 4.2 Root Nodes for Unconditional Probabilities

Risk Parameters	Representation	Final Normalised weights (PV)	Type of Node
Political risk	C12	0.582	Starting node
Environmental risk	C13	0.418	Starting node
Design risk	C21	0.293	Starting node
Construction risk	C22	0.551	Starting node
Operational risk	C23	0.156	Starting node
FOREX risk	C32	0.661	Starting node
Inflation risk	C33	0.339	Starting node
Staff unreliability risk	C42	0.661	Starting node
Lack of coordination/communication risk	C43	0.339	Starting node
External risk	C1	0.154	Intermediate node
Engineering Risk	C2	0.416	Intermediate node
Financial Risk	C3	0.253	Intermediate node
Organisational Risk	C4	0.177	Intermediate node
Decision	OWFD	-	Target node

4.13.2 Customisation for BNs modelling of OWFD (step 2)

The generic model shown in Figure 3.6 is customised with respect to the specific goal of the subject of investigation. The significant influencing variables are identified and extracted to develop the specific model (refer to Figure 4.11). The relationships between certain variables are modified and some states are redefined in order to ease the complexity of the modelling process for the test case.

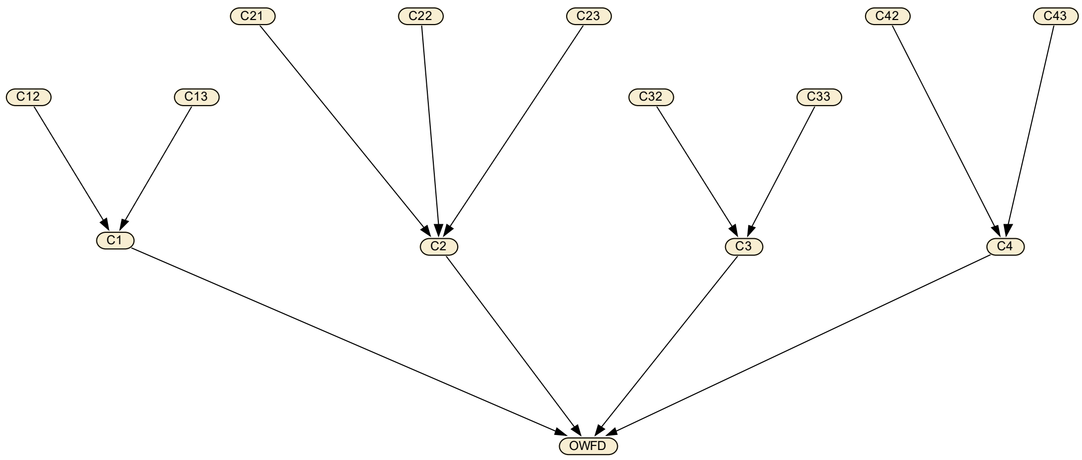


Figure 4.11 A BN specific model of risk factors in OWFD

The concept of the D-separation algorithm is applied to modify the above model in Figure 4.11. This is achieved by analysing each individual factor in order of hierarchy with effect from the starting nodes. The graphical features of the Bayesian networks are useful in the evaluation of the requisite nodes needed for computational analysis of the marginal probability of a variable under uncertainty following observations of the BNs. The D-separation algorithm is a useful analytical tool widely applied in complex systems to speed-up inferences under uncertainty. This is applied in this study in order to determine the accuracy of the networks. For instance, Figure 4.11 shows that, if node C_2 is a given evidence, a change of probability distribution of node C_{22} will affect nodes C_{21} and C_{23}. Hence, this conforms to the concept of the D-separation algorithm.

4.13.3 Specification of variable states and assignment of nodes (step 3)

Based on expert opinions, nodes were assigned to various states in accordance with the individual characteristics. In the risk-based nodes, the BNs constructed were assigned two exclusive states, "Yes and No" and "Likely and Unlikely", where "Yes" denotes that the probability of the corresponding nodes is unsafe and "No" indicates the probability of the related nodes is safe. "Likely" indicates the probability of occurrence of an unwanted event is significant, and "Unlikely" shows the likelihood of occurrence of the unwanted event is insignificant. Given that the 'likelihood' of the frequency of occurrence of the event aligns closely to the probability requirements in the BNs structure, the assigned states are reasonable. As illustrated in

Table 4.2, the relative normalised weights (N_w) generated are used to determine the weights of the states (Likely and Unlikely).

NETICA software has been applied in the evaluation process in this study. NETICA is part of the Bayesian network software package and it has proven successful in providing an application programming interface (API). In this study, the model structure is defined while the software provides the Expectation Maximisation (EM) algorithm that supports the computation of the CPT. Considering the fact that the data and BNs model structure are established, the EM algorithm in NETICA calculates the estimated maximum likelihood for the variables. The EM algorithm is designed to cater for the challenges of random missing data that are dependent on the states of other variables. According to Riahi *et al.,* (2012), NETICA supports the use of decision and utility variables. Riahi's study also declares that NETICA allocates the continuous data into the correct bins providing the bins in the networks are defined.

The EM algorithm is an iterative approach, which cycles between two forms. The first form attempts to estimate the missing or latent variables, generally known as estimation-step or E-step; whereas the second form attempts to optimise the parameters of the model to best explain or evaluate the data, known as the maximization-step or M-step (Chai *et al*., 2017).

- **E-Step**. Estimate the missing variables in the dataset.
- **M-Step**. Maximize the parameters of the model in the presence of the data.

This iterative process is repeated until the algorithm converges on a fixed point. Although the EM algorithm is most popular in machine learning sector for use in unsupervised learning problems such as density estimation and clustering, it can be widely applied (Dempster *at al.*, 1977).

4.13.4 Evaluation assessment and results (step 4)

The computation of both the conditional and unconditional probabilities for the child node and parent node is performed using the NETICA analytical software and the results are presented in the conditional probability table (CPT) format. The symmetrical model is used to synthesise the mapped data derived from the analytical results of the application of the *AHiP-Evi modelling system* from the previous chapter. In the symmetrical model, expert opinions are allocated by the relative importance of each parent node to its corresponding child node. The normalised weights N_w determine the strength of direct dependence of each child node to its corresponding parent node, using Equation (4.11) and data in Table 4.2 (derived normalised weights for the significant risk factors). Hence, $P(A = present \mid X_1 = present) = P(\dot{\hat{B}}_1)$ denotes the relative importance of the first parent node to its corresponding child node. Consequently (Riahi, 2010):

$$P(A = present \mid X_1 = present) = P(\dot{\hat{B}}_1) = \frac{P(B_1)}{\sum_{m=1}^{n} P(B_m)}$$

$$\vdots$$

$$P(A = present \mid X_n = present) = P(\dot{\hat{B}}_n) = \frac{P(B_n)}{\sum_{m=1}^{n} P(B_m)} \tag{4.16}$$

$$\therefore$$

$$P(\dot{\hat{B}}_1) + P(\dot{\hat{B}}_2) + P(\dot{\hat{B}}_3) + \cdots + P(\dot{\hat{B}}_n) = 1$$

Based on axioms of probability theory, the relative importance of parent node to its child node can be estimated as:

$$P(\dot{\hat{B}}_1 \cup \dot{\hat{B}}_2 \cup \dot{\hat{B}}_3 \cup \cdots \cup \dot{\hat{B}}_n)$$

$$= P(\dot{\hat{B}}_1) + P(\dot{\hat{B}}_2) + \cdots P(\dot{\hat{B}}_n) - P(\dot{\hat{B}}_1 \cap \dot{\hat{B}}_2) - P((\dot{\hat{B}}_1 \cap \dot{\hat{B}}_2) \cup (\dot{\hat{B}}_2 \cap \dot{\hat{B}}_3)) - \cdots$$

Considering the normalisation in the normalised space, $\dot{\hat{B}}_1, \dot{\hat{B}}_2, \dot{\hat{B}}_3, ..., \dot{\hat{B}}_n$ remain disjointed given:

$$P(\dot{\hat{B}}_1 \cap \dot{\hat{B}}_2) = P(\dot{\hat{B}}_2 \cap \dot{\hat{B}}_3) = \cdots = 0 \tag{4.17}$$

Hence,

$$P(\dot{\hat{B}}_1 \cup \dot{\hat{B}}_2 \cup \dot{\hat{B}}_3 \cup \cdots \cup \dot{\hat{B}}_n) = P(\dot{\hat{B}}_1) + P(\dot{\hat{B}}_2) + P(\dot{\hat{B}}_3) + \cdots + P(\dot{\hat{B}}_n)$$

Based on Equation (4.17) in the symmetry approach, the probability of a binary node A conditional upon n binary nodes, X_r where $r = 1,2,\cdots,n$, can be estimated by the application of Equation (4.11). Thus, considering Equation (4.11) and (4.13), the following can be determined in the construction of the CPT:

$$P(A = likely \mid X_1, X_2, \cdots, X_n = unlikely) = 0$$
$$P(A = unlikely \mid X_1, X_2, \cdots, X_n = unlikely) = 1$$
$$P(A = likely \mid X_1, X_2, \cdots, X_n = likely) = 1$$
$$P(A = unlikely \mid X_1, X_2, \cdots, X_n = likely) = 0$$

In order to complete the evaluation using the symmetrical approach to obtain probability distributions, the variable weights are to be normalised. This will ease off the computational analysis of the BNs using the NETICA software. By applying Equation (4.16), the following mathematical expression can be used to calculate the normalised relative weights, Nw:

$$Nw_1 = \frac{Nw_1}{Nw_1 + Nw_2 + Nw_3} = P(\dot{\hat{B}}_1)$$

$$Nw_2 = \frac{Nw_2}{Nw_1 + Nw_2 + Nw_3} = P(\dot{\hat{B}}_2)$$

$$Nw_3 = \frac{Nw_3}{Nw_1 + Nw_2 + Nw_3} = P(\dot{\hat{B}}_3)$$

Hence, $P(\dot{\hat{B}}_1) + P(\dot{\hat{B}}_2) + P(\dot{\hat{B}}_3) = 1$.

In addition, by application of Equation (4.11), aggregated values can be obtained in order to construct a CPT as illustrated in Table 4.3 below.

4.13.4.1 Quantification of relationship (CPTs)

The Conditional Probability Table below defines the relationship between the child node C2 and the associated parents (C21, C22, and C23). The CPT determines the probability within a state for engineering risk factors. This is illustrated by employing a symmetrical modelling approach and applying Equation 4.11 to obtain the results shown in Table 4.3.

Table 4.3 Condition Probability Table (CPT) for C2

	C_2 (Y)				C_2 (N)			
	C_{21}		C_{23}		C_{23}		C_{21}	
	C_{22}	C_{23}	C_{21}	C_{22}	C_{22}	C_{21}	C_{23}	C_{22}
(L)	1	84.4	44.9	29.3	70.7	55.1	15.6	0
(U)	0	15.6	55.1	70.7	29.3	44.9	84.4	1

In table 4.3, Y denotes Yes and

N denotes No;

L and U denotes Likely and Unlikely respectively.

$$\Omega(L) = P(Engineering\ Risk\ Factors = likely \mid C21, C22, C23)$$

$$\Omega(\neg U) = P(Engineering\ Risk\ Factors = unlikely \mid C21, C22, C23)$$

Bayes Chain Rule proposes that the marginal probabilities of the likelihood of Engineering Risk Factors are mathematically represented as follows (Zhou *et al.*, 2011 and Riahi, 2010):

$$P(Engineering\ Risk\ Factors = likely) = 0.5$$

$$P(Engineering\ Risk\ Factors = unlikely) = 0.5$$

The above expression is based on the modelling principles of NETICA software, which describes the likelihood of input data as 50% and the unlikelihood as 50% based on a symmetrical approach. The outcome of the output of the Engineering Risk Factor is either ‘Yes’ or ‘No’ and ‘Likely’ or ‘Unlikely’. Hence, the probability of the occurrence remains 50% as supported by the experts and the input data on NETICA software. For example, if a person is uncertain about the existence and non-existence of a child’s parents, he/she should remain uncertain about the existence and non-existence of their child. In order to effectively apply this modelling technique, it is important to first define the input variables (i.e. starting nodes) by using their probability distributions, which describe the current conditions of the system under investigation.

The results obtained from the computation using NETICA software are presented in Figure 4.12, which indicates that the extent of the risk found at the target node or goal is evaluated as: Goal = {[Yes = 51.6% or 0.516], [No = 48.4 or 0.484]}. Assuming the C_{21}, C_{23} and C_2 are known with 100% certainty; such conditions will have a substantial impact on the probability of occurrence of overall effect of the risk scenarios. By using the NETICA software to compute the effect of C_{21}, C_{23} and C_2 on the model, the probability of occurrence can be estimated as shown in Figure 4.13. Similarly, the effect of randomly varying other nodes to 100% certainty can be seen in Figures 4.14 and 4.15.

4.13.4.2 Result validation

The outcome of the analyses obtained from the application of the *BN-SAT* is compared to the analytical outcome of the application of the *AHiP-Evi* in order to validate the effectiveness and coherency of the models developed in this study.
The percentage variation between the two models may be expressed as:

$$\%\Delta = \left(\frac{OWFD_{AHiP-Evi} - OWFD_{BN-SAT}}{OWFD_{AHiP-Evi}}\right) \times 100 \tag{4.18}$$

Or

$$\%\Delta = \left(\frac{OWFD_{BN-SAT} - OWFD_{AHiP-Evi}}{OWFD_{BN-SAT}}\right) \times 100 \tag{4.19}$$

Where $\%\Delta$ indicates the percentage error between the results of the two analytical tools and

$OWF_R = represents\, OWFD_{AHiP-Evi}$

$OWF_R = result\, of\, AHiP - Evi$ analysis and

$OWFD_{BN-SAT} = result\, of\; BN - SAT\; analysis$

Application of either of the above equations depends on which modelling system is higher, providing the percentage variation remains a positive value. The posterior probability of the decision node obtained by using NETICA software to compute the BN model is 0.516 or 51.6% (see Figure 4.12). Once the BN structure and the parameters have been established in the CPT, the BN is ready to draw inferences. The final result obtained at the target node (Goal) from analysing the case study by a symmetrical approach and with the use of NETICA software can be presented as follows (see Figure 4.12 below):

$$Goal = \{(Yes = 0.516 or 51.6\%),\ (No = 0.484 or 48.4\%)\}.$$

Based on the input variables and the result obtained for the probability occurrence of the goal (OWFD) as shown in Figure 4.12, it is imperative to note the significance of each starting node variations and the magnitude of influence; such that the likelihood of OWFD failure with major consequence as a result of its associated risks factors is about 51.6% or 0.516 and 48.4% or 0.484 unlikely to occur i.e. Goal = {(Yes = 0.516 or 51.6%), (No = 0.484 or 48.4%)}. The significant risk factors that influenced such eminent potential failure are as a result of External (C_1), Financial (C_2) and Organisational (C_4) risks respectively. A 51.6% failure is a highly significant failure with potential for devastating consequences such as loss of life and failure of critical infrastructures and operation.

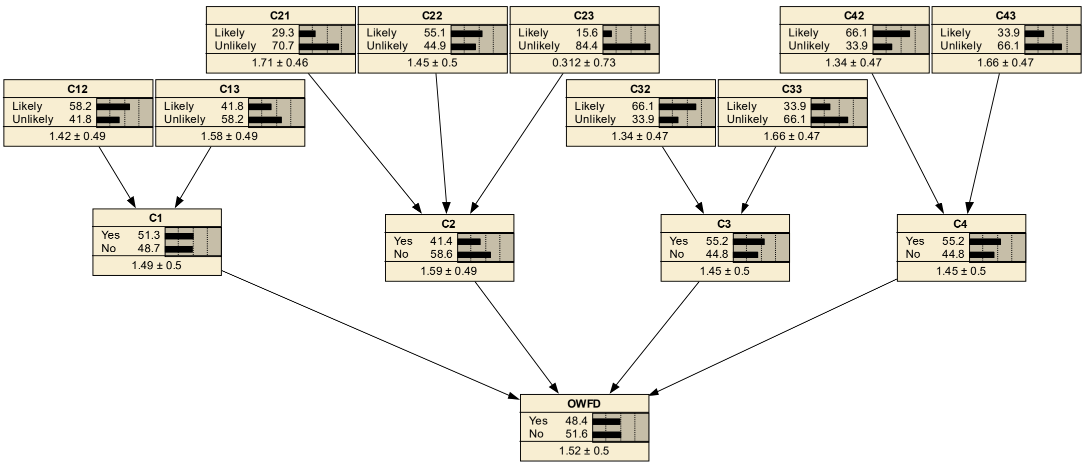


Figure 4.12 Aggregated result for associated risk of OWFD

Figure 4.13 illustrates that C_{21} (design risk) and C_{23} (operational risk factors) have the lowest values in the child node C_2 (engineering risk factor); therefore, their values are varied to 100% certainty to evaluate the effect on the BN structure. The overall effect of these changes on the target node becomes:

$$Goal = \{(Yes = 0.634 or 63.4\%),\ (No = 0.366 or 36.6\%)\}$$

This indicates a slight increase of the value at the target node by 0.9%.

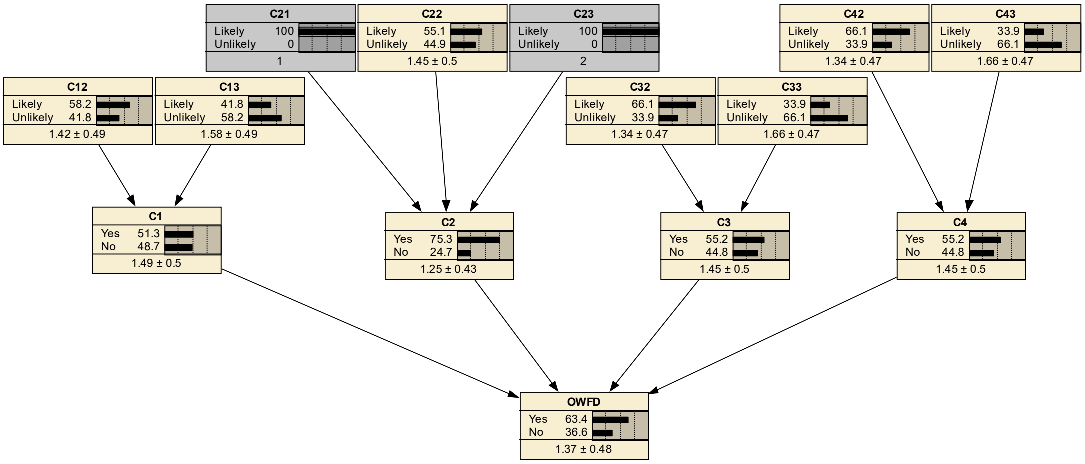


Figure 4.13 The effect of design risk and operational risk on the probability of occurrence of the risks associated with OWFD

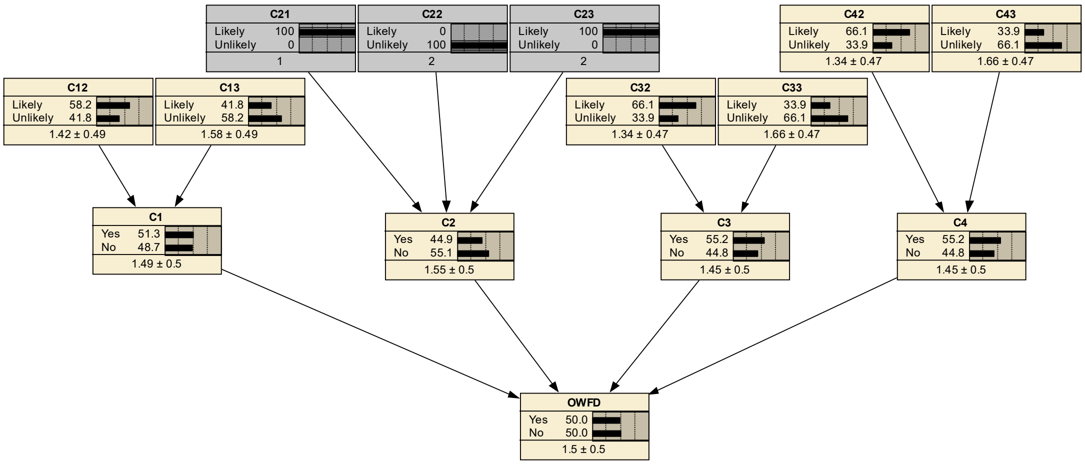


Figure 4.14 The effect of design risk, construction risk and operational risk on the probability of occurrence of the risks associated with OWFD

In the scenario presented in Figure 4.14 above, it is assumed that C_{21}, C_{22} and C_{23} are known with 100% certainty. The BN indicates a further increase at the target node in the likelihood of occurrence of an incident because of this new evidence for C_{22}.

The new outcome is represented as follows:

$$Goal = \{(Yes = 0.500\ or 50.0\%),\ (No = 0.500\ or 50.0\%)\}$$

This time, a slight increase of 3.1 % is recorded.

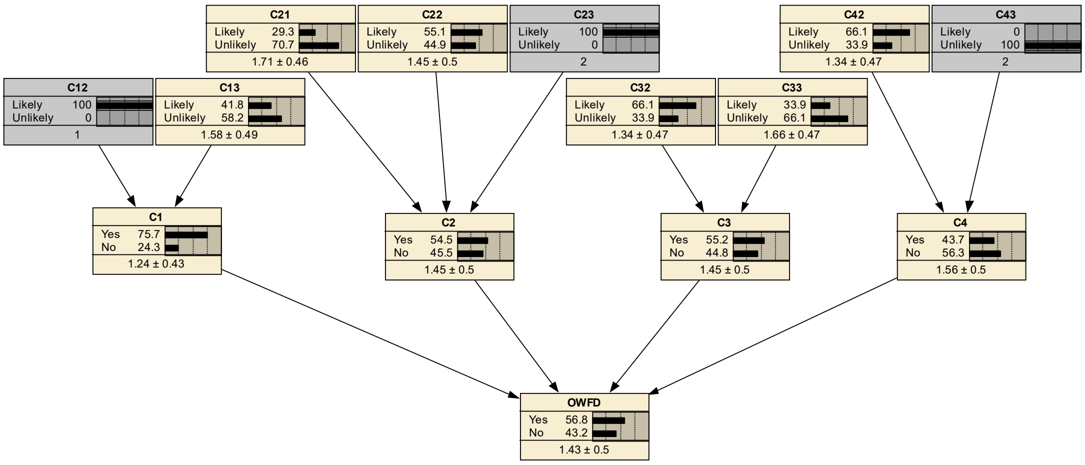


Figure 4.15 The effect of C_{23}, C_{43} and C_{12} on the probability of occurrence of an incident scenario for OWFD

In this instance, C_{12}, C_{23} and C_{43} are randomly selected and assumed to be known with 100% certainty. These variables have something in common because they are the nodes with the lowest values of likelihood of occurrence. It is observed that the total likelihood of occurrence at the target node has increased significantly due to the emergence of this set of new evidence (see Figure 4.15). The updated results imply the following:

$$Goal = \{(Yes = 0.568\ or\ 56.8\%),\ (No = 0.432\ or\ 43.2\%)\}$$

This increase from the initial value, from 51.6% to 56.8% indicates a sharp change in the likelihood of occurrence by 9.2%.

In order to compare the results obtained from application of the base cases of *AHiP-Evi* modelling (Chapter Three) and that of the current *BN-SAT* approach, Equation (4.18) is applied as follows:

$$\%\Delta = \frac{0.5160 - 0.5112}{0.5160} \times 100 \approx 0.9\%$$

The negligible percentage error calculated above demonstrates the consistency of both methodologies applied in Chapter Three (*AHiP-Evi* modelling) and Chapter Four (*BN-SAT* modelling). It is noteworthy to state that the *BN-SAT* approach accommodates the evaluation of dependency and independency relations among the problem-domain variables whereas the *AHiP-Evi* approach does not provide for such.

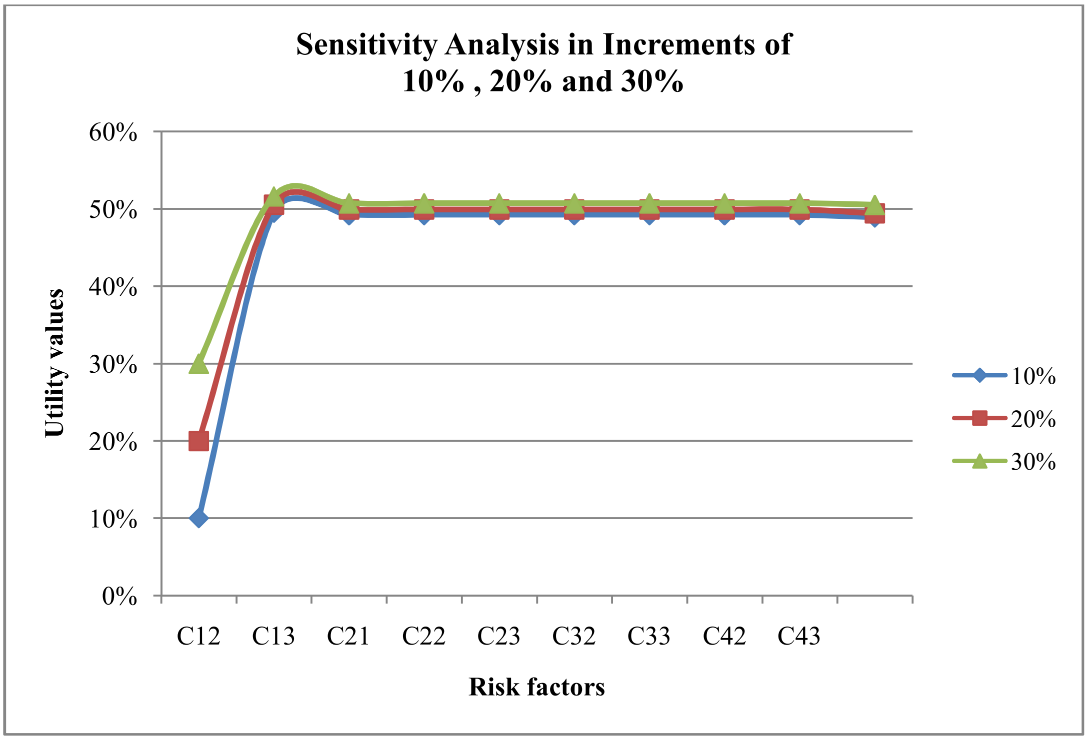


Figure 4.16 The effect of increasing the target node (OWFD) input value to 100%

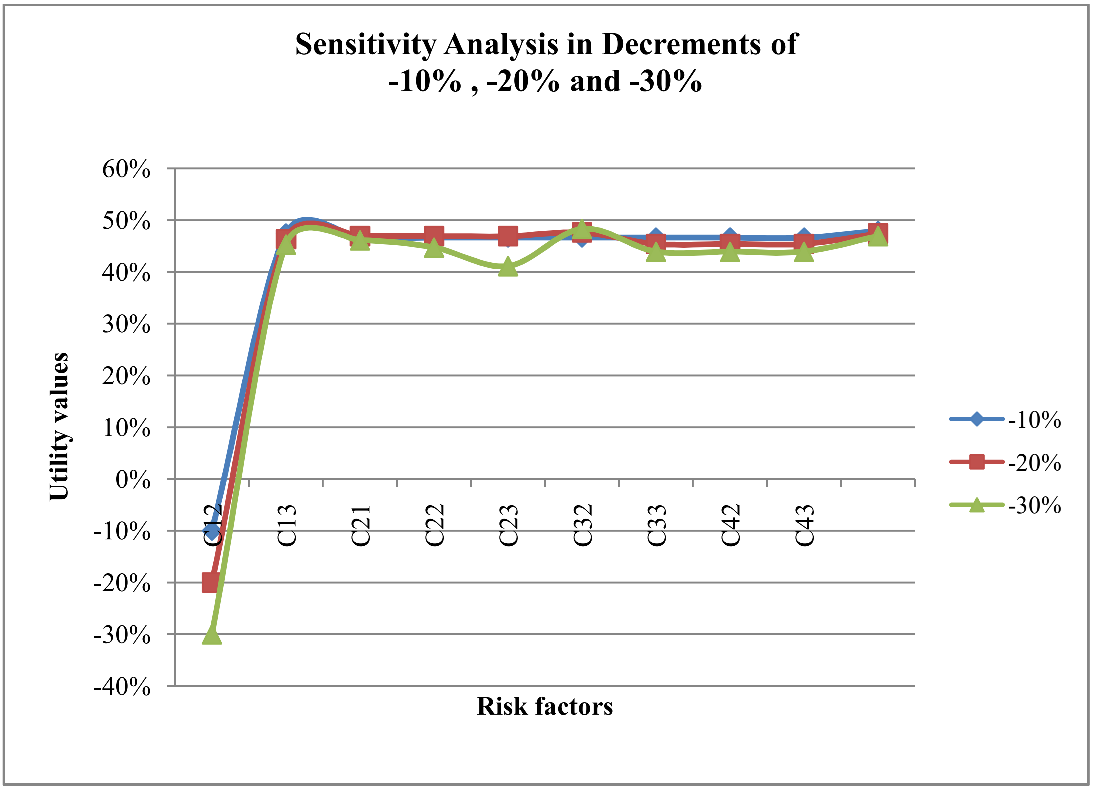


Figure 4.17 The effect of decreasing the target node input value (OWFD) to 100%

The above Figures 4.16 and 4.17 conform to Axiom 4, which states that when the target node input value is increased to 100%, the probabilities of the likelihood of occurrence increase and the unlikelihood occurrence decrease by equal amount on all the nodes in the Bayesian modelling structure. Conversely, the probabilities of likelihood of occurrence decrease and the unlikelihood of occurrence increase by equal amount on all other nodes in the BN structure when the target node value is decreased by 100%. For instance, when the input value of the target node is increased to 100% the likelihood of occurrence of node C_{21} increased by 5.5% and the unlikelihood of occurrence also decreased by equal amount i.e. 5.5%; the likelihood of occurrence of node C_{22} increased by 12.4% and the unlikelihood of occurrence decreased by 12.4%; the likelihood of occurrence of node C_{23} increased by 1.9% and the unlikelihood of occurrence also decreased 1.9%; the rest of the computation can be found in Appendix 2. In the same vein, when the input value of the target node is decreased to 100% the likelihood of occurrence of node C_{21} decreased by 5.2% and the unlikelihood of occurrence also increased by equal amount i.e. 5.2%; the likelihood of occurrence of node C_{22} decreased by 11.7% and the unlikelihood of occurrence increased by 11.7%; the likelihood of occurrence of node C_{23} decreased by 1.8% and the unlikelihood of occurrence also increased 1.8%; the rest of the computation can be found in Appendix 2.

4.14 Sensitivity analysis (*BN-SAT*) (step 5)

Table 4.4 Increasing variable's likelihood by 10%, 20% and 30%

Risk factors	10%	20%	30%
C12	0.495	0.505	0.516
C13	0.492	0.499	0.507
C21	0.492	0.499	0.507
C22	0.492	0.499	0.507
C23	0.492	0.499	0.507
C32	0.492	0.499	0.507
C33	0.492	0.499	0.507
C42	0.492	0.499	0.507
C43	0.489	0.494	0.505

The set of values displayed in Table 4.3 is the derived output of the new input data evidence entered into the BNs. The new updated derived output data is obtained by the use of the NETICA analytical software. The new evidence emerges from increasing the original data by 10%, 20% and 30%. This process is repeated for each individual starting node in the BNs model in a methodical manner in order to establish the probability values of the decision node at every instance. For example, the original input data for parent nodes of C_2 is C_{21}= 0.293, C_{22} = 0.551 and C_{23} = 0.156, which is increased by 20%; the resultant output data or decision node was determined to be 0.499, 0.499 and 0.499 respectively when compared to the frame reference output data assessed as 0.516. The sensitive nature is observed as the slightest changes made to the network are significant in the analysis of the influence of each variable on the decision node. Table 4.4 conforms to Axiom 1, given that the slightest increment in the rate or probability of occurrence of an input variable results in a relative increment of the model output data.

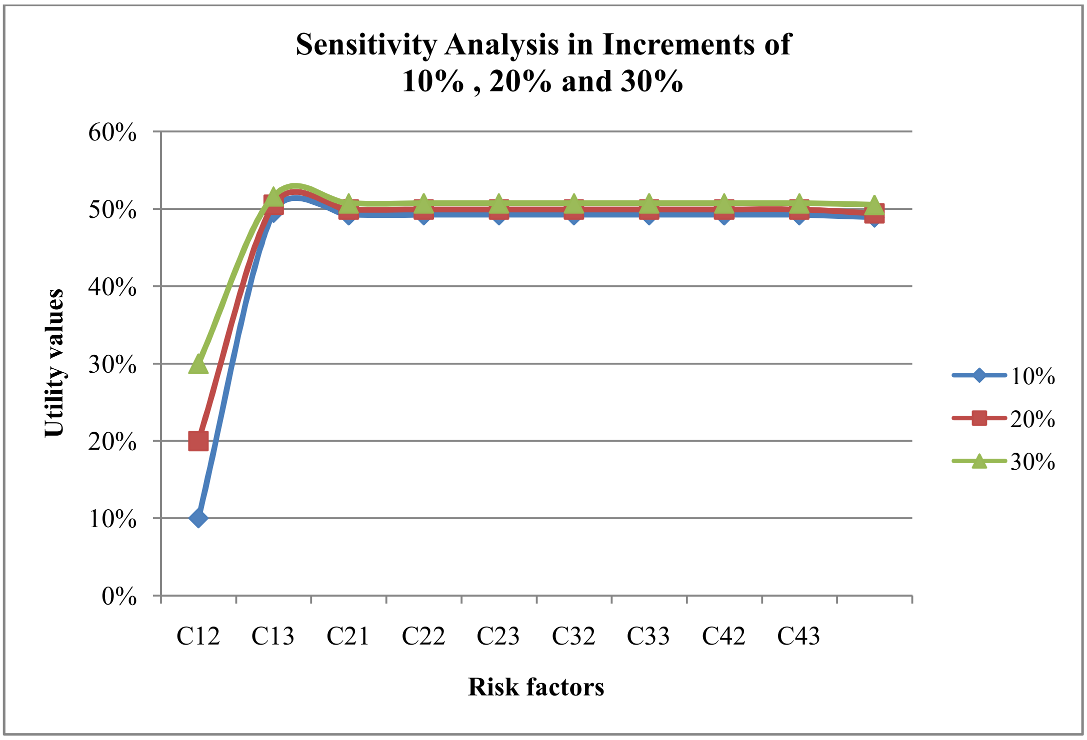


Figure 4.18 Sensitivity analysis of the model output based on increasing the values of the variations by predetermined percentages

In consideration of the axioms defined in section 4.12, the sensitivity analysis curve in Figure 4.18 shows the relative impact of various nodes assigned in the modelling process on the output of the categories of decision node (OWFD). It also indicates that the most sensitive changes to the variables occurred at 10% increment followed by 20% and then 30% increments. This is important in identifying the degree of the influence of each parameter in the BN in order to analyse their interdependency relationships under high uncertainty.

Table 4.5 Increasing variable's likelihood by -10%, -20% and -30%

Risk factors	-10%	-20%	-30%
C12	0.474	0.463	0.453
C13	0.466	0.469	0.461
C21	0.466	0.469	0.447
C22	0.466	0.469	0.411
C23	0.466	0.476	0.483
C32	0.466	0.454	0.439
C33	0.466	0.454	0.439
C42	0.466	0.454	0.439
C43	0.479	0.474	0.469

The sensitivity analysis curve in Figure 4.19 conforms to Axiom 1 and Axiom 2 and shows the relative impact of various nodes assigned in the modelling process on the output of the categories of decision node (OWFD). It also indicates that the most sensitive changes to the variables occurred at 30% decrement followed by 20% and then 10% decrement. This is important in identifying the influence of each parameter in the BNs in order to analyse their interdependency relationships under high uncertainty. Based on the data presented in Table 4.5, it can be seen that, when the input data of C_{32} is decreased by 10%, 20% and 30% in Table 4.4, the results are assessed to be 0.466, 0.454 and 0.439 respectively; the rate of the occurrence of the output data progressively reduces at each 10% decrement. Given that 0.466 is greater than 0.454 and 0.454 is greater than 0.439, the output data conforms to Axiom 3.

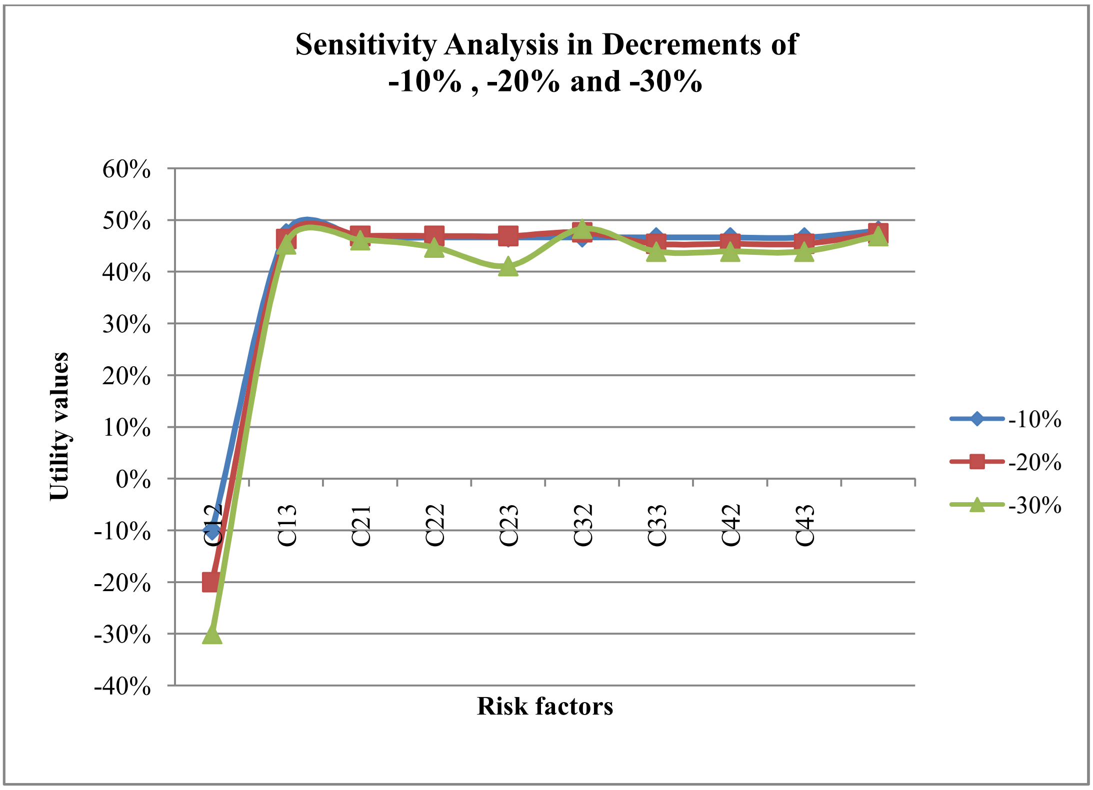


Figure 4.19 Sensitivity analysis of the model output based on decreasing the values of the variations by predetermined percentages

4.15 Discussion and Conclusion

The sensitivity analysis conducted above is to determine the relative impacts of the various nodes on the final outcome of the decision node. The analysis was based on a symmetrical approach in line with the axioms discussed in section 4.12. The sensitivity analysis in this study mainly focused on observation of how the independent variables impact on the target node output given any small changes made to the input data of the variables.

Based on the result of the analysis presented in Table 4.4, the magnitude of the influence of the input variables shows the accuracy of the output data. Figure 4.18 indicates various inferences of the associated risks of OWFD, with C_{42} and C_{43} as subsets of Organisational Risk factors being the most sensitive nodes influencing the offshore wind farm development, followed by C_{13} in all the increasing variations of 10%, 20% and 30% and the behaviours remained consistent in all three variations. In the same vein, C_{22} and C_{23} as subsets of Engineering Risk factors are the least sensitive, indicating it has less influence on the decision node. Conversely, this is also evident in the sensitivity analysis based on decrement of the variations (see Figure 4.19), given that variable C_{42} and C_{43} appear to be the least sensitive nodes and C_{22} and C_{23} become the most sensitive nodes in the BN structure.

Evidently, the sensitivity analysis further highlights the fact that the human resources are, perhaps, one of the most if not the most important asset of a project. If the right people, right skills or right working atmosphere is lacking, it will have a knock-on effect on the output of the project regardless of the financial resources made available for that project. In light of this, it is reasonable to suggest more investment is made in employing staff with relevant skill sets, good work ethics and proven track records of accomplishment. In addition, provisions should also be made for personal and professional development of the staff as this is likely to further reduce risks associated with staffing and staff performance. A further study on human reliability will provide insight into the extent of the risk exposure and the best approach to reduce or eliminate its C_{42} variable in the development of an offshore wind farm. Riahi *et al.,* (2012) completed a similar study on the reliability of seafarers under high uncertainties and how operational efficiency can be improved following a good understanding of the human reliability analysis outcome.

Based on Figure 4.12, the frame reference obtained from the analysis using the BN-SAT model is 0.5240, which is in line with the output data of the previous study in Chapter Three obtained using the *AHiP-Evi* modelling system. This further shows that the application of the *BN-SAT* in this study is successful regardless of the uncertainties. In order to validate the efficiency of the application of the *BN-SAT* model, a comparison is drawn with the results obtained previously in Chapter Three. The outcomes of both analyses show an insignificant difference that can be measured by applying Equation (4.19). Hence, both analytical methodical approaches have proven to be robust in the evaluation of risks associated with OWFD. Following the evaluation of the unconditional prior probabilities of all the root nodes and their corresponding weights from the previous chapter (see sub-section 3.10.5) using the current *BN-SAT* approach, the marginal probability of the associated OWFD risks obtained is to the value of 0.524 whereas the result of the analysis obtained from the previous chapter using the *AHiP-Evi* modelling tool is 0.5112.

Thus, the percentage difference as given by Equation (4.19) is 2.4%, which is not significant and therefore proves the consistency of the two analytical modelling approaches applied in this study. The development of the *BN-SAT* forms a framework largely aimed at assisting the decision maker to understand the probability of occurrence and the degree of uncertainty of the system. This will provide the basis for developing a functional strategy for improving the system. This proposed *BN-SAT* approach provides a robust platform capable of handling and integrating both qualitative and quantitative data.

CHAPTER FIVE: AN INTEGRATED FRAMEWORK FOR SELECTING A STRATEGIC RISK MANAGEMENT TECHNIQUE FOR THE IMPROVEMENT OF OWFD USING FAHP AND FTOPSIS

Summary

Due to the complexity of the estimated risks and the inherent uncertainties associated with offshore wind farm development (OWFD), this study applies the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) as the multi-criteria decision-making (MCDM) technique for the selection of the most appropriate risk management system. The determination of the most appropriate risk management system is useful in the performance and safety optimisation of the design, construction and operation of the OWFD.

A Fuzzy Analytic Hierarchy Process (FAHP) is adopted in order to obtain the weight of each criterion and sub-criterion where applicable. Similarly, a fuzzy TOPSIS is adopted specifically for ranking the importance of the risk management alternatives with respect to costs and benefits under a fuzzy environment ((Roy, 2005). The implementation of the case study using a combination of FAHP and FTOPSIS illustrates the robustness and effectiveness of the proposed model to optimise the performance of the critical components of the framework for OWFD.

5.1 Introduction

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision-making method that was first proposed by Yoon in 1980 (Yoon, 1980) with further developments by Hwang and Yoon (1981), Yoon in 1987 (Yoon, 1987), Hwang, Lai and Liu in 1993 (Hwang *et al.,* 1993) and Yoon and Hwang (1995). TOPSIS is a multi-attribute or multi-criteria decision-making analysis approach (MADM or MCDM) that is employed to identify solutions from a finite set of alternatives based on minimum distance from a positive ideal point and maximum distance from a negative ideal point (Zeleny, 982; Chen and Hwang, 1992). A fuzzy multi-attribute decision-making (FMADM) or fuzzy multi-criteria decision-making (FMCDM) approach is an ideal decision-making tool most suited for group decision-making cases under a fuzzy environment (Li, 2007).

TOPSIS has recently been applied successfully in such areas as critical transportation and infrastructural development (Tzeng *et al*., 2005), design engineering of products (Lin *et al.,* 2008) and supply chain management systems (Shyur and Shih, 2006). However, despite the successes in the application of TOPSIS, most uncertain data may not be accurately evaluated given that judgements have the potential to be vague due to human bias. Thus, fuzzy values or interval values are usually determined by evaluating the relative importance of criteria and the preference of each alternative in the TOPSIS model.

The TOPSIS methodology has a number of drawbacks; these include:

a) The first drawback identified is that the normalised scale for each criterion in the normalised decision matrix is usually derived from a narrow gap among the performed measures. Therefore, the true dominance of the alternatives is not adequately represented in the TOPSIS model.
b) The second drawback is the lack of provision for consideration of the potential risk associated with the DM. The opinions of the DMs are often far apart, despite the DMs having the same or similar experience. The propensity for a DM to overestimate or underestimate a gain or loss in the assessment is very probable and as such is seen as a risk (risk propensity). The DMs' attitudes to risks are usually categorised as risk-seeking, risk-neutral, and risk-averse. Therefore, the subjective propensity associated with each individual DM's preference can only be determined if their risk propensity is taken into consideration.

In order to overcome these setbacks in the TOPSIS approach, this study is proposing the following solutions:

a) A new normalised method is considered in order to produce a wider gap amongst the performed measures.
b) The risk propensity is taken into consideration in the TOPSIS method.

This study will evaluate the decision makers' (DMs) opinions by application of a fuzzy multi-attribute group decision-making (MAGDM) or multi-criteria decision-making (MCDM) approach (Hsu and Chen, 1996). The DMs' opinions are aggregated in order to determine the performance rating with respect to all the attributes for each risk management system likely alternative. The DMs' opinions are represented in fuzzy decision matrices that are transformed into an aggregated decision matrix in order to establish the most preferable option among all likely risk management system alternatives.

As proposed by Li (2007), FMADM approach is applied in this chapter in order to handle the aggregation and synthesis of the DMs' opinions in respect of the selection of the most appropriate risk management system for OWFD. In this chapter, the proposed novel approach for group multi-attribute decision-making represented as FAHP-FTOPSIS entails the use of linguistic terms (LT), the Fuzzy Analytic Hierarchy Process (FAHP) for evaluation of the significant importance of attributes considered in the proposed TOPSIS model. The obtained results are customised into a deterministic weight vector by applying the extent analysis technique while the ranking of the alternatives is completed by the using the FTOPSIS (Lin *et al.,* 2008).

5.2 Literature Review

The multi-criteria decision-making (MCDM) tool is widely applied in various industries and has proved to be successful in recent years. Kannan *et al.,* (2014) proposed a fuzzy multi-attribute group decision-making approach based on practices from the high-risk supply chain perspectives and has made a valuable contribution to the invention of effective MCDM decision-making methodologies.

According to Chang *et al.,* (2007) and Chan *et al.* (2008), the fuzzy analytic hierarchy process is useful in prioritising or ranking alternatives under a fuzzy

environment. Shih (2008) investigated the incremental analysis applied to overcome the shortcomings of ratio scales in various MCDM techniques. Shih *et al.,* (2007) also proposed that the advantages of TOPSIS are characterised by the rationale of human choices; ability to represent both the best and the worst alternatives; and the ability to determine performance measures of all alternatives on given attributes.
Yang and Hung (2007) proposed fuzzy TOPSIS to improve the design of plant layout challenges whilst Jahanshahloo *et al.,* (2006) and Jahanshahloo *et al.,* (2009) proposed TOPSIS modelling for interval data and another method for ranking the score of each alternative. However, these applications still faced some setbacks, as explained in section 5.1 above. Fuzzy TOPSIS methodology resulting from extended TOPSIS has been successfully utilised in various applications and proposals such as those in Chamodrakas *et al.,* (2009), Chen (2000), Chen *et al.,* (2006), Chu (2002), Dagdeviren *et al.,* (2009), Jahanshahloo *et al*., (2006), Wang and Elhag (2006), Wang and Lee (2007) and Wang and Lee (2009).

The combination of Fuzzy AHP and TOPSIS has also been applied in other studies undertaken by Balli and Korukoglu (2009) and Ertugrul and Karakasoglu (2009). TOPSIS with interval data was also proposed by Jahanshahloo *et al.,* (2006a) and Ye and Li (2009). Application of TOPSIS with grey relation analysis was also investigated by Chen and Tzeng (2004) and application of Group TOPSIS was successfully demonstrated by Shih *et al.,* (2007), Wang and Lee (2007) and Ye and Li (2009). Chen (2000) applied a TOPSIS approach by describing the rating of each alternative and the weight of each criterion in linguistic terms and expressed in triangular fuzzy numbers (Mikhailov, 2003). The ranking of all alternatives was determined by calculating the distances to both the fuzzy PIS and fuzzy NIS simultaneously.

A successful application of a fuzzy group TOPSIS model under different subjective attributes in which the membership function is aggregated by interval arithmetic and $\alpha - cuts$ of fuzzy numbers and alternatives are ranked by means of the integral values was proposed by Chu (2002). Wang and Elhag (2006) introduced a fuzzy TOPSIS method on alpha-level sets and presented a nonlinear programming solution procedure. Jahanshahloo *et al.,* (2006b) extended the TOPSIS method for decision-making problems with fuzzy data.

Balli and Korukoglu (2009) and Ertugrul and Karakasoglu (2009) introduced the application of a combination of Fuzzy Analytic Hierarchy Process (FAHP) and TOPSIS by taking subjective judgements of decision makers into consideration. Wang and Lee (2009) proposed a Fuzzy TOPSIS approach integrating subjective and objective weights. Fuzzy methods based on TOPSIS and the AHP for decision-making problems were also investigated by Chamodrakas *et al.,* (2009) and Dagdeviren *et al.,* (2009).

Multiple-criteria decision-making (MCDM) involves the systematic structuring and solving of decision-making challenges based on multiple criteria. This typically entails potential interpretation of the problems in various ways, i.e. the preferred alternative of a decision maker involving various attributes (MADM) or choosing the base case scenario from a set of conflicting goals by means of advanced computational techniques with objective functions (Lai *et al.,* 1994). Multiple-Attribute Decision-Making (MADM) techniques are tools employed for evaluation and selection of a preferred alternative from a predetermined number of alternatives, which are characterised by multiple attributes.

Based on the investigations completed by Jiang *et al.,* (2011), Yang *et al*., (2011), Behzadian *et al.,* (2012) and Aruldoss *et al*., (2013), TOPSIS, VIKOR, AHP, ANP, ELECTRE, Grey theory, SMART, ER, DEA, AIRM and DEMATEL are considered some of the most optimum tools for solving real-life decision problems. These claims are evident in the various MCDM applications published in the professional and academic journals of diversified disciplines such as economics, airline performance evaluation, behavioural decision theory, and software development and information systems. Dependent on the uniqueness of each problem, the following researchers have identified specific methods for evaluating the MCDM/MADM problems: Belton (1986), Watson and Bued (1987), Saaty (1987, 1990), Lai *et al.,* (1994), Yoon and Hwang (1995), Edward and Barron (1994), Barron and Barrett (1996), Triantaphyllou (2000), Goodwin and Wright, 2014), as cited in Yang and Xu, 2002), Chen and Chen (2010), Yang *et al.,* (2011), Behzadian *et al.,* (2012), Aruldoss *et al.,* (2013), John *et al.,* (2014b) and Tadic *et al.,* (2014).

Despite the pros and cons of the evaluation tools mentioned above, each method has the partial or whole involvement of the decision maker. It is a common trend for the MCDM techniques to be combined in order to achieve a more robust and effective decision outcome. Behzadian *et al.,* (2012) demonstrated that TOPSIS is the most widely combined MCDM/MADM tool in recent times. In view of the literature review, TOPSIS involving the analytic hierarchy process (AHP) and fuzzy set theory (FST) will be applied in this chapter for the selection of the best-case risk management technique for OWFD.

5.3 Fuzzy AHP (FAHP) and Fuzzy TOPSIS (FTOPSIS) Concept Theory

5.3.1 Fuzzy AHP

The AHP proposed by Saaty is a useful tool in determining the weights of criteria. However, Buckley extended his fuzzy theory to AHP and successfully proposed the fuzzy AHP. Therefore, the fuzzification process is applied in order to obtain fuzzy weights of identified criteria. The systematic process of fuzzy AHP includes (Mikhailov, 2003):

Step 1. Construction of the fuzzy pairwise comparison matrix

In this step, each DM assigns linguistic terms represented by triangular FN to the pairwise comparison in all the criteria.

Let $\widetilde{F} = [\widetilde{a}_{ij]}]$ be a $n \times n$ matrix

where $\widetilde{a}_{ij}$ represents the importance of the criterion C_i with respect to the criterion C_j.

Based on the fuzzy preference scale presented in Table 5.1, the formula below applies to the pairwise construction.

$$\tilde{F} = \begin{bmatrix} (1,1,1) & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & (1,1,1) & \cdots & \tilde{a}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & (1,1,1) \end{bmatrix} = \tilde{F} = \begin{bmatrix} (1,1,1) & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ (1,1,1)/\tilde{a}_{21} & (1,1,1) & \cdots & \tilde{a}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ (1,1,1)/\tilde{a}_{n1} & (1,1,1)/\tilde{a}_{2n} & \cdots & (1,1,1) \end{bmatrix} \tag{5.1}$$

Step 2. Computation of fuzzy weights by normalisation

The fuzzy weight $\tilde{w}_i$ of criterion C_i can be determined by:

$$\tilde{w}_i = \tilde{r}_i \times (\tilde{r}_1 \times (\tilde{r}_1 + \tilde{r}_2 + \cdots + \tilde{r}_n)^{-1}$$

Where $\tilde{r}_i = [\tilde{a}_{i1} \times \tilde{a}_{i2} \times \cdots \times \tilde{a}_{in}]^{1/n}$ (5.2)

Table 5.1 Fuzzy preference scale

Linguistic terms	Triangular FN ($\tilde{a}_{ij}$)
Absolutely important	(7,8,9)
Very strongly extremely important	(6,8,9)
Very strongly important	(5,7,9)
Strongly important	(4,6,8)
Moderately strong important	(3,5,7)
Moderately important	(2,4,6)
Weakly important	(1,3,5)
Equally moderate important	(1,2,4)
Equally important	(1,1,3)

Refer to chapters two and three of this study for further details of AHP.

5.3.2 The TOPSIS modelling

The basic principle of the TOPSIS method requires that the selected alternative has the shortest distance from PIS and the farthest distance from the NIS. Thus, it simply means that the chosen alternative should be as close as possible to the ideal solution and as far as possible from the negative ideal solution. The ideal solution in this case is a composite of the best performance values demonstrated in the decision matrix by any alternative for each given criterion. This approach compares a set of alternatives by identifying weights for each criterion, normalising scores for each criterion, and calculating the geometric distance between each alternative and the ideal alternative, which is the best score in each criterion. It is fair to assume that the identified criteria in TOPSIS are monotonically decreasing or increasing. The criteria or parameters are often of incongruous dimensions; thus, normalisation is required (Yoon, 1980).

Linguistic criteria in TOPSIS are quantified within the established and agreed value scale. The value scales most commonly used are as follows:

i. Ordinal scale – the ranking of actions, whereas the relative distances between the ranks are not taken into account. Data is only measured in order of magnitude without a standard to measure the difference. For instance, one person may be better than another but no measure of how much is stated.
ii. Interval scale (equal differences between the criterion values and defined benchmarks are determined). The interval measurements are the distance between attributes and are interpretable. For example, the percentage change between 10% and 20% is the same as between 20% and 30%. Also, when we measure temperature the distance from 50-60 degrees Celsius is the same as the distance from 90-100 degrees Celsius.
iii. Ratio scale (equal relations between the criterion values but the benchmarks are not defined beforehand). In other words, this refers to the level of measurements in which the attributes composing variables are measured on specific numerical scores or values that have equal distances between attributes or points along the scale and are based on a "true zero" point. For example, the difference between a length of 60 feet and 40 feet is the same as the interval between 30 feet and 10 feet. The zero in a ratio scale simply depicts that the attribute does not exist

Ratio scale refers to the level of measurement in which the attributes composing variables are measured on specific numerical scores or values that have equal distances between attributes or points along the scale and are based on a "true zero" point.

Considering the above scales, the interval scale is the most suitable tool to use when performing quantification of qualitative criteria. It is usually comprised of a 1 to 9 scale given that the extremes of the identified criteria being analysed are often unknown. The qualitative criteria are transformed into quantitative for ease of data computation (see Table 5.2).

Table 5.2 A quantification of qualitative criteria

Qualitative estimation	Small (bad)	Average	Very high (very good)	Extremely high (excellent)	Type of criteria
Symbol	α β γ	α β γ	α β γ	α β γ	
Qualitative estimation	1 1 2	4 5 6	6 7 8	8 9 9	Benefit (max)
	9 9 8	6 5 4	4 3 2	1 1 2	Cost (min)

Qualitative criteria can be quantified in many ways; one such way is known as fuzzification, as illustrated in Table 5.2. This fuzzification approach will later be applied in the selection process for the best-case RMT for OWFD.

5.3.3 Fuzzy TOPSIS

Fuzzy TOPSIS is one of the most effective approaches for solving MCDM problems and it is based on the principle that the chosen alternative will have the shortest distance to the PIS (the solution that minimises the cost criteria and maximises the benefit criteria) and the farthest distance to the NIS. The triangular fuzzy numbers (FN) will be used in the FTOPSIS approach in this study. The triangular FN has several beneficial features such as the ease of use for the decision maker in carrying out empirical analysis (Dagdeviren *et al.*, 2009). The use of triangular FNs is a proven approach and is widely used in MCDM under a subjective and incomplete condition (Dagdeviren *et al.*, 2009).

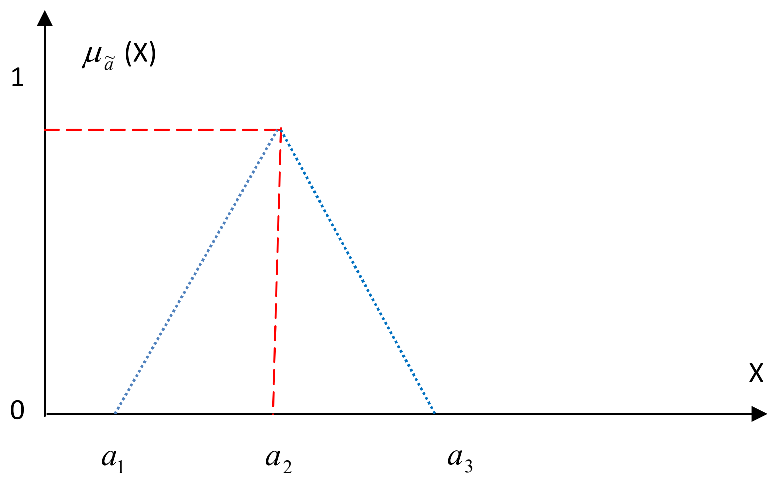


Figure 5.1 A Triangular fuzzy number $\tilde{a}$

The triangular fuzzy number $\tilde{a}$ is defined by the triplets $(a_1, a_2\, a_3)$ and $(b_1, b_2\, b_3)$ as presented in Figure 5.1 above. Therefore, the membership function $\mu_{\tilde{a}}$(x) is defined as stated in equation (2.3).

$$\mu_{\tilde{a}}(x) = \begin{cases} 0 & x < a_1 \\ \dfrac{x - a_1}{a_2 - a_1} & a_1 < x < a_2 \\ \dfrac{x - a_3}{a_2 - a_3} & a_2 < x < a_3 \\ 0 & x < a_3 \end{cases} \tag{5.3}$$

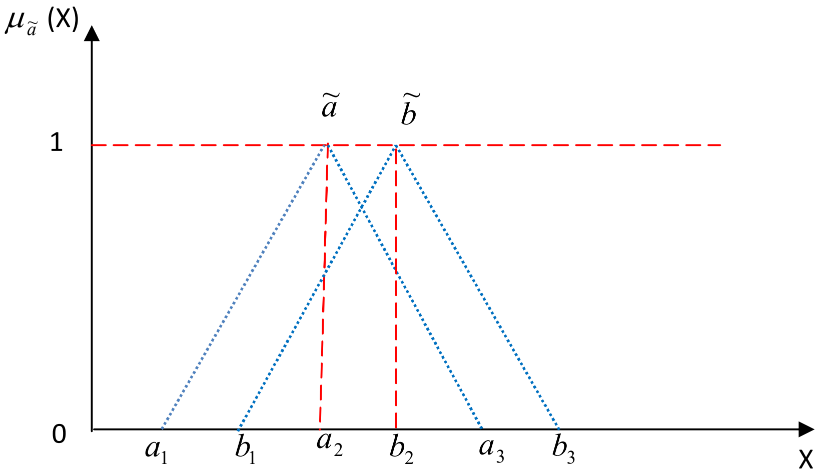


Figure 5.2 Membership function of two triangular FNs

Assuming $\tilde{a}$ and $\tilde{b}$ represent the two positive triangular FNs denoted by the triplets $(a_1, a_2\, a_3)$ and $(b_1, b_2\, b_3)$ as shown in Figure 5.2 above, the basic functions of these two FNs may be mathematically represented (Dubios and Prade, 1997 and Dubois and Prade, 1980) as follows:

$$\tilde{a}(+)\tilde{b} = (a_1, a_2, a_3)(+)(b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{5.4}$$

$$\tilde{a}(-)\tilde{b} = (a_1, a_2, a_3)(-)(b_1, b_2, b_3) = (a_1 - b_1, a_2 - b_2, a_3 - b_3) \tag{5.5}$$

$$\tilde{a}(\times)\tilde{b} = (a_1, a_2, a_3)(\times)(b_1, b_2, b_3) = (a_1 b_1, a_2 b_2, a_3 b_3) \tag{5.6}$$

$$\tilde{a}(\div)\tilde{b} = (a_1, a_2, a_3)(\div)(b_1, b_2, b_3) = (\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1}) \tag{5.7}$$

$$\tilde{a} = (ka_1, ka_2, ka_3) \tag{5.8}$$

A complex condition is expressed in linguistic variables such as very low, low, medium, high, very high (Zadeh, 1976); and the linguistic values are also represented by fuzzy numbers (Amiri, 2010).

According to Chen (2000), distance between two triangular FNs can be calculated by the application of the vertex method to determine the distance between $\tilde{a}$ and $\tilde{b}$ using Equation (5.9) below:

Assuming $\tilde{a} = (a_1, a_2, a_3)$, $\tilde{b} = (b_1, b_2, b_3)$, are two triangular FNs, then

$$d(\tilde{a}, \tilde{b}) := \sqrt{\frac{1}{3}[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2)]} \qquad (5.9)$$

See also subsection 2.10.1 in Chapter Two of this study for an elaborate review of the literature on the Fuzzy set modelling and TOPSIS approaches in line with investigations completed by Bowles and Palaez (1995) and Pillay and Wang (2003).

5.3.4 Fuzzy MCDM problem formulation

In order to evaluate a multi-criteria decision-making (MCDM) problem, a basic procedure is followed. For example, an MCDM with multiple m alternatives $\{A_1, A_2, \cdots, A_m\}$ will be determined by the application of n attributes/criteria $\{C_1, C_2, \cdots, C_n\}$ and may be represented by the decision matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \qquad (5.10)$$

where x_{ij} represents the value of the i^{th} alternative with respect to the j^{th} criterion.

The importance of the criteria is also described as weight w_j of the criterion C_j of the decision. Assuming w is the vector, $w = [w_1, w_2, \cdots, w_n]$ (5.11)

These weights are subjective and are determined by a single decision maker or group of experts. In order to assign the degree of importance to the criteria, equivalence between the importance of an attribute and triangular fuzzy number or trapezoidal fuzzy number through an empirical method may be applied (Yang and Hung, 2007). For the purpose of this study, only the triangular fuzzy numbers will be used (see Table 5.3).

Similarly, the alternatives can also be evaluated by using the linguistic terms represented by triangular FN or trapezoidal FN (Chen, 2000). As mentioned above, only the triangular FN will be applied in this study for the evaluation of the alternatives as shown in Table 5.3. In cases where the decision maker is unable to assign precise value to an alternative A_i for a particular criterion C_i, the fuzzy MCDM problem can be expressed by the decision matrix:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}, \tag{5.12}$$

where $\tilde{x}_{ij}$ denotes fuzzy value (for possible triangular FN, trapezoidal FN, IFS, IVIFS, trapezoidal hesitant fuzzy element and others).

5.3.5 Risk Management under fuzzy environment

Risk management is defined as an operational process consisting of various sources of uncertainty. The processes include risk identification, estimation of consequences of uncertain events/risk analysis, and generation of response strategies following determination of expected outcome or based on feedback received on the actual outcomes. The processes are repeated throughout the life cycle of the project in order to ensure the risk factors are eliminated, contained or appropriately managed (Tserng *et al.*, 2009).

5.3.6 TOPSIS method for selection of risk management technique (RMT)

The risk factors in wind farm construction are very high. The risks originate from various sources and the complexity of the construction and operational objects increases the risks, especially in offshore wind farm development (Zavadskas *et al.*, 2010). TOPSIS is one of the simplified techniques for evaluating MCDM problems such as the selection of appropriate risk management from multiple alternative options.

The TOPSIS methodology is based on the following assumptions:

i. A monotonically increasing or decreasing utility is assumed by each criterion in the MCDM approach.
ii. The criteria will have a set of weights.
iii. An appropriate scaling technique is used to quantify any outcome that is not expressed in numerical terms.

The TOPSIS method identifies the most appropriate RMT from a finite set of alternatives based on simultaneous minimisation of distance from a positive ideal point and the maximisation of distance from a negative ideal point (Shih *et al.*, 2007). However, the required subjective input remains the weights of the relative criteria (Lin *et al.*, 2008).

5.4 Methodology

The proposed FAHP-FTOPSIS model presented in Figure 5.5 has been used to evaluate a decision-making process for selection of the most suitable RMT for OWFD. The decision-making process (evaluation and selection of the ideal solution) has been categorised into five main stages based on the evaluation criteria:

Stage 1: Assigning the decision-making team and determining the decision-making alternatives to be evaluated for OWFD risk management.

Stage 2: Identifying the criteria to be used in the evaluation process.

Stage 3: Structuring of the fuzzy decision-making matrix and assigning the criteria weights using FAHP.

Stage 4: Computing of the scores of alternatives with fuzzy TOPSIS and ranking the overall evaluation outcome.

Stage 5: Analysing the results.

The decision-making processes illustrated in the flow diagram shown in Figure 5.4 are applied to select the best-case RMT for OWFD. The decision makers completed these evaluation processes based on their subjective experience and judgement on wind energy development and operational systems.

Table 5.3 Linguistic values of triangular FNs for alternatives (Alidoosti *et al,* 2012 and Junior *et al.,* 2014)

Linguistic terms	**Triangular FN**
Very Low (VL)	(0.00, 0.00, 0.25)
Low (L)	(0.00, 0.25, 0.50)
Medium (M)	(0.25, 0.50, 0.75)
High (H)	(0.50, 0.75, 1.00)
Very High (VH)	(0.75, 1.00, 1.00)

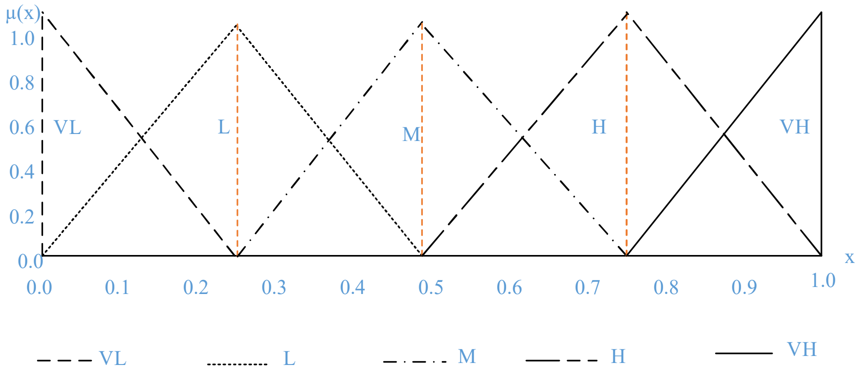


Figure 5.3 Membership function for linguistic rating (as adapted from Junior *et al.,* 2014).

The above Figure 5.3 and Table 5.3 show that the linguistic assessment between 0.00 and 0.25 is Very Low and the performance score is 100% Very Low at 0.00. Between 0.00 and 0.50, the linguistic assessment is Low and considered 100% Low at 0.25. Between 0.25 and 0.75, the linguistic assessment is Medium and the performance score at 0.50 is 100% Medium. Between 0.50 and 1.0, the linguistic assessment is considered High and the performance score is 100% High at 0.75. Equally, between

0.75 and 1.00, the linguistic assessment is Very High and the performance score at 1.00 is 100% Very High.

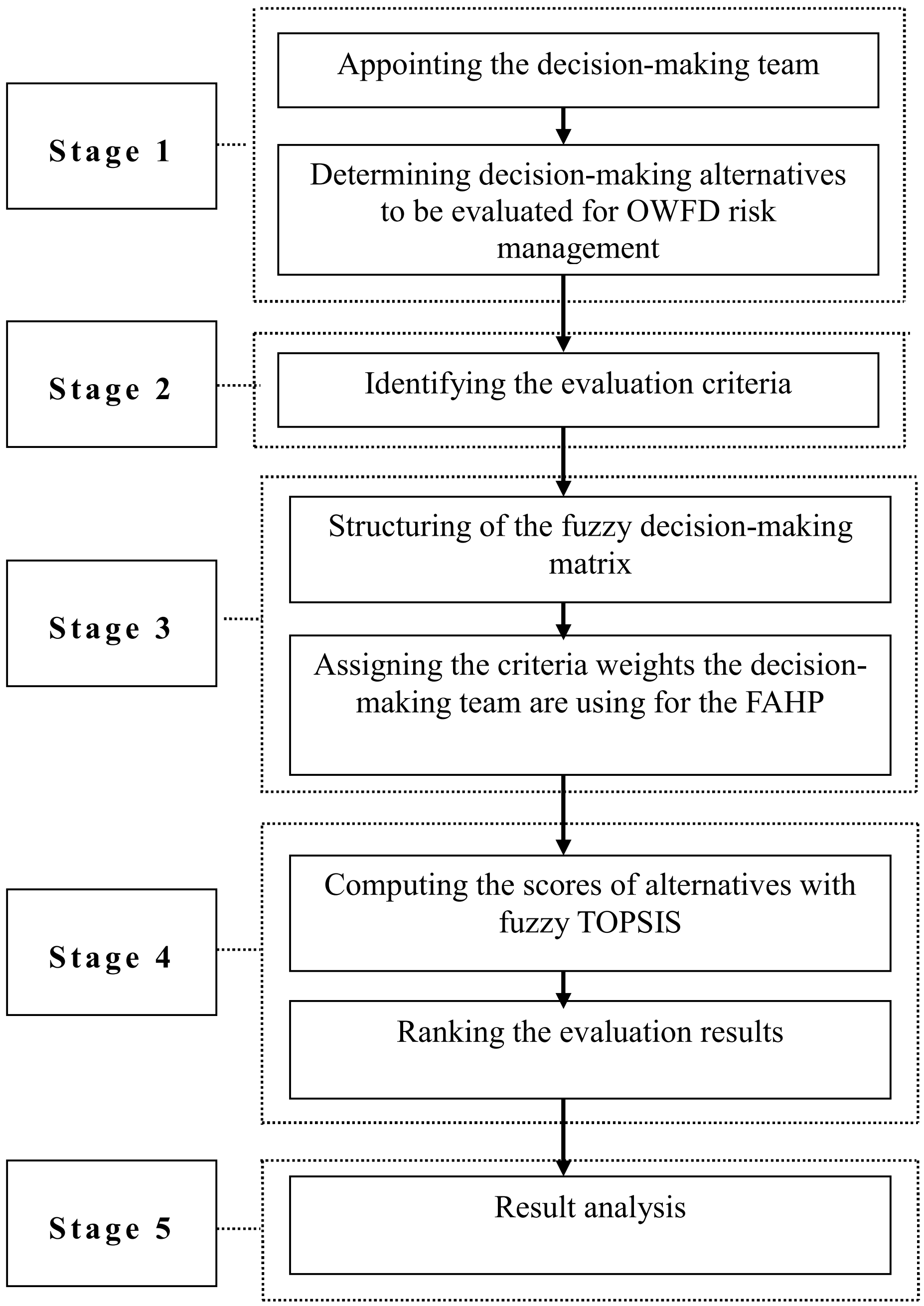


Figure 5.4 A fuzzy TOPSIS model for evaluation for selection of the best RMT for OWFD

5.4.1 Appointment of the decision-making team

The decision-making team is drawn from highly experienced individuals with specific qualifications in the subject matter as shown in Table 5.4. Certain qualification criteria may be set for the nomination of the suitable decision-making team members.

Table 5.4 Nominated experts and their assigned degree of competency (DoC)

Decision Makers (DM)	Work Position (WP)	Service Time (ST)	Education Qualification (EQ)	Degree of Competency (DoC)
DM1	Senior Project Manager	>30 year	PhD	0.333
DM2	Construction Manager	>30 year	M.Eng	0.333
DM3	Senior QHSE Manager	>30 year	MSc	0.333

5.4.2 Determine the decision-making alternatives to be evaluated for OWFD risk management

A number of RMTs are being applied in various industries; however, some are more commonly applied than others. Some of these RMTs are more cost effective while others may require more efforts than the derived benefits. For this reason, the decision maker must be clear about what is intended from the applicable RMT and how the alternative solution fits into the criteria being assessed. Many proprietary methods of risk management that seem to have been successfully applied fall into the following categories (IMA, 2007):

i. Structured brainstorming and evaluation
ii. Probability-impact calculations
iii. Probabilistic modelling
iv. Informal direct assessment of risks
v. Checklists method
vi. Risk indicator scales

5.4.2.1 Structured brainstorming and evaluation/workshop (SBS)

This type of RMT allows an experienced group of experts to exchange ideas about risk perceptions in order to estimate the relevant associated risk factors (IMA, 2007). The risk estimation process is as crucial as the proposed RMT; therefore, the importance of the experts in the process cannot be substituted. One of the challenges faced with this risk management technique is the unavailability of the experts (SASNZ, 2004). The few experienced individuals are often very busy and can only offer a small amount of time to this process, hence the need to have a structured system to use their time in a more cost-effective manner (Jani and Todd, 1993). Some of the overlooked risks that are picked up in a brainstorming exercise include people risks, environmental risks, financial risks and other more technical risks. People risks include potential lack of continuity of skill in planning, execution and management if a competent member of staff leaves the project (SASNZ, 2004).

5.4.2.2 Probability-impact calculations (PICs)

This type of risk management technique (RMT) entails the use of a generated list of project risks with the probability and impact values assigned to each risk factor (Dumbravă, and Iacob, 2013). These assigned values are multiplied through and summed up; the average outcome is determined by applying similar logic to that used by a bookmaker (Hillson and Hulett, 2004). One of the challenges with this approach remains the fact that most risk factors are not easily characterised as uncertain events with a single probability potential. Such risk factors are better expressed as uncertain variables with a range of possible values and a distribution of likelihoods within that range; this is very common with probabilities conducted under high uncertainty (Iacob, 2014). Other challenges may arise in situations where risks are considered very significant in the risk calculations such that, if any of those types of risks become probable, a substantial impact will be seen on the contingency budget allocated to cater for such costs (Iacob, 2014). The best-case scenario of these types of PICs is that they provide a false sense of security; whereas the worst-case scenario is that the project may be unintentionally left exposed (Hillson and Hulett, 2004; Nelson, 2005). The bookmaker analogy in practice only offers a 50/50 chance, which could easily see the contingency budget overrun. Ideally, it would make sense to seek an alternative

RMT or corroborate the PICs approach with another RMT (Hillson and Murray-Webster, 2004).

5.4.2.3 Probabilistic modelling (PM)

This type of technique involves the evaluation of the proposed model in a modelling tool such as a spreadsheet, Lotus 123 or any other inexpensive risk-modelling package. The output of the quantitative risk model provides understanding of the realistic likely range of outcomes expected within the project risk profile (Nelson, 2005). In order to effectively manage project risks, robust assessments of the inherent uncertain events using the two-dimensional approach, i.e. how likely the uncertainty is to occur (probability), and what the effect would be if it occurred (impact), have to be undertaken. Although unambiguous frameworks can be developed for risk impact assessment, probability assessments are often determined under a fuzzy environment (Hamm, 1991). This is particularly the case where the data on risk probability from previous projects or experiences is either unavailable or irrelevant (Hillson and Hulett, 2004).

5.4.2.4 Informal direct assessment (IDA)

Informal direct assessment of risk traditionally includes a variety of approaches such as empirical method and/or by use of internal procedures based on observations, trends and other relevant information compiled over a period. The informal direct assessment approach relies heavily on the participation of experienced professionals (Kevin and Ann, 2016). The experts' judgements cannot be undermined as the risk management framework is based on the experts' contributions. However, some of the shortfalls with the IDA method are that the experienced professionals are often in short supply (Cui, *et al.,* 2018). Secondly, project risk factors are often dynamic, and as such require regular review and close monitoring.

The IDA is as good as its original status at any point in time given that any changes in its structure, technical content, commercial setup, resourcing arrangements, judgements or any key feature render the system potentially unreliable. The trickiest part of the IDA approach is that it is often difficult to realise when the system is no longer valid due to the changes in key features. As a result, formal direct assessment is more recommendable than informal direct assessment (Kevin and Ann, 2016).

5.4.2.5 Checklists method (CLM)

This approach involves generating a list of actions to be completed, which is usually drawn from what had gone wrong and the lessons learned from previous projects. Although this is very popular in the industry and the objective is to forestall repetition of the same or similar error, the problem with it is that the first mistake on a project sometimes may just be catastrophic enough to end the project or someone's career. The checklist serves as a good reference point; however, the population of the list is usually an ongoing exercise requiring close attention (Dolan and Doyle, 2000). One of the challenges of the checklist approach is that the list may end up so large that it becomes daunting to access the information.

5.4.2.6 Risk indicator scales (RIS)

Risk management professionals have made tremendous progress over the past decades in developing risk indicator scales that can be adapted on most projects. This is based on producing predetermined scoring schemes against which the riskiness of a given project can be measured (Chiang and Chang, 2018). For example, 4 points can be assigned to a factor such as lack of experienced staff, 3 points to a technical complexity and 2 points to a constrained environment and so on. These scores are then summed up to produce an overall score (Birkmann, 2007). The risk experts will assign the threshold limits representing the risk levels such as low risk, moderate risk and high risk (John *et al*, 2014).

One of the major challenges of this risk management technique is the potential for bias. In this kind of approach, it is easy for the professionals to find themselves acting for or against the project depending on individual interests. Therefore, a good project may suffer as a result of bias in the decision-making process and a bad project may equally scale through. This is possible because the scoring system has no real established practical methodology to measure such factors as time and money as it is largely dependent on what went wrong and lessons learned from the past or previous projects.

Table 5.5 A summary of the features of the risk management techniques (RMTs)

RMT	Identification and prioritisation of risks	Contingency setting
Structured brainstorming and evaluation	This is solely dependent on the level of experience of the team carrying out the brainstorming. It is considered more cost effective than when completed by an individual evaluation or inexperienced team.	This technique has the capacity to cover most of the potential to influence the outcome of the input variables.
Probability-impact calculations	This approach relies on risks factors already identified through other means; it does not in itself identify the risk factors.	It does not consider uncertainty in the risk evaluation and tends to play down the risk exposure as well as the contingency requirement. This, in effect, leads to a false sense of security.
Probabilistic modelling	The modelling is a framework for risk factors identification and is used to highlight any gaps in operational planning and optimistic assumptions.	This takes into account the uncertainty in the risk estimation, contingency setting and the impact of unmanaged risk factors.
Informal direct assessment of risks	This approach fits in well if the operational content is a routine and the expertise is available to evaluate the project risks and manage them.	This can be as good or as bad as an unaided judgement.
Checklists method	This approach works well if the experience and lessons learned from the most recent project upon which the list is drawn are exhaustive.	This approach provides no direct value other than the input to subjective judgement.
Risk indicator scales	This system acts as support for subjective judgement if the operational content is a routine and the scales are regularly calibrated.	Often misused by inexperienced personnel who try to convert scales into dollar or time values.

5.4.3 Evaluation criteria

The evaluation criteria identified and applied to the proposed model in order to determine the most suitable alternative include the following:

i. Reliability,
ii. Operability,
iii. Maintainability,
iv. Availability,
v. Cost and
vi. Safety

Reliability may be described as the consistent measurement of the quality of performance of the system. It is the degree to which the outcomes of a measurement and specification are depended upon to be accurate. In the context of offshore wind farm development, reliability is the ability of the wind farm systems to operate efficiently for a specific period of time under predetermined conditions (Patrick and O'Connor, 2002). Reliability is also known as dependability, which can be described as the probability of success in simple terms (Saleh *et al.*, 2006). It is usually expressed as Mean Time Between Failures (MTBF). In context, failure is the cessation of the ability of a system to perform its predetermined functions in the specified time (Stapelberg, 2009).

Operability is the ability of equipment or a system to operate in safe and reliable conditions in accordance with the predetermined operational requirements. In other words, operability is achieved when the system has the capability to perform safely, efficiently and profitably under the predefined operational conditions (Lawley, 1974). This implies that the fewer hazards associated with a system, the more operable that system is likely to be (Gupta and Charan, 2016). An operable system or plant delivers not only the reliable industrial or end user functionality, but also performs efficiently based on the evaluation of the operations engineering team. Various factors can affect the operability of a plant or system; these include design engineering, manufacturing process, installation process, environmental conditions, resource availability, skill sets and operational expertise with the system.

Maintainability is the ability of a system or plant to maintain or restore a functional state of quality performance under the predefined conditions when maintenance is carried out in accordance with prescribed procedures and resources. This is usually expressed as Mean Time To Repair (MTTR). In other words, maintainability can be defined as the probability of carrying out a successful repair in a given time. Therefore, it signifies a measure of the ease and speed with which a system can be restored to operational status after a breakdown or scheduled repair or maintenance (Stapelberg, 2009).

Availability is the probability of a system to be available for use at a specified time (Stapelberg, 2009). It is a function of reliability and maintainability expressed as operating time divided by the time, which is the available time per day minus the planned downtime. Inherent availability is, therefore, mathematically expressed as:

$$A_i = \frac{MTBF}{MTBF + MTTR}$$

where A_i represents availability of the system, $MTBF$ is the mean time between failures and $MTTR$ is the mean time to repair.

Only the corrective maintenance in an ideal support environment with neither administrative nor logistic delays is accepted in the inherent availability evaluation. Reliability of a system or plant diminishes when the system or any of its integral components is in a failed state and it is no longer functional. The longer the system or plant remains in a failed state, the lower the maintainability of that system (Mobley, 2002). The reliability, availability, maintainability and safety (RAMS) of a system or plant are interrelated as integral factors that enable performance of specific functions of the system. This may be defined as design reliability or operational reliability. In other words, availability is the ability of a system to be kept in a functioning state within a given time (Stapelberg, 2009).

Cost may be defined for accounting purposes as cash amount or the equivalent forfeited for an asset. Associated costs include all those costs necessary to have an asset in place and ready for use (Didkovskaya and Akhmetzyanov 2014). This includes a comprehensive breakdown of all costs to be incurred on a project. The process of such cost analysis may vary from one organisation to another (Mamayeva, 2014).

Costs are analysed in different forms such as soft costs and hard costs. Soft cost is a construction industry term used to identify those costs that are not directly related to the construction activities. These include engineering costs, architectural costs, financing costs, legal fees, and costs of permits, insurance, taxes and other pre- or post-construction expenditure (Didkovskaya and Akhmetzyanov 2014). Hard costs are the tangible assets or expenses that are directly linked to the construction activities.

Both the soft and hard costs are taken into consideration during the development of wind farms. Decisions made during the design, engineering and construction phases of the development have an impact on the reliability, operability, availability and maintenance of the wind farm. Therefore, the life cycle performance of the system is dependent on the decisions made from the onset of the project. In most cases, decisions are cost driven depending on the perceived benefits. Certain decisions may not necessarily yield the best results due to the drive to save costs. It is therefore important for design engineers to consider the impact the decisions made at the design stage may have on the project's operations and maintenance costs. Moreover, the safety of the asset and the operating personnel must be the overriding factors when these decisions are made. The typical costs of operation and maintenance of a wind turbine depending on size range from about £3,600 (55kW-Endurance E-3120) to about £102,000 (2 to 3MW-Enercon E82) per annum (Renewable First, 2018).

Safety in an occupational health context is the act of protecting equipment and personnel against harm from physical, psychological and occupational activities, mechanical failure, accident, death, injury, or any such undesirable damage. It can also be described as a situation where there is positive control of known hazards in order to manage an acceptable degree of calculated risk such as a permissible exposure limit (Wang and Trbojevic, 2007). Therefore, the plant or equipment must be designed, manufactured, constructed and operated for its intended purpose at all times by suitably qualified and experienced personnel who are trained to do so in order to minimise accidents and injuries caused due to neglect or misuse of the plant. A well-designed and properly installed plant is likely to be easily maintained and as such will operate efficiently. An adequately maintained plant or system is less likely to breakdown or cause damage or harm (Mobley, 2002; Collins *et al.,* 2009). In addition, the efficiency and the overall life cycle of the system are improved.

Several risk management techniques (RMT) have been reviewed during the course of this study. However, the RMTs to be considered for the selection of the best case for OWFD include structured brainstorming, probability-impact calculations, informal direct assessment of risks and the checklists method.

5.4.4 Structuring the fuzzy decision-making matrix and assigning the criteria weights using FAHP

FAHP has been briefly introduced above in subsection 5.31. Reference can also be made to Fuzzy AHP fully described in Chapter Two and applied in Chapter Three of this study. Similarly, FAHP is also applied here in order to determine the degree of importance or weight of decision alternatives.

5.4.5 Compute the scores of alternatives with fuzzy TOPSIS

The decision matrix is formed through the expert opinion for each alternative with respect to each attribute. These expert opinions may be presented in the form of linguistic terms such as low, medium or high (see Table 5.3). In order to obtain a performance rating for the decision alternatives, the fuzzy variables are represented in triangular fuzzy numbers. For ease of computation and modelling, the linguistic terms are transformed into fuzzy numbers using the conversion scale (Chen and Hwang, 1992). The conversion scale is also used for the rating of the evaluation criteria with respect to the decision alternatives. As presented in Figure 5.3, the performance of both score (x) and the membership degree (μ_x) fall within the range of 0 and 1 (An *et al.*, 2007).

The linguistic values of the triangular FNs presented in Figure 5.3 and Table 5.3 are used to establish a decision matrix for the evaluation process, expert opinions on the decision alternatives with respect to the corresponding criteria by the application of the linguistic terms. The linguistic variables conform to the proposal of Zadeh

(1970), which allows computation with words as opposed to numbers. Therefore, such linguistic terms defined by fuzzy sets are increasingly used in problems of decision-making theory for modelling data under high uncertainty.

The weights of the criteria and experts are calculated during the modelling process. The linguistic variables concept applied here is particularly useful in handling scenarios that are too complex to be reasonably expressed in conventional quantitative format (Zadeh, 1965).

5.4.5.1 Estimating weights of criteria or attributes

This process applies the FAHP algorithm principles for weight evaluation of weights of the attributes or criteria. Refer to Chapter Two and Chapter Three of this study for a detailed literature review and application of AHP respectively. Assuming there are n experts in a group collaborative decision-making process with different weights, each element in a fuzzy pairwise comparison matrix can be computed as illustrated in subsection 5.31:

$$\tilde{a}_{i,j} = (w_1^e e_{i,j}^1 \oplus w_2^e e_{i,j}^2 \oplus \ldots w_n^e e_{i,j}^k) \tag{5.13}$$

$$\tilde{a}_{j,i} = \frac{1}{\tilde{a}_{i,j}} \tag{5.14}$$

where $\tilde{a}_{j,i}$ is the relative importance of criterion i with respect to criterion j expressed by n expert judgement, and $e_{i,j}^k$ is the k^{th} expert judgement on the comparison of attribute i with attribute j in a fuzzy number format. For instance, A $n \times n$ fuzzy pairwise comparison matrix $\tilde{F}$ can be obtained from applying Equations 5.1 and 5.2 (see subsection 5.31).

The same method as applied in Chapter Three (section 3.7 and Equation 3.10) of this study will be replicated to verify the consistency check of the experts' judgements. The weight factors of the attributes in the hierarchy structure can be calculated by applying the geometrical mean technique (Buckley, 1985).

$(\tilde{a}_{i,1}^l, \tilde{a}_{i,1}^m, \tilde{a}_{i,1}^u)$ presents the lower bound (l), median (m) and upper bound (u) values of $\tilde{a}_{i,1}$.

$$\widetilde{f}_i = (\widetilde{a}_{i,1} \otimes \widetilde{a}_{i,2} \otimes \cdots \widetilde{a}_{i,j} \cdots \otimes \widetilde{a}_{i,n})^{\frac{1}{n}} = ((\widetilde{a}_{i,1}^{l} \times \widetilde{a}_{i,2}^{l} \times \cdots \times \widetilde{a}_{i,n}^{l})^{\frac{1}{n}}, (\widetilde{a}_{i,1}^{m} \times \widetilde{a}_{i,2}^{m} \times \cdots \times \widetilde{a}_{i,n}^{m})^{\frac{1}{n}}, (\widetilde{a}_{i,1}^{m} \times \widetilde{a}_{i,2}^{m} \times \cdots \times a_{i,n}^{m})^{\frac{1}{n}})$$

$$\widetilde{w}_i = \frac{\widetilde{f}_i}{\widetilde{f}_1 \oplus f_2 \oplus \cdots \widetilde{f}_i \cdots \oplus \widetilde{f}_n} = (\sigma, \beta, \delta) \tag{5.15}$$

where $\widetilde{f}_i$ represents the geometrical mean of the i^{th} row in the fuzzy pair-wise comparison matrix and $\widetilde{w}_i$ represents the fuzzy weight factor of the i^{th} attribute. Given that the outputs of the geometric mean methods are triangular fuzzy weight factors, defuzzification is applied in order to convert them into the corresponding crisp weight factors. This is in line with the defuzzification approach used in FAHP (Cheng, 1997; Mikhailov, 2004; An *et al.*, 2007). This approach is similarly adopted in this study for weight evaluation and is represented as follows:

$$DF\widetilde{w}_i = \frac{1}{3}(\sigma + \beta + \delta) \tag{5.16}$$

where $DF\widetilde{w}_i$ = defuzzified mean value of a fuzzy weight factor. Therefore, the normalised weight of attribute i (w_i) can then be obtained using Equation (5.17) below.

$$w_i = \frac{DF\widetilde{w}_i}{\sum_{i=1}^{n} DF\widetilde{w}_i} \tag{5.17}$$

5.4.5.2 Estimating weights of experts

The weighting of the experts is determined by assigning scores to the experts according to their overall experience and/or qualifications (illustrated in Table 5.4 above). For example, if an expert is considered ‘more experienced’ than others because of his/her proficiency during a group decision-making, then he/she will be given a greater score. Similarly, if the proficiency of the experts is on a par with one another; then they will be assigned equal weighting. Let $E_1, E_2, E_3 \cdots E_n$ represent the scores of the experts, the weighting of the experts may be obtained by applying Equations (5.28) and (5.29) below.

Weight score of expert E_i = Score of PP of expert E_i + Score of ST of expert E_i + Score of EQ of expert E_i.

$$\text{Weight factor of expert } E_i = \frac{\text{Weight score of expert } \mathrm{E_i}}{(\sum_{\mathrm{i=1}}^{\mathrm{n}} \text{Weight score of expert } \mathrm{E_i})}$$

5.4.5.3 Aggregating stage

Considering that the experts may possess differing opinions depending on their levels of expertise in the relevant field, it becomes necessary to aggregate their opinions when conducting collaborative evaluations of complex engineering systems in order to reach a consensus (refer to Chapter Two of this study for a detailed review of the literature). According to Hsu and Chen (1996), the algorithm to aggregate the linguistic opinions of both homogeneous and heterogeneous groups of experts is given by the following systematic approaches:

Step 1: Evaluate the degree of agreement (degree of similarity) $S_{uv}(\breve{\delta}_u \breve{\delta}_v)$ of the opinions $\breve{\delta}_u$ and $\breve{\delta}_v$ of a pair of experts E_u and E_v where $S_{uv}(\breve{\delta}_u \breve{\delta}_v) \in (0,1)$. Therefore, $\tilde{X} = (a_1, a_2 a_3 a_4)$ and $\tilde{Y} = (b_1, b_2 b_3 b_4)$ are trapezoidal fuzzy numbers. The degree of similarity between these two fuzzy numbers can be evaluated by the similarity function S and can be represented below (Hsu and Chen, 1996):

$$S(\tilde{X}, \tilde{Y}) = 1 - \frac{1}{4}\sum_{i=1}^{4} \left| a_i - b_i \right| \tag{5.18}$$

where $S(\tilde{X}, \tilde{Y}) \in (0,1)$. The larger the value of $S(\tilde{X}, \tilde{Y})$, the greater the similarity between two fuzzy numbers of $\tilde{X}$ and $\tilde{Y}$ respectively.

Step 2: the degree of average agreement (AA) of expert E_u can be obtained as follows:

$$AA(E_u) = \frac{1}{N-1}\sum_{\substack{u \neq v \\ v=1}}^{N} S(\tilde{\delta}_u, \delta_v) \tag{5.19}$$

Step 3: the degree of relative agreement (RA) $RA(E_u)$ of the experts can be evaluated as follows:

$$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{N} AA(E_u)} \quad (5.20)$$

Step 4: the degree of consensus coefficient CC of experts $E_u (u = 1,2,\cdots,N)$ can be evaluated as follows:

$$CC(E_u) = \beta.w(E_u) + (1-\beta).RA(E_u) \quad (5.21)$$

where $\beta (0 \leq \beta \leq 1)$ is a relaxation factor of the proposed approach. It highlights the important of $w(E_u)$ over $RA(E_u)$. It is important to note that when $\beta = 0$ no importance has been given to the weight of experts, and thus a homogeneous group of experts is used. When $\beta = 1$, then the consensus degree of an expert is the same as its importance weight. The consensus coefficient degree of each expert is a good measure for evaluating the relative worthiness of judgement of all experts participating in the decision-making process. According to John *et al*., (2014), it is the responsibility of the decision maker to assign an appropriate value of β; hence, β is considered to be 0.75 in this study.

Step 5: The expert aggregation judgement $\tilde{R}_{AGG}$ can be obtained as follows:

$$\tilde{R}_{AGG} = CC(E_1) \times \tilde{R}_1 + CC(E_2) \times \tilde{R}_2 + \cdots + \cdots CC(E_M) \times \tilde{R}_N \quad (5.22)$$

where $\tilde{R}_i (i = 1,2,\cdots N)$ is the subjective rating of a given criterion with respect to alternative by expert $E_i (i = 1,2,...N)$.

5.4.5.4 Defuzzifying stage

Each alternative under each subjective attribute is aggregated at this stage. For the alternatives of the decision problem to be properly ranked, all aggregated fuzzy numbers must be defuzzified. Therefore, all the components of the decision matrix are crisp numbers and any classical method can be applied at the selection stage. For instance, each of the subjective factors of the matrix $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij})$ can be converted to its corresponding crisp value using Equation (5.23) as proposed by Sugeno (1999).

$$X^* = \frac{1}{3} \frac{(a_4 + a_3)^2 - a_4 a_3 - (a_1 + a_2)^2 + a_1 a_2}{a_4 + a_3 - a_1 - a_2} \tag{5.23}$$

5.4.6 Selection stage

At this selection stage, the classical MADM approach is used to determine the ranking order alternatives. Consider x possible alternatives $A_1, A_2, A_3, \cdots A_x$ from which y decision makers $D_y = (1, 2, 3, \cdots, y)$ have to choose the most desirable risk management technique (RMT) on the basis of n sets of attributes $AT_1, AT_2, AT_3 \cdots AT_n$. In order to make an appropriately informed decision, the following procedures are observed:

5.4.6.1 Construction of normalised fuzzy decision matrix

The corresponding suitable linguistic variables with respect to the criteria are selected at this stage. Assume the aggregation rate of alternatives $A_i (i = 1,2,3...n)$ for attributes $AT_j (j = 1,2,3, \cdots, n)$ is f_{ij}. Hence, TOPSIS can be expressed in matrix order as follows:

$$D = (f_{ij})_{y \times n} = A_1 \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} AT_1 & AT_2 & \cdots & AT_n \end{array} \\ \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{x1} & \tilde{f}_{x2} & \cdots & f_{xn} \end{bmatrix} \end{array} \tag{5.24}$$

5.4.6.2 Normalisation of fuzzy decision matrix

Given that n attributes can be evaluated in different ways, the decision matrix D has to be normalised. Different attributes' dimensions can be transformed into nondimensional attributes that allow comparison across the attributes. The normalised attributes can be obtained using:

$$R=(r_{ij})_{y\times n}=\begin{array}{c c} & \begin{array}{cccc} AT_1 & AT_2 & \cdots & AT_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_n \end{array} & \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & f_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{x1} & \widetilde{r}_{x2} & \cdots & r_{xn} \end{bmatrix} \end{array} \tag{5.25}$$

$$i=1,2,3\cdots,x;=1,2,3,\cdots,n$$

Assume the normalised fuzzy decision is represented by $\widetilde{R}=[r_{ij}]$

where,

$$\widetilde{r}_{ij}=\left(\frac{a_{ij}}{c_j^*},\frac{b_{ij}}{c_j^*},\frac{c_{ij}}{c_j^*}\right) \text{ and } c_j^*=\max_i\{c_{ij}\} \text{ for benefit criteria} \tag{5.26}$$

or

$$\widetilde{r}_{ij}=\left(\frac{a_j^-}{c_{ij}^*},\frac{b_j^-}{c_{ij}^*},\frac{c_j^-}{c_{ij}^*}\right) \text{ and } c_j^-=\min_i\{a_{ij}\} \text{ for cost criteria} \tag{5.27}$$

For linear vector normalisation, the ratings of each attribute or alternative are divided by its value in order to obtain each normalised rating given by $r_{i,j}$ applying Equation (5.28) below:

$$R_{i,j}=\frac{r_{i,j}}{\sqrt{\sum_{i=1}^{n} r_{i,j}^2}},i=1,2,\cdots m; j=1,2,\cdots n \tag{5.28}$$

5.4.6.3 Construction of the weighted normalised decision matrix

In order to construct the weighted normalised decision matrix, each element r_{ij} is multiplied by its associated weight w_i. Therefore,

$$v_{ij}=w_i\times r_{ij} \quad i=1,2,\cdots,x;\ j=1,2,\cdots,n \tag{5.29}$$

5.4.6.4 Computation of the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) can be determined by:

$$S^{+} = (\tilde{z}_1^{+}, \tilde{z}_2^{+}, \cdots, \tilde{z}_n^{+}) \tag{5.30}$$

where $\tilde{z}_j^{+} = \max_i \{z_{ij3}\}$;

$$S^{-} = (\tilde{z}_1^{-}, \tilde{z}_2^{-}, \cdots, \tilde{z}_n^{-}) \tag{5.31}$$

Where $\tilde{z}_j^{-} = \min_i \{z_{ij1}\}$.

Hence, j_1 and j_2 are associated with the sets of benefits and costs criteria respectively.

5.4.6.5 Computation of distance from each alternative to the FPIS and to the FNIS

The distance of each alternative A_1 from FPIS (d^{+}) and FNIS (d^{-}) can be evaluated using Equation (5.32) and (5.33) below:

Assuming $d_i^{+} = \sum_{j=1}^{n} d(\tilde{z}_{ij}, \tilde{z}_j^{+}),$ (5.32)

Or

$$d_i^{-} = \sum_{j=1}^{n} d(\tilde{z}_{ij}, z_j^{-}) \tag{5.33}$$

The above Equation represents the distance from each alternative A_i to the FPIS and FNIS respectively.

5.4.6.6 Computation of the relative closeness coefficient RCC_i for each alternative

For each alternative A_i, the relative closeness coefficient can be determined by applying Equation (2.79). This expression may be represented as:

$$RCC_i = \frac{d_i^{-}}{d_i^{-} + d_i^{+}} \quad i = 1, 2, 3, \cdots, n \tag{5.34}$$

5.4.6.7 Ranking of the alternatives

These alternatives are ranked according to their relative closeness coefficient, RCC_i, in decreasing order. The alternative with the highest relative closeness coefficient represents the best alternative, meaning that the best alternative is closest to the FPIS and farthest from the FNIS (Zimmermann and Zysno, 1985).

5.4.7 Perform sensitivity analysis of the results

A sensitivity analysis is performed in order to validate the overall output of the proposed methodology (see section 5.5) for modelling the problem. It is aimed at providing a degree of confidence in the modelling output results. Considering that the overall model output is dependent on the collective subjective judgements of the decision makers, sensitivity analysis is therefore performed on a set of scenarios that cut across various views on the relative importance of the attributes in order to test the robustness of the model output by monitoring the level of the changes observed.

The sensitivity analysis involves the following systematic steps:

Step 1: Increasing or decreasing the weight of any attribute will result in changes in the output; and the sum of the weights must be equal to 1.

Step 2: If the weights of the cost attributes (negative attributes) and benefit attributes (positive attributes) are assumed to be 0 and 1 respectively, then the result output must be dependent on a positive attribute.

Step 3: Different p values must result in different outcomes. $p=1$ and $p=\infty$ are the two extreme values considered. Hence, the outcome of ranking for $p=1$ and $p=\infty$ must be different. The ranking outcome will remain unchanged irrespective of the different membership values once a certain value of p is attained. According to steps 1 and 2, the weights of the attributes are changed and the expected output is evaluated. Step 3 considers the final ranking outcome by considering different p values.

5.5 A Test Case Illustrating Applicability of FAHP-FTOPSIS

The test case will demonstrate application of the proposed decision-making model in the selection of the most rational RMT (described in section 5.4.2) for OWFD. The objective, decision alternatives and evaluation criteria have been determined and described in detail in section 5.4.3. These have also been used to develop a working FTOPSIS model structure, as illustrated in Figure 5.4. The analytical computation process of this methodology relies on the decision makers' subjective evaluation of the attributes with respect to the potential RMT alternatives presented in Figure 5.5. The decision makers consist of experts of varying levels of responsibilities in the same industry with different thought processes and perceptions. Therefore, the robustness of the proposed model is tested on its ability to aggregate these opinions and judgements in order to produce a consolidated output result.

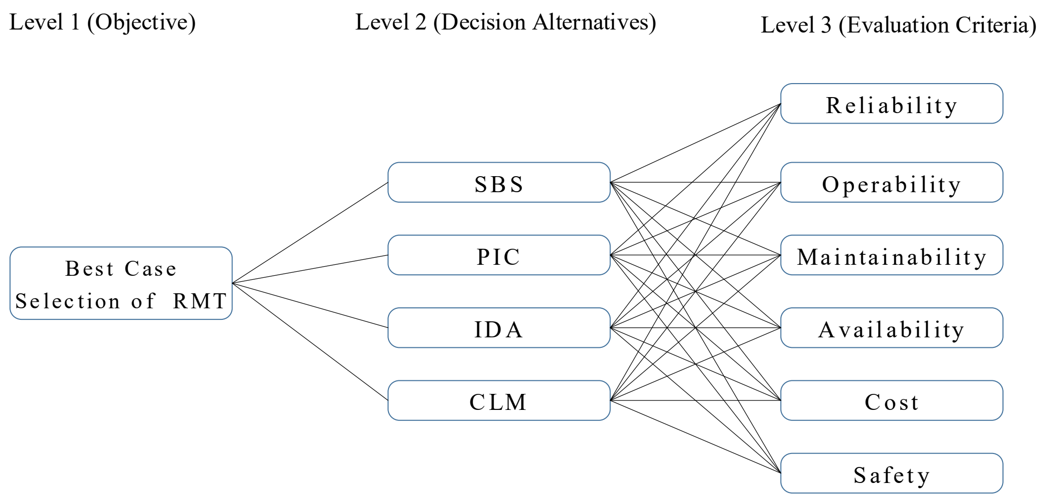


Figure 5.5 Decision Hierarchical structure for selection of the best RMT

5.5.1 Nomination of the decision-making team

The team members participating in the decision-making exercise are selected according to their relevant expertise in the subject area. The nominated experts are assigned a degree of importance dependent on practical position (PP), service time (ST) and educational qualification (EQ) (see Table 5.4). For the purpose of this study, the experts' degree of competency is considered equal.

5.5.2 Determine the decision-making alternatives

The decision-making alternatives are obtained from literature reviews of widely applied industry-established risk management techniques. Valuable information was also drawn from consultations with time-served industry experts in order to select the RMTs discussed in subsection 5.4.2 according to the industry best practice. These identified decision alternatives were narrowed down to key relevant alternatives as highlighted in subsection 5.4.3.

5.5.3 Determine the evaluation criteria

The evaluation criteria identified for this study are as follows: reliability, operability, maintainability, availability, cost and safety (see subsection 5.3 for details).

Table 5.6 Evaluation criteria properties of the case study

Attributes	Type of assessment	Category of attribute	Judgement
Reliability	Linguistic term	Benefit	Subjective
Operability	Linguistic term	Benefit	Subjective
Maintainability	Linguistic term	Benefit	Subjective
Availability	Linguistic term	Cost	Subjective
Cost and	Linguistic term	Cost	Subjective
Safety	Linguistic term	Benefit	Subjective

5.5.4 Structure the decision-making matrix using AHP

In line with the AHP procedure (see Chapter Two), the relative importance of the evaluation criteria will be determined using the fuzzy numbers of the linguistic terms. Note that the evaluation criteria in this case are categorised as subjective (as shown in Table 5.6) given that the evaluation is based on expert judgement under a fuzzy environment. Therefore, the subjective criteria are evaluated with respect to corresponding alternatives as presented in tables 5.7, 5.8 and 5.9 below.

Table 5.7 Linguistic assessment of the alternatives with respect to criteria completed by expert no.1

DM1				
EVALUATION CRITERIA	**SBS**	**PIC**	**IDA**	**CLM**
Reliability	VH	H	H	M
Operability	H	M	H	H
Maintainability	H	M	H	H
Availability	VH	M	M	M
Cost	H	L	M	VL
Safety	H	M	M	M

Table 5.8 Linguistic assessment of the alternatives with respect to criteria completed by expert no. 2

DM2				
EVALUATION CRITERIA	**SBS**	**PIC**	**IDA**	**CLM**
Reliability	VH	H	H	M
Operability	H	M	M	H
Maintainability	H	M	M	H
Availability	VH	H	H	L
Cost and	H	VL	M	M
Safety	H	H	H	M

Table 5.9 Linguistic assessment of the alternatives with respect to criteria completed by expert no. 3

No. 3 Expert				
EVALUATION CRITERIA	**SBS**	**PIC**	**IDA**	**CLM**
Reliability	H	VH	H	L
Operability	H	L	H	H
Maintainability	H	L	H	VH
Availability	H	H	H	L
Cost and	VH	H	L	VL
Safety	VH	H	H	L

For the purpose of this study, the weights of all evaluation criteria are considered to be of equal importance.

5.5.5 Assign the criteria weights of the decision-making team

The three experts selected to make the judgements with respect to the subjective attributes are expected to be of equal weights, as expressed in Table 5. 4.

5.5.6 Compute the scores of the alternatives with fuzzy TOPSIS

Four decision alternatives (DA) and six evaluation criteria (EC) are selected for the application of FTOPSIS, as shown in Table 5.10. These will be used in the construction of the fuzzy decision matrix.

Table 5.10 Decision alternatives and evaluation criteria

	Key	Description
Decision Alternatives	DA1	Structured brainstorming and evaluation (SBS)
	DA2	Probability-impact calculations (PIC)
	DA3	Informal direct assessment of risks (IDA)
	DA4	Checklists method (CLM)
Evaluation Criteria	EC1	Reliability
	EC2	Operability
	EC3	Maintainability
	EC4	Availability
	EC5	Cost
	EC6	Safety

The computation process at this stage includes the evaluation of the alternatives by pairwise comparisons using AHP. The resultant outcome is then to be used to construct the fuzzy decision matrix.

5.5.6.1 Aggregation of subjective criteria ratings with respect to alternatives

This is comprised of several calculations aggregating the criteria ratings with respect to alternatives. The decision-making process of the OWFD risk management technique involves complex strategies of collaborative multi-attribute group decision-making in a fuzzy environment. The linguistic terms and membership function (see Table 5.3 and Figure 5.3) are transformed into fuzzy numbers of alternatives with respect to corresponding criteria based on the judgement of the DMs and are represented in tables 5.11, 5.12 and 5.13. The DMs' judgements presented in tables 5.7, 5.8 and 5.9 form the bases of these transformations.

Table 5.11 Fuzzy numbers for alternatives with respect to criteria completed by DM1

DM1				
EC	**DA1**	**DA2**	**DA3**	**DA4**
EC1	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)
EC2	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
EC3	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)

EC4	(0.75, 1.00, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)
EC5	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)	(0.25, 0.50, 0.75)	(0.00, 0.00, 0.25)
EC6	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)

Table 5.12Fuzzy numbers for alternatives with respect to criteria completed by DM2

DM2				
EC	**DA1**	**DA2**	**DA3**	**DA4**
EC1	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)
EC2	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)
EC3	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)
EC4	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)
EC5	(0.50, 0.75, 1.00)	(0.00, 0.00, 0.25)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)
EC6	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)

Table 5.13Fuzzy numbers for alternatives with respect to criteria completed by DM3

DM3				
EC	**DA1**	**DA2**	**DA3**	**DA4**
EC1	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)
EC2	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
EC3	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)
EC4	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)
EC5	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)	(0.00, 0.00, 0.25)
EC6	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)

Table 5.14 Aggregation computation for reliability with respect to SBS

Decision Maker (DM)	**Linguistic Assessment**	**FNs for alternatives**
DM1	VH	(0.75, 1.00, 1.00)
DM2	VH	(0.75, 1.00, 1.00)
DM3	H	(0.50, 0.75, 1.00)
S(DM1 & 2)	$1-\frac{(0.75-0.75)+(1-1)+(1-1)}{3}=1$	
S(DM1 & 3)	$1-\frac{(0.75-0.5)+(1-0.75)+(1-1)}{4}=0.833$	
S(DM2 & 3)	$1-\frac{(0.75-0.5)+(1-0.75)+(1-1)}{4}=0.833$	
AA(DM1)	$\frac{1+0.833}{2}=0.917$	

AA(DM2)	$\frac{1+0.833}{2}=0.917$
AA(DM3)	$\frac{0.833+0.833}{2}=0.833$
RA(DM1)	$\frac{0.917}{0.917+0.917+0.833}=0.344$
RA(DM2)	$\frac{0.917}{0.917+0.917+0.833}=0.344$
RA(DM3)	$\frac{0.833}{0.917+0.917+0.833}=0.312$
AGGREGATED RESULT $(\widetilde{R}_{AGG})$	$\widetilde{R}_{AGG}=0.344(0.75,1,1)+0.344(0.75,1,1)+0.312(0.5,0.75,1)$ $\widetilde{R}_{AGG}=(0.672,\ 0.922,\ 1.000)$

The 'VH', 'VH' and 'H' shown in Table 5.14 reflect DM1's linguistic assessment of the alternatives with respect to criteria as presented in Table 5.7. The FNs in Table 5.14 also reflect the transformed values of the fuzzy numbers for alternatives with respect to criteria completed by DM1 as presented in Table 5.11 by application of the TFN shown in Table 5.3. Recall that the DMs' weights are considered equal (see Table 5.4); therefore, the consensus coefficient (CC) of degree is of no relevance to this study.

5.5.6.2 Constructing the decision matrix of the FTOPSIS

The aggregation computation for reliability with respect to SBS presented in Table 5.14 incorporates the opinions of DM1, DM2 and DM3 as an example. The remaining calculation of the aggregated results for the rest of the evaluation criteria with respect to the decision alternatives can be found in Appendix 4. The results of the aggregated computations of the DMs are obtained to form the fuzzy decision matrix tables shown in tables 5.15a and 5.15b.

Table 5.15a Decision matrix

DA	EC1	EC2	EC3
AT1	(0.672, 0.922, 1.000)	(0.500, 0.749, 0.999)	(0.500, 0.749, 0.999)
AT2	(0.588, 0.838, 1.000)	(0.497, 0.747, 0.913)	(0.175, 0.425, 0.675)
AT3	(0.500, 0.749, 0.999)	(0.417, 0.667, 0.917)	(0.417, 0.667, 0.917)
AT4	(0.175, 0.425, 0.675)	(0.500, 0.749, 0.999)	(0.590, 0.840, 1.0000)

Table 5.16b Decision matrix

DA	EC4	EC5	EC6
DA1	(0.672, 0.922, 1.000)	(0.590, 0.840, 1.0000)	(0.590, 0.840, 1.000)
DA2	(0.410, 0.660, 0.910)	(0.196, 0.364, 0.614)	(0.410, 0.660, 0.910)
DA3	(0.410, 0.660, 0.910)	(0.175, 0.425, 0.675)	(0.410, 0.660, 0.910)
DA4	(0.075, 0.325, 0.575)	(0.083, 0.167, 0.417)	(0.175, 0.425, 0.675)

5.5.6.3 Defuzzification (transformation of attributes into crisp values)

The values of results obtained from tables 5.15a and5.15b are transformed into crisp numbers using Equation 5.23. The fuzzy numbers transformed into crisp values are presented in Table 5.16.

Table 5.17 Fuzzy TOPSIS Decision matrix

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	0.865	0.749	0.749	0.810	0.810	0.810
DA2	0.809	0.719	0.425	0.660	0.391	0.660
DA3	0.749	0.667	0.667	0.660	0.425	0.660
DA4	0.425	0.749	0.810	0.325	0.222	0.425

5.5.6.4 Normalisation of the fuzzy decision matrix

In order to construct the normalised fuzzy decision matrix, the fuzzy TOPSIS decision matrix shown in Table 5.16 is normalised by applying Equation (5.28).

$$\frac{0.865}{[(0.865^2+0.809^2+0.749^2+0.425^2)]^{\frac{1}{2}}}=0.591$$

The above solution illustrates the normalisation of EC1 with respect to DA1. This calculation is similarly repeated for the rest of the evaluation criteria with respect to the decision alternatives and the results are presented in Table 5.17 below.

Table 5.18 Normalisation of the Decision Matrix

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	0.591	0.519	0.552	0.634	0.795	0.620
DA2	0.552	0.498	0.313	0.516	0.384	0.505
DA3	0.512	0.443	0.491	0.516	0.417	0.505
DA4	0.290	0.519	0.597	0.254	0.218	0.325

5.5.6.5 Determine the weighted normalised fuzzy decision matrix

Weighted normalised fuzzy decision matrix can be determined based on Equation (5.29).This is achieved through the multiplication of each element r_{ij} (presented in Table 5.17) by its associated weight w_i, as follows:

$$\tilde{v}_{ij} = w_i \times r_{ij} \qquad i = 1, 2, \cdots, x; \; j = 1, 2, \cdots, n$$

$$\tilde{v}_{ij} = normalised\ weight \times weight\ of\ the\ criteria$$

where weight of criteria is $= \dfrac{100}{6} \times 100 = 0.167$ (6 is the no. of criteria)

$$\tilde{v}_{1,1} = 0.591 \times 0.167 = 0.099$$

The above calculation is similarly replicated for the rest of the decision alternatives as presented in Table 5.18.

Table 5.19 Weighted Normalised Decision Matrix

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	0.098	0.086	0.092	0.106	0.132	0.103
DA2	0.092	0.083	0.052	0.086	0.064	0.084
DA3	0.085	0.074	0.082	0.086	0.069	0.084
DA4	0.048	0.086	0.099	0.042	0.036	0.054

5.5.6.6 Determination of the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)

Based on application of Equations (5.30) and (5.31), FPIS and FNIS can be determined as follows:

$$S^{+} = [(1), (1), (1), (1)]$$

$$S^{-} = [(0), (0), (0), (0)]$$

5.5.6.7 Computation of distance from each alternative to the FPIS and to the FNIS

The largest value of the element of each benefit criterion and the smallest value of the element of each cost criterion are selected from Table 5.18 for the FPIS whereas the reverse is the case with FNIS, as presented in Table 5.19. These values are then used to compute the distance of each alternative to FPIS and FNIS by applying Equations (5.32) and (5.33) as demonstrated below.

Table 5.20 Representation of FPIS and FNIS values

Evaluation Criteria	Category	Key	FPIS	FNIS
Reliability	Benefit	**EC1**	0.098	0.048
Operability	Benefit	**EC2**	0.086	0.074
Maintainability	Benefit	**EC3**	0.099	0.052
Availability	Cost	**EC4**	0.042	0.106
Cost	Cost	**EC5**	0.036	0.132
Safety	Benefit	**EC6**	0.103	0.054

The distances of DA1 to S^{+} and DA1 to S^{-} are given by:

$$D^{+} = [(0.098-0.098)^2 + (0.086-0.086)^2 + (0.099-0.092)^2 + (0.042-0.106)^2 + (0.036-0.132)^2 + (0.103-0.103)^2]^{\frac{1}{2}} = 0.116$$

$$D^{-} = [(0.048-0.098)^2 + (0.074-0.086)^2 + (0.052-0.092)^2 + (0.106-0.106)^2 + (0.132-0.132)^2 + (0.054-0.103)^2]^{\frac{1}{2}} = 0.082$$

In a similar manner, the above computations are replicated in order to obtain the rest of the values of distance from each alternative to FPIS and FNIS and the results are presented in Table 5.20 below.

Table 5.21 Distance between each alternative to FPIS and FNIS

FPIS/FNIS	AT1	AT2	AT3	AT4
D^{+}	0.116	0.073	0.063	0.070
D^{-}	0.082	0.089	0.087	0.125

5.5.6.8 Computation of the relative closeness coefficient RCC_i for each alternative

The relative closeness coefficient can be determined by applying Equation (5.34) to the results presented in Table 5.20. As an example, the relative closeness coefficient for decision alternative 1 (DA1) is calculated as follows:

$$RCC_i = \frac{d_i^-}{d_i^- + d_i^+}$$

$d_1^+ = 0.116$, $d_1^- = 0.082$

$$RCC_1 = \frac{0.082}{0.116 + 0.082} = 0.414$$

The above calculation is similarly replicated for the rest of the decision alternatives and the results are presented in Table 5.21.

Table 5.22 Relative closeness coefficient for each alternative and ranking

Decision Alternative	RCC	Ranking
DA1	0.414	4
DA2	0.550	3
DA3	0.579	2
DA4	0.641	1

Table 5.23 Summary of the FTOPSIS analysis results

Key	Decision alternatives	d^+	d^-	RCC	Ranking
DA1	Structured brainstorming and evaluation	0.178	0.101	0.414	4
DA2	Probability-Impact calculations	0.095	0.134	0.550	3
DA3	Informal direct assessment of risks	0.087	0.128	0.579	2
DA4	Checklists method	0.088	0.187	0.641	1

5.5.6.9 Ranking preference

The ranking preference order as reflected in Table 5.21 and Table 5.22 indicates that DA4>DA3>DA2>DA1. This is obtained by comparing the RCC of the values of the DAs shown in tables 5.21 and 5.22; see also a comparison chart of the RCC in Figure

5.6 below. According to the outcome of this analysis, DA4 and DA3 with relative closeness coefficient values of 0.641 and 0.579 respectively appear to be the most proffered RMT for the offshore wind farm development under varying constraints. The decision makers may have considered various variables such as time, cost, benefit, alternative, suitability, staff experience, availability, adaptability, sustainability and ability to implement the preferred RMT whilst deciding on the preferred option. The robustness of this selection model will be tested and validated in the sensitivity performance study.

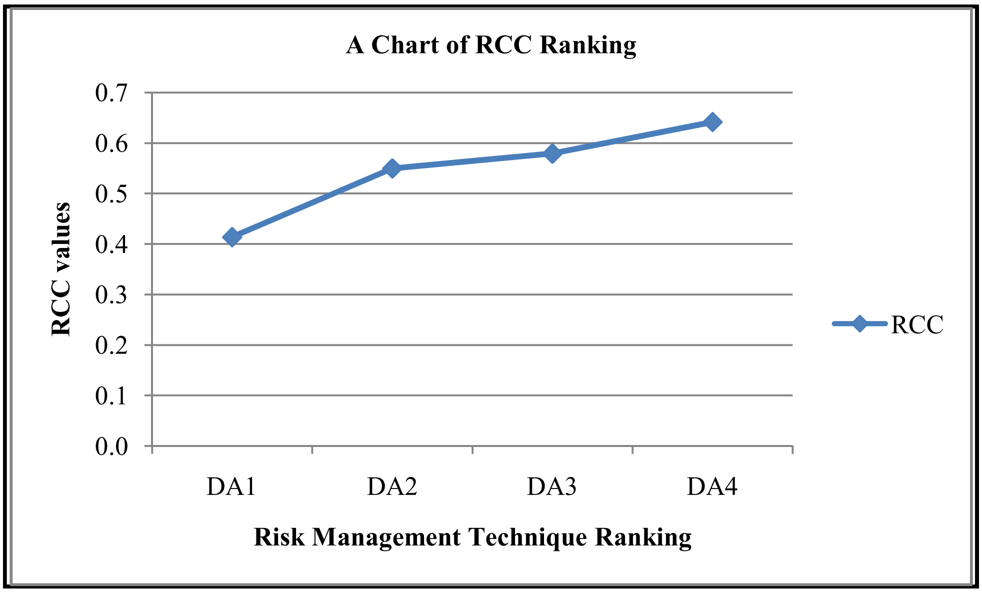


Figure 5.6 Ranking order of risk management technique

5.6 Result analysis

The sensitivity study is conducted in order to validate the effectiveness and robustness of the proposed model for the selection of the best-case RMT. This involves the increment and decrement of input values (see Table 5.16) by certain percentages such as 10%, 20% and/or 30%, for instance, whilst monitoring the behavioural responses to the changes. The variations are expected to have an impact on the output results and the final ranking of the decision attributes (Roy, 2005). However, for ease of computation the sensitivity of the decision alternatives in this case will be analysed by increasing the evaluation criteria values of the 'benefit' category by 20% and decreasing the values of the evaluation criteria of the 'cost' category by 20% (Table 5.16).

The two rules applied in this sensitivity analysis are: (1) the performance of the analysis by investigating the values and ranking of the alternatives due to weight variations. The weights of all the attributes are considered to be of equal importance; and (2) the weights of positive attributes equal to 1 and the weights of negative attributes equal 0. The alternatives with higher values will indicate preferred ranking order (see Table 5.27).

Table 5.23 indicates that the values of the evaluation criteria (EC) of the benefit element increased by 20% and the cost element decreased by 20% resulting from the corresponding changes in weights of the alternatives observed.

Table 5.24 FTOPSIS Decision Matrix of EC 'benefit' element increased by 20% and 'cost' element decreased by 20%

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	1.038	0.899	0.899	0.648	0.648	0.972
DA2	0.970	0.863	0.510	0.528	0.313	0.792
DA3	0.899	0.800	0.800	0.528	0.340	0.792
DA4	0.510	0.899	0.972	0.260	0.178	0.510

Table 5.25 Normalisation of the Decision Matrix upon variation of EC 'benefit' and 'cost' categories' input values

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	0.591	0.519	0.552	0.634	0.795	0.620
DA2	0.552	0.498	0.313	0.516	0.384	0.505
DA3	0.512	0.462	0.491	0.516	0.417	0.505
DA4	0.290	0.519	0.597	0.254	0.218	0.325

Table 5.26 Weighted Normalised Decision Matrix upon variation of input EC 'benefit' and 'cost' categories' values

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	0.098	0.086	0.092	0.106	0.132	0.103
DA2	0.092	0.083	0.052	0.086	0.064	0.084
DA3	0.085	0.077	0.082	0.086	0.069	0.084
DA4	0.048	0.086	0.099	0.042	0.036	0.054

Obtain the distance of each alternative to the FPIS and FNIS by following the steps below:

Table 5.27 Representation of FPIS and FNIS values

Evaluation criteria	Category	Key	PIS	NIS
Reliability	Benefit	**EC1**	0.098	0.048
Operability	Benefit	**EC2**	0.086	0.077
Maintainability	Benefit	**EC3**	0.099	0.052
Availability	Cost	**EC4**	0.106	0.042
Cost	Cost	**EC5**	0.132	0.036
Safety	Benefit	**EC6**	0.103	0.054

$$D^{-} = [(0.048-0.098)^2 + (0.077-0.086)^2 + (0.052-0.092)^2 + (0.042-0.106)^2 + (0.036-0.132)^2 + (0.054-0.103)^2]^{\frac{1}{2}}$$

$$D^{+} = [(0.098-0.098)^2 + (0.086-0.086)^2 + (0.099-0.092)^2 + (0.106-0.106)^2 + (0.132-0.132)^2 + (0.103-0.103)^2]^{\frac{1}{2}}$$

Table 5.28 Distance between each alternative to FPIS and FNIS

PIS/NIS	DA1	DA2	DA3	DA4
D^{+}	0.007	0.087	0.073	0.135
D^{-}	0.141	0.075	0.079	0.047

In order to obtain the relative closeness coefficient and ranking of alternatives, apply:

$d_1^{+} = 0.007,\ d_1^{-} = 0.141$

$$RCC_1 = \frac{0.141}{0.007 + 0.141} = 0.953$$

Table 5.29 Relative closeness coefficient for each alternative and ranking

Alternative	RCC	Ranking
DA1	0.953	1
DA2	0.461	3
DA3	0.520	2
DA4	0.258	4

As can be seen in Table 5.28 above, the ranking with the highest value has changed from DA4 to DA1 upon the performance of the sensitivity analysis process. It would appear the two extreme cases (uppermost and lowest result cases) of the ranking preference order are completely swapped, resulting in DA1>DA3>DA2>DA4. The reasons for these changes following the variations of the input values are elaborated in the discussion and conclusion.

5.7 Discussion and Conclusion

The selection of DA4 as the preferred RMT in this study seems reasonably practical in the circumstances considered by the DMs as explained under subsections 5.4.2 and 5.5.6.9. According to subsection 5.4.2, DA1 would appear to be the most preferred option for any project but appears to be most expensive of all the RMTs considered. DA4 appears to be the second most suitable option for any sizeable OWFD project based on the literature review and the expert opinions collated. However, the final ranking based on the DMs' judgements showed that DA4 is the preferred option having considered various constraints highlighted in subsection 5.6.6.9. Moreover, the variations of the input values of 'benefit' category and 'cost' category elements of the evaluation criteria by 20% (sensitivity analysis) respectively validate the fact that the emergence of DA4 as the preferred option will have been cost driven (demonstrated in section 5.6) . This is to say that, although the most suitable RMT for OWFD projects may seem to be DA1, the DMs have made their decision based on costs amongst other variables. Such decisions are generally acceptable in most commercial-scale projects, providing health, safety and environmental integrity are demonstrably uncompromised.

Based on the results obtained, DA4 may be suitable in cases where investment is limited by resources. With absolute carefulness and close monitoring of some of the shortfalls highlighted in section 5.6, this preferred option will still be reasonably practical without problems. However, in cases where the resources and know-how are available, DA1 will be the most ideal preferred solution assuming cost is not a limiting factor. According to Cooper *et al.,* (2014), DA1 (Structured brainstorming and evaluation) is a proven RMT for identifying risks and obtaining a clear understanding of their relative significance. This relies broadly on a carefully planned and executed workshop process usually internally prepared by the organisation to suit its operations. It systematically covers all known and perceived risks associated with a project and delivers a cost-effective output whilst making good use of the scarce resources (Cooper *et al.,* 2014). Although the initial investment cost may be relatively higher, it is known to save cost; therefore, it is considered the most cost effective in the long run.

Probabilistic modelling may be applied to complement the brainstorming technique by incorporating all identified risks to ensure that the significant influences potentially impacting on the project's cost and schedule are realistically taken into account when evaluating the overall project key performance indicators (KPIs). This will equally provide a reasonably practical basis for setting targets and agreeing contingencies.

This decision-making process for the selection of the best RMT is crucial in the handling of the associated risk factors of OWFD. In practice, the MCDM modelling of multi-alternative evaluations of alternatives (MAEA) is determined under a fuzzy environment. The proposed FAHP-FTOPSIS model and solution outcomes have both a practical and a scientific interest in the industry. This study is expected to add great value to the industry given the little or no attention currently being invested in this area of studies. It provides an insight to encourage further exploration of related and specific subject matters of interest in this relatively new industry.

This chapter has presented an effective fuzzy MCDM method that is suitable for solving multiple-attribute group decision-making (MAGDM) cases under a fuzzy environment, in which the available information is subjective, incomplete and imprecise. The proposed approach allows a group of decision makers to collaborate and aggregate their subjective opinions. Application of the basic FTOPSIS analytical approach is such that the chosen alternative has the farthest distance from the FNIS and shortest distance from the FPIS. However, the selected alternative may not often be the closest to the ideal solution. Therefore, the proposed model in this chapter, known as the FAHP-FTOPSIS, is applied to balance the shortest distance from the PIS and the farthest distance from the NIS. This is applicable as an alternative tool for cases where both the quantitative and qualitative data are to be synthesised in a complex multiple decision-making scenario.

CHAPTER SIX: INTEGRATION OF DEVELOPED MODELS

Summary

This chapter highlights the integration of the developed models and the logical relationships of the chapters of the thesis into a functional framework. It also discusses the significance of the integrated models as a generic proposal for efficient development of offshore wind farm under high uncertainties.

6.1 Introduction

This research involves a holistic review of energy generation through the wind resources; including the identification of risk variables associated with the development of offshore wind farms. The data gathering involved existing reliable industry based record of reported incidents and accidents including the direct industry expert opinions. Although this study recognises that the existing records of the accidents and incidents in the construction and operations of offshore wind farms are by no means exhaustive, they are still of great concern in the development of the OWF. Therefore, it has become pertinent to understand the extent of the challenges and how they can be methodically evaluated and effectively managed.

The identified potential risk parameters associated with the OWFD are categorised and are arranged into main criteria, sub-criteria and sub sub-criteria of a hierarchical structure. The hierarchical structure highlights the dependency interactions among the variables in order to determine their overall impact on the target node. It also facilitates the analysis of the risk variables by enabling transparent evaluations of each of the parameters under uncertainty.

Considering the magnitude of the risks involved in the development of the offshore wind farm, various decision-making tools have been applied. These include Analytical Hierarchy Process (AHP) in order to determine the weights of the risk variables identified (Kahraman *et al*., 1998). Evidential Reasoning (ER) and Fuzzy Rule Based (FRB) were employed to evaluate the risk relevance of those variables (Yang and Singh, 1994). A Bayesian Network (BN) risk modelling approach was also applied to determine the risk dependencies of the variables and their probability of occurrences over one another (Wang and Trbojevic, 2007). Finally, the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) was employed for the decision-making of the selection of suitable Risk Management Technology (RMT). This section reveals the logical methodologies applied in this study and how they are integrated (Liaoand Kao, 2011).

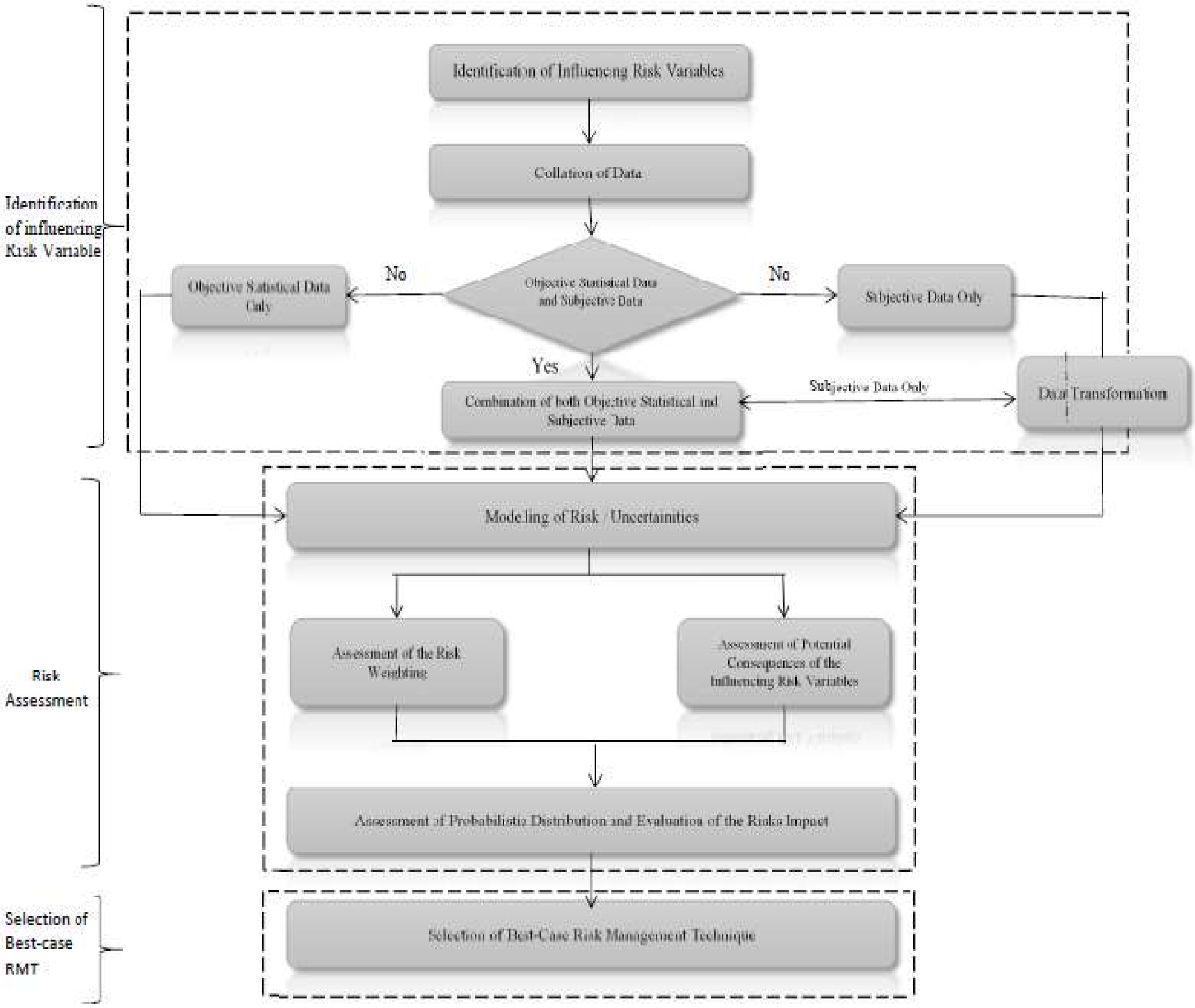


Figure 6.1 A Novel Risk-Based Verification Framework for OWFD

A holistic comprehension of the propensity of the risks and vulnerabilities associated with the development of wind energy generations and operations is essential in order to implement the necessary risk models developed in Chapters Three, Four and Five of this thesis that are aimed at bolstering the design, installation, operations and maintenance of offshore wind farms based on the proposed generic risk-based framework. Thus, this requires the integration of both the quantitative and qualitative data collated through the literature review and case studies. The data are then transformed into the format usable for risk evaluation and decision-making purposes.

6.2 Chapter One: Thesis Introduction

Detailed the processes of the work completed during the research, the rationale of the study, aims & objects, investigations, analysis and outcome of the study are reflected in this chapter. This section also introduces the research background, research hypothesis, problem statement of the research, methodology, scope of research and thesis structure.

6.3 Chapter Two: Robust Literature Review

Literature review including the trend of wind energy development, current status, types of installation sites of wind turbine generators, record of accidents & incidents, detailed review of the methodologies including risk analysis and decision making analysis approaches are also discussed. It also touched base on the contemporary types of WTGs, components of the turbines and its operating principles ((Islam, *et al.,* 2013).

6.4 Chapter Three: Application of ER and AHP

This chapter encompasses the compilation of various risk levels of the wind farm development following a robust literature review and brainstorming sessions of industry experts. The academic qualifications, specialty and industry experience of the participating experts varied to cover wide range of opinions. This list of risk variables was used to construct a generic hierarchical risk modelling structure. This generic risk modelling structure was subsequently narrowed down to a more specific risk model used for the risk evaluations and validation of the proposed methodology.

The Evidential Reasoning (ER) risk modelling approach was applied to demonstrate a structured method that decision makers can employ to handle the multi-attribute decision-making (MADM) cases under uncertainties by establishing the relevance of the risk variables in the hierarchical structure. Analytical Hierarchy Process (AHP) was used to calculate the weights of the risk variables. Relative pairwise comparisons of the risk variables of the OWFD hierarchical structure are performed in order to determine these risk weightings. ER through the application of FRB and linguistic variables was used to assess the relevance of the risk variables in the hierarchical structure and the potential overall impact on the system. The ER algorithm was applied in order to aggregate the individual risk factors and generating an overall risk assessment at any level in the risk hierarchy (Yang, 2021). Moreover, the results obtained from the aggregation process are presented in distributed formats. However, they can also be easily consolidated into percentages of the project risk attributes by summing up the multiplications of the assessment grades and the associated belief degrees. Although the developed analytical model known as *AHiP-Evi* is robust, flexible and practical, it has limitations in dealing with the dependencies of the risk criteria. Therefore, it was pertinent to develop fuzzy analytical modelling tool to compensate for such drawback.

6.5 Chapter Four: Application of Bayesian Network

This session validated the test case of the risk evaluation from the previous chapter by using the Bayesian networks to determine the influence of each risk variable on the other, and the probability of occurrences of one over the other. The process entails identification of the relevant risk factors via a specific risk-based hierarchy model, which was evaluated, prioritised and ranked in accordance with the dependency nature of the highlighted variables (Nadkarni and Shenoy, 2001). Sensitivity analysis was applied in order to provide the decision maker with a more in-depth knowledge of how responsive the selected optimum solution will be to any changes in the input values of one or more parameters under uncertainties. The sensitivity analysis also provides indication of the relative impacts of the various risk variables on the final outcome of the decision node.

The result output obtained from the analytical modelling system in Chapter Three was adapted as the input data for Chapter Four using the Bayesian Network modelling. In order to validate the efficiency of the application of the *BN-SAT* model, a comparison is drawn with the results obtained previously in Chapter Three. The outcomes of both analyses show an insignificant difference that can be measured by applying Equation (4.19). Hence, both analytical approaches have proven to be robust in the evaluation of risks associated with OWFD. Furthermore, the application of this fuzzy Bayesian modelling tool known as *BN-SAT* demonstrated a solution to shortfalls of the *AHiP-Evi* modelling tool previously developed in Chapter Three in respect of providing a high degree of confidence in dealing with the dependencies of the risk criteria.

6.6 Chapter Five: Application of FTOPSIS

This chapter applied the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) model for the selection of the most suitable risk management techniques to effectively manage these risk variables determined and validated in chapters Three and Four. A Fuzzy Analytic Hierarchy Process (FAHP) was first adopted in order to obtain the weight of each criterion and sub-criterion where applicable. Likewise, a fuzzy TOPSIS approach was also adopted specifically to rank the importance of the risk management alternatives with respect to costs and benefits under a fuzzy environment (Boran *et al.,* 2009). The implementation of the case study using a combination of FAHP and FTOPSIS illustrates the robustness and effectiveness of the proposed model aimed at optimising the performance of the critical components of the framework for OWFD.

A list of Risk Management Techniques (RMT) was drawn up through robust literature review and brainstorming sessions of the industry experts. These RMT were assessed with respect to the identified evaluation criteria in order to determine the most suitable technique for the management of the relevant risks associated with the OWFD. This decision making process successfully presented an effective fuzzy MCDM method that is suitable for solving multiple-attribute group decision-making (MAGDM) cases under a fuzzy environment, in which the available information is subjective, incomplete and imprecise. The proposed decision-making approach also accommodates group decision making through collaborative aggregation of subjective opinions.

6.7 Chapter Six: Model Integration

This entails the integration of the all sections of the thesis, which summarises the outcomes of each section and the how they logically connect with one another. The recorded accidents and incidents in the wind energy industry are considered failures in the recognition and effective management of those risk factors. Therefore, it is crucial to identify the risk variables relevant to the development of OWF and represent them in a hierarchical structure to aid the decision-making process, especially when there are many criteria to be considered. This hierarchical structure formed the basis for the system modelling and each of the risk attributes is considered to be complimentary in contributing to the target goal. A combination of the developed analytical models employed to formulate the proposed generic framework shown in figure 6.1 can be utilised by decision-makers to arrive at robust decisions on risk evaluations and risk management investment strategies for OWFD.

6.8 Discussion

This section demonstrates that the risk modelling tools developed in this study as detailed in Chapters Three, Four, and Five through the application of various decision-making tools such as AHP, ER, BN and FTOPSIS can be integrated to develop a generic framework for an efficient risk-based verification approach to design, installation, operations and maintenance of offshore wind farm development. These models are generic and as such have practical applications in dealing with the risk challenges at the various phases of the OWF development; they form the basis of effective and improved sustainable decision-making processes. Moreover, the robustness of these models lends flexibility to potential application to other works of life and industries.

A sensitivity analysis is carried out in each of the modelling evaluation in order to determine the response of the reaction of the changes in the input variables of the system model. Various types of sensitivity analysis with various boundary conditions were performed in each chapter in order to evaluate the robustness of the models under high uncertainties. Further details of sensitivity analysis can be found in each section.

6.9 Conclusion

This chapter has demonstrated a logical integration of the chapters in this study. This is evident in the coherently developed Risk-Based Verification (RBV) framework shown in Figure 6.1 that can be applied as basis for an advanced risk evaluation and effective risk management in such rapidly growing industry as offshore renewable energy. As can be seen, the risk assessment and risk management approaches employed in this research touches on the broad aspects of design risks, engineering risks, financial risks and organisational risks bordering largely on all key stages of wind energy development. They also provide insights to various perspectives in respect of risks associated with OWFD, and highlight how both qualitative and quantitative information can be utilised in a transparent and consistent manner, especially in situations where data is lacking, so that uncertainties can be revealed and addressed logically.

According to Ramezani and Memariani (2011), the application of fuzzy technologies is beneficial in amassing the wealth of knowledge of the experts through the judgements or brainstorming sessions. This method of data collation was particularly useful due to lack of data availability. The applications of the analytical modelling tools are considered more robust in dealing with risk evaluations in dynamic environment than most of the traditional methods of risk assessments, which end up producing poor outcomes. The models are flexible to use and can accommodate emerging information as and when they become available. They are also able to demonstrate the interdependencies of the variables as can be seen in Figure 6.1.

CHAPTER SEVEN: RECOMMENDATIONS AND CONCLUSIONS

Summary

This chapter summarises the main conclusions from the research programme, which highlight the contributions that have been made to the academic research area as well as the industry knowledge gap in the design, construction, operations and maintenance of offshore wind farm development.

7.1 Main Conclusions

The main area of this research is the formulation of an effective risk-based framework for the development of offshore wind farms. This involved the identification, control and evaluation of a best-case risk management technique for the system's solution. The combined systematic approaches employed in this research involved the application of probabilistic data in combination with objective and subjective data under a high uncertainty environment. The data obtained in qualitative formats was transformed into quantitative inputs in order to aid decision-making using the analytical modelling tools developed in this research.

The main aim of this research was to produce a risk-based framework for evaluating the risks associated with OWFD with the view of eliminating the unnecessary costs, and high rates of accidents, incidents and fatalities currently being recorded. This was achieved through the development of specific analytical models and the application of such decision-making tools as Fuzzy Set Theory (FST), Fuzzy Analytic Hierarchy Process (FAHP), Evidential Reasoning (ER), Bayesian Networks (BNs) and Technique for Order of Preference by Similar to Ideal Solution (TOPSIS).

The analytical models developed in this research are robust to deal with high uncertainties in the offshore renewable energy sector. The research does not only provide an academic research solution to unavailability of qualified data in this field of study; it also provides practical solutions to the industry-based challenges currently being faced in the vast majority of offshore wind farm developments in the UK and across the globe.

This research has successfully achieved its objectives as set out in Chapter One as follows:

- Undertake a literature review of the risks associated with offshore wind farm turbines (OWFTs): An extensive literature review of the subject matter has been completed in Chapter Two of this thesis. This covers the trend development of wind energy and the progressive innovations in the wind turbine design, installation, operations and maintenance. A review of the wind turbine generator structures including the critical components was also carried out. The EU commitment to OWDF development, the challenges facing OWDF and a review of the historical data of accidents and near-misses in the wind energy development were also presented. A thorough review was undertaken of the decision-making methodologies applied, which includes AHP, ER, FTOPSIS and BN.
- Estimate the inherent risk factors of wind farm design, pre-construction, construction and operational phases: A list of perceived risks associated with the development of OWF was compiled through a literature review and the brainstorming exercise involving several experts as presented in Chapter Three.
- Develop a risk assessment model for the residual risk factors and a decision-making tool: This list of risk factors was used to develop a generic risk model for OWFD. A more specific risk model was developed and the risk factors were evaluated using FAHP and ER in Chapter Three. Based on the outcome of the evaluation, the most significant risk factors were selected for estimation of their probability of occurrence using BN as contained Chapter Four.
- Develop an innovative risk-based management tool aimed at improving the design, inspection and maintenance of OWFT foundations: Various risk management techniques were considered for OWFD. FTOPSIS methodology was employed to determine the most suitable RMT for the system.

- Create a commercial-scale mechanism for managing the risk levels: A robust model known as *AHiP-Evi* was successfully developed in Chapter Three for estimation of risk weighting associated with OFWD. Another model known as *BN-SAT* was also developed in Chapter Four for computing the probability of occurrence of those risks associated with OWFD. A special modelling tool was also applied in Chapter Five by applying specific evaluation criteria in order to determine the most suitable risk management technique for the OWFD.

7.2 Research Contribution

The research contributions to knowledge include but are not limited to:

- The risk-based framework for evaluation of risks associated with OWFD as detailed in Chapter Six of this thesis.
- The proposed models for risk-based verification framework for an offshore wind farm, which include the *AHiP-Evi* throught the applications of fuzzy analytical hierarchy process and evidential reasoning modelling techniques; the *BN-SAT* through the application of Bayesian Network structure adapted for estimation of the probability of occurrence of the risk variables with significant relative weights; the application of fuzzy technique for order of preference by similarity to ideal solutions approach employed for evaluation for selection of the best RMT for OWFD.
- The extensive literature review and the commercial-scale mechanism for managing the risk levels in the development of OWF provides for a huge knowledge gap to both the industry and academic sector. There is currently little or no efforts being made in terms of advanced risk assessment and risk management approach that holistically overviews the development from inception of design stage through engineering, construction, operations and maintenance through to decommissioning of the wind farms. Although risk evaluation modelling approaches similar to the proposed models developed in this research have been applied in various industries, they are currently non-existent in the offshore renewable sector.

This research work has identified the critical influential risk factors pertinent to the development of offshore wind farms. Obviously, the identification of these risk-based industry challenges in the design, construction, operations and maintenance forms the basis of determining solutions to these problems. The main aim of this research is born out of the drive to proffer solutions to these identified challenges of wind farm development. This has been achieved through the deployment of a risk-based framework that employed a number of analytical approaches for the evaluation of both quantitative and qualitative data. The framework models include both generic and specific methods in order to allow for sustained decision-making processes of all potential risk factors associated with the system. The benefits of the solutions provided within this research work include but are not limited to increase in return on investment by way of minimisation of the direct and indirect costs associated with wind energy development, and optimisation of wind turbines' reliability and availability.

Considering that the offshore renewable industry is still a relatively new focus for green energy production, there is a huge knowledge gap in both the theoretical and practical aspects of the industry. The lack of specific risk evaluation literature on the uncertainties in the wind energy and offshore wind farm development highlights the significance of the subject area. Therefore, this study will not only help improve the return on investments of offshore wind farms but will also plug the academic knowledge gap as well as provide an effective practical approach to tackle the risk assessment problems currently facing the industry.

7.3 Limitations of the Research

Due to time constraints and unavailability of data for the research, this study has not investigated any specific projects' risk evaluation. However, industry experience revealed substantial design challenges in the support structures; although this research has not paid attention to investigation of this widespread failure of support structures in the offshore renewable industry. The renewable energy companies are not willing to release a certain level of information into the public domain; this has made it difficult to access reliable information related to some of the challenges bordering on the design, construction, operations and maintenance of offshore wind farms.

Although the industry expert judges recruited in this research study have been carefully selected to ensure that they have relevant qualifications and experience in this subject matter, the reliability of the data collated through the experts' judgements may still be of poor quality due to a number of reasons. For instance, the expert may be biased due to personal experience; the expert's personal opinion may overrule their actual experience; their frame of mind at the time of completing the questionnaire may affect their judgement, etc. This host of uncertainties will affect the analysis of the framework one way or another and produce unexpected poor outcomes. Nonetheless, repetition of the analytical modelling process and random comparison of case studies were employed to eliminate the potential for this impact.

7.4 Future Research Potential

This PhD research provides the premise upon which further research on complex failures of the support structures, turbine critical components and ancillaries can be carried out. A wide scope of opportunity exists in the area of risk mitigation for development of wind energy in either the onshore or offshore sector. These possible extensions are presented as follows:

- Investigation of the impact of risk mitigation strategies on the performance of the wind farm, in terms of reduction in operating expenses (OPEX), will be an interesting subject matter for future research.
- Specific investigations can be carried out on the failures of monopile-type support structures in the offshore renewable industry.
- Increasing the number of main criteria and sub-criteria considered in the specific model of this research. Only four sample expert judgements are considered in this research due to the data complexity; future research may consider increasing the number of participating experts.
- There is need to undertake commercial scale study of the environmental impact exerted on OWF assets that may affect its design, construction, operations and maintenance.

- A study area on the health and safety risks posed by the environment to the offshore personnel working in the offshore wind energy industry will be beneficial.
- Other MCDM/MADM decision-making tools such as VIKOR, ANP, ELECTRE, Grey theory, SMART, DEA, AIRM and DEMATEL may be explored in the evaluation of the risks associated with the development of offshore wind farms
- Surprisingly, these special decision-making tools are not currently popular in the offshore wind farm industry. This made it particularly difficult to access related resources for the thesis. More should be done to create the awareness of these robust tools for in-depth evaluation of these risk factors that are currently posing huge challenges to the industry.

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APPENDICES

Appendix 1: Solution to Test Case of Chapter Three

A 1.0 An Evaluation of the Judgements of the Four Experts' survey feedback by Modelling of the Hierarchy to obtain the Weights of Risk Parameters using AHP Approach

A1.1 Survey feedback from the participating experts in the survey

Table A1.1 Expert 1 survey feedback of Group A: OWFD risk components

PART 1: Group A: OWFD Risk components																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
External Risk						x												Engineering Risk
External Risk													x					Financial Risk
External Risk													x					Organisational Risk
Engineering Risk														x				Financial Risk
Engineering Risk														x				Organisational Risk
Financial Risk								x										Organisational Risk

Table A1.2 Expert 1 survey feedback of Group B: external risk factors

PART 1: Group B: External Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Vandalism Risks										x								Political Risks
Vandalism Risks												x						Environmental Risks
Political Risks												x						Environmental Risks

Table A1.3 Expert 1 survey feedback of Group C: engineering risk factors

PART 1: Group C: Engineering Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Design Risks								x										Construction Risks
Design Risks										x								Operational Risks
Construction Risks									x									Operational Risks

Table A1.4 Expert 1 survey feedback of Group D: financial risk factors

PART 1: Group D: Financial Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Accounting Risks														x				FOREX Risks
Accounting Risks															x			Inflation Risk
FOREX Risks										x								Inflation Risk

Table A1.5 Expert 1 survey feedback of Group E: organisational risk factors

PART 1: Group E: Organisational Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Lack of functional procedure Risks													x					Staff Unreliability Risks
Lack of functional procedure Risks										x								Lack of coordination / communication Risks
Staff Unreliability Risks					x													Lack of coordination / communication Risks

Table A1.6 Expert 2 survey feedback of Group A: OWFD risk components

PART 1: Group A: OWFT Risk components																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
External Risk															x			Engineering Risk
External Risk											x							Financial Risk
External Risk								x										Organisational Risk
Engineering Risk					x													Financial Risk
Engineering Risk			x															Organisational Risk
Financial Risk					x													Organisational Risk

Table A1.7 Expert 2 survey feedback of Group B: external risk factors

PART 1: Group B: External Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Vandalism Risks													x					Political Risks
Vandalism Risks								x										Environmental Risks
Political Risks					x													Environmental Risks

Table A1.8 Expert 2 survey feedback of Group C: engineering risk factors

PART 1: Group C: Engineering Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Design Risks					x													Construction Risks
Design Risks									x									Operational Risks
Construction Risks					x													Operational Risks

Table A1.9 Expert 2 survey feedback of Group D: financial risk factors

PART 1: Group D: Financial Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Accounting Risks													x					FOREX Risks
Accounting Risks											x							Inflation Risk
FOREX Risks											x							Inflation Risk

Table A1.10 Expert 2 survey feedback of Group E: organisational risk factors

PART 1: Group E: Organisational Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Lack of functional procedure Risks											x							Staff Unreliability Risks
Lack of functional procedure Risks										x								Lack of coordination / communication Risks
Staff Unreliability Risks								x										Lack of coordination / communication Risks

Table A1.11 Expert 3 survey feedback of Group A: OWFT risk components

PART 1: Group A: OWFT Risk components																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
External Risk													x					Engineering Risk
External Risk											x							Financial Risk
External Risk													x					Organisational Risk
Engineering Risk			x															Financial Risk

Engineering Risk						x												Organisational Risk
Financial Risk												x						Organisational Risk

Table A1.12 Expert 3 survey feedback of Group B: external risk factors

PART 1: Group B: External Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Vandalism Risks													x					Political Risks
Vandalism Risks													x					Environmental Risks
Political Risks													x					Environmental Risks

Table A1.13 Expert 3 survey feedback of Group C: engineering risk factors

PART 1: Group C: Engineering Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Design Risks									x									Construction Risks
Design Risks							x											Operational Risks
Construction Risks						x												Operational Risks

Table A1.14 Expert 3 Survey Feedback of Group D: Financial Risk Factors

PART 1: Group D: Financial Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Accounting Risks												x						FOREX Risks
Accounting Risks									x									Inflation Risk
FOREX Risks											x							Inflation Risk

Table A1.15 Expert 3 survey feedback of Group E: organisational risk factors

PART 1: Group E: Organisational Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Lack of functional procedure Risks									x									Staff Unreliability Risks
Lack of functional procedure Risks												x						Lack of coordination / communication Risks
Staff Unreliability Risks										x								Lack of coordination / communication Risks

Table A1.16 Expert 4 survey feedback of Group A: OWFT risk components

PART 1: Group A: OWFT Risk components																		
	Scale of relative importance																	
Criterion	Absolute **(9)**	Intermediate **(8)**	Very strong **(7)**	Intermediate **(6)**	Strong **(5)**	Intermediate **(4)**	Weak **(3)**	Intermediate **(2)**	Equal **(1)**	Intermediate **(2)**	Weak **(3)**	Intermediate **(4)**	Strong **(5)**	Intermediate **(6)**	Very strong **(7)**	Intermediate **(8)**	Absolute **(9)**	Criterion
External Risk													X					Engineering Risk
External Risk									X									Financial Risk
External Risk						x												Organisational Risk
Engineering Risk								X										Financial Risk
Engineering Risk					X													Organisational Risk
Financial Risk						X												Organisational Risk

Table A1.17 Expert 4 survey feedback of Group B: external risk factors

PART 1: Group B: External Risk Factors		
	Scale of relative importance	

Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Vandalism Risks													X					Political Risks
Vandalism Risks								X										Environmental Risks
Political Risks						X												Environmental Risks

Table A1.18 Expert 4 survey feedback of Group C: engineering risk factors

PART 1: Group C: Engineering Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Design Risks										X								Construction Risks
Design Risks								X										Operational Risks
Construction Risks					X													Operational Risks

Table A1.19 Expert 4 survey feedback of Group D: financial risk factors

PART 1: Group D: Financial Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion
Accounting Risks									X									FOREX Risks
Accounting Risks											X							Inflation Risk
FOREX Risks										X								Inflation Risk

Table A1.20 Expert 4 survey feedback of Group E: organisational risk factors

PART 1: Group E: Organisational Risk Factors																		
	Scale of relative importance																	
Criterion	Absolute (9)	Intermediate (8)	Very strong (7)	Intermediate (6)	Strong (5)	Intermediate (4)	Weak (3)	Intermediate (2)	Equal (1)	Intermediate (2)	Weak (3)	Intermediate (4)	Strong (5)	Intermediate (6)	Very strong (7)	Intermediate (8)	Absolute (9)	Criterion

Lack of functional procedure Risks											X							Staff Unreliability Risks
Lack of functional procedure Risks								X										Lack of coordination / communication Risks
Staff Unreliability Risks						X												Lack of coordination / communication Risks

Table A1.21 Evaluation of relative risk of the sub-criteria with respect to external risk

External risk (example of matrix of pairwaise comparison using Expert 1 opion)

Sub-Criterion	Vandalism Risk	Political Risk	Environmental Risk	3rd Root	Priority vector (PV)
Vandalism Risk	1.000	0.500	0.250	0.500	0.131
Political Risk	2.000	1.000	0.250	0.794	0.208
Environmental Risk	4.000	4.000	1.000	2.518	0.660
Sum	7.000	5.500	1.500	3.812	1.000
Sum x PV	0.919	1.146	0.991	3.055	

The above Table A1.21 shows the three matrices constructed in order to determine the ratings of each decision alternative (sub-criterion) for a particular criterion relative to the main corresponding risk criteria. The matrix constructed from the feedback received from the expert 1 (see Tables A1.2) indicates that:

- The political risk factor is more 'slightly important' than the risk of vandalism (2)
- The environmental risk is 'moderately plus' more important that the risk of vandalism (4)
- The environmental risk is 'moderately plus' more important that the political risk factors (4)
- The values represented as '1' are the 'equally important' consisting of comparison of each sub-criterion to itself, which makes it equal to '1'
- The rest of the values in the matrix represent the reciprocal pairwise comparisons of relationships between one sub-criterion and the other.

Calculating the n^{th} root (i.e. 3^{rd} root given the three sub-criteria)

Vandalism risk: 3^{rd} root = $(1.000 \text{ x } 0.500 \text{ x } 0.250)^{1/3 =}$ $(0.125)^{1/3}$= 0.500

Political risk: 3^{rd} root = $(2.000 \text{ x } 1.000 \text{ x } 0.250)^{1/3 =}$ $(0.500)^{1/3}$= 0.794

Environmental risk: 3^{rd} root = $(4.000 \text{ x } 4.000 \text{ x } 1.000)^{1/3 =}$ $(16.000)^{1/3}$ = 2.518

Based on the equation 3.7,

Priority Vector (PV)

$$PV = \frac{n^{th} root}{Sum of\ PV}$$

Vandalism Risk: $PV = \frac{3^{rd} root}{Sum of\ PV} = \frac{0.500}{3.812} = 0.131$

Political risk: $PV = \frac{3^{rd} root}{Sum of\ PV} = \frac{0.794}{3.812} = 0.208$

Environmental Risk: $PV = \frac{3^{rd} root}{Sum of\ PV} = \frac{2.518}{3.812} = 0.660$

Applying equation 3.8,

Lambda Max $(\lambda_{\max})$

$$\text{Lambdamax}\,(\lambda_{\max}) = \sum(\text{sum of individual pairwise comparison} \times \text{PV})$$

Social Risk: $\sum(sum of\ pairwise comparison \times PV) = (7.000 \times 0.131) = 0.917$

Political risk: $\sum(sum of\ pairwise comparison \times PV) = (5.500 \times 0.208) = 1.144$

Labour Risk: $\sum(sum of\ pairwise comparison \times PV) = (1.500 \times 0.660) = 0.990$

$$Lambda(\lambda_{\max}) = \sum(0.917 + 1.144 + 0.990) = 3.051$$

Consistency Index (CI)

$$\text{CI} = \frac{(\lambda_{\max} - 1)}{(\text{n} - 1)}$$

Where n = 3 i.e. the number of sub-criteria being compared

$$\text{CI} = \frac{(3.051 - \text{n})}{(3 - 1)} = \frac{0.051}{2} = 0.026$$

$$\text{CI} = 0.026$$

Consistency Ratio (CR)

$$\text{CR} = \frac{(\text{CI})}{(\text{RI})}$$

where $CI = Consistenc\ y\ Ratio$ and

$RI = is\ value\ obtained\ \ from\ the\ Random\ \ Index\ table$ as shown above.

From the random index Table, nth root = 3 = 0.58

Therefore, $\text{CR} = \frac{(\text{CI})}{(\text{RI})} = \frac{0.026}{0.58} = 0.044$

$\text{CR} = 0.044$

Table A1.22 Evaluation of relative risk of the Sub-Criteria with respect to engineering risk

Engineering risk (example of matrix of pairwise comparison using Expert 1 opion)

Sub-Criterion	Design Risk	Construction Risk	Operational Risk	3rd Root	Priority vector (PV)
Design Risk	1.000	2.000	1.000	1.260	0.413
Construction Risk	0.500	1.000	1.000	0.794	0.260
Operational Risk	1.000	1.000	1.000	1.000	0.327
Sum	2.500	4.000	3.000	3.054	1.000
Sum x PV	1.031	1.040	0.982	**3.054**	

CI	0.027
CR	0.046

The above Table A1.22 shows the three matrices constructed in order to determine the ratings of each decision alternative (sub-criterion) for a particular criterion relative to the main corresponding risk criteria (engineering risk).

The above matrix (see Table A1.22) constructed from the expert feedback (in Table A1.3) indicates that:

- The design risk is more ‘slightly important’ than construction risk (2)
- The construction risk is more ‘strongly important’ than the operational risk (5)
- The operational risk is more ‘slightly important’ than design risk (2)
- The values represented as ‘1’ are the ‘equally important’ consisting of comparison of each sub-criterion to itself, which makes it equal to ‘1’

- The rest of the values in the matrix represent the reciprocal pairwise comparisons of relationships between one sub-criterion and the other.

Table A1.23 Evaluation of relative risk of the sub-criteria with respect to financial risk

Financial risk (example of matrix of pairwaise comparison using Expert 1 opion)

Sub-Criterion	Accounting Risks	FOREX Risks	Inflation Risk	3rd Root	Priority vector (PV)
Accounting Risks	1.000	0.167	0.143	0.288	0.070
FOREX Risks	6.000	1.000	0.500	1.442	0.348
Inflation Risk	7.000	2.000	1.000	2.408	0.582
Sum	14.000	3.167	1.643	4.138	1.000
Sum x PV	0.975	1.103	0.956	**3.034**	
CI	0.017				
CR	0.029				

The above matrix (see Table A1.23) constructed from the expert feedback (in Table A1.4) indicates that:

- The FOREX risk is more 'strongly important' than accounting risk (6)
- The inflation risk is more 'very strongly important' than the accounting risk (7)
- The inflation risk is more 'slightly important' than the FOREX risk (2)
- The values represented as '1' are the 'equally important' consisting of comparison of each sub-criterion to itself, which makes it equal to '1'
- The rest of the values in the matrix represent the reciprocal pairwise comparisons of relationships between one sub-criterion and the other.

Table A1.24 Evaluation of relative risk of the sub-criteria with respect to organisation risk

Organisational risk (example of matrix of pairwaise comparison using Expert 1 opion)

Sub-Criterion	Lack of functional procedure Risks	Staff Unreliability Risks	Lack of communication Risks	3rd Root	Priority vector (PV)
Lack of functional procedure Risks	1.000	0.200	0.500	0.465	0.113
Staff Unreliability Risks	5.000	1.000	5.000	2.921	0.709
Lack of communication Risks	2.000	0.200	1.000	0.737	0.179
Sum	8.000	1.400	6.500	4.122	1.000
Sum x PV	0.901	0.992	1.162	**3.055**	
CI	0.028				
CR	0.048				

The above matrix (see Table A1.24) constructed from the expert feedback (in Table A1.5) indicates that:

- The risk of staff unreliability is more 'strongly important' than the risk of lack of functional procedure (5)
- The risk of staff unreliability is more 'strongly important' than the risk of lack of functional communication (5)
- The risk of lack of functional communication is more 'slightly important' than the risk of lack of functional procedure (2)
- The values represented as '1' are the 'equally important' consisting of comparison of each sub-criterion to itself, which makes it equal to '1'
- The rest of the values in the matrix represent the reciprocal pairwise comparisons of relationships between one sub-criterion and the other.

The above sample matrix shows how the matrix can be constructed using the expert 1 opinions.

A1.2 Aggregation of pairwise comparison of the four experts for main criteria with respect to the goal (x_1, x_2, x_3, x_4)

Let the four experts be represented as x_1, x_2, x_3 and x_4.

Computing the judgements of the experts for each criterion;

$$Combined\ \ pair - wise\, comparison\ = (x_1 \times x_2 \times x_3 \times x_4)^{1/4}$$

$$ExtR - EngR\ = (4 \times \frac{1}{7} \times \frac{1}{5} \times \frac{1}{5})^{1/4}\ = 1.460$$

$$ExtR - FinR = (\frac{1}{5} \times \frac{1}{3} \times \frac{1}{3} \times 1)^{1/4}\ = 1.169$$

$$ExtR - OrgR = (\frac{1}{5} \times 2 \times \frac{1}{5} \times 4)^{1/4}\ = 1.627$$

$$EngR - FinR = (\frac{1}{6} \times 5 \times 7 \times 2)^{1/4}\ = 1.940$$

$$EngR - OrgR = (\frac{1}{6} \times 7 \times 4 \times 5)^{1/4}\ = 2.005$$

$$FinR - OrgR = (2 \times 5 \times \frac{1}{4} \times 4)^{1/4}\ = 2.005$$

Construct pairwise comparison matrix from the values derived from the above calculations.

Table A1.25 aggregated pairwise comparisons for the main criteria

OWFD	ExtR	EngR	FinR	OrgR	4th Root	Priority vector
ExtR	1.000	0.389	0.669	0.752	0.665	0.154
EngR	2.572	1.000	1.848	2.198	1.798	0.416
FinR	1.495	0.541	1.000	1.778	1.095	0.253
OrgR	1.330	0.455	0.562	1.000	0.764	0.177
Sum up	6.397	2.385	4.079	5.728	4.322	1.000
Sum up x PV	0.984	0.992	1.034	1.012	**4.022**	

CI	0.007
CR	0.008

Similarly, the aggregated pairwise comparisons for the sub-criteria with respect to the corresponding main criterion from the four experts can be calculated using the same methodology.

Applying the same equation as above,

$Combined\ \ pair-wise\,comparison=(x_1\times x_2\times x_3\times x_4)^{1/4}$ where x_1, x_2, x_3 and x_4 represents the opinions of the experts.

Computing the pairwise comparison for the sub-criterion with respect to the corresponding main criterion.

A1.26 External risk factors

$$ValR-PolR=(\frac{1}{2}\times\frac{1}{5}\times\frac{1}{5}\times\frac{1}{5})^{1/3}\ =1.032$$

$$ValR-EnvR=(\frac{1}{4}\times2\times\frac{1}{7}\times2)^{1/3}\ =1.367$$

$$PolR-EnvR=(\frac{1}{4}\times5\times\frac{1}{5}\times4)^{1/3}\ =2.113$$

Table A1.26 Aggregated pairwise comparisons for the sub-criteria (external risk)

External risk

ExtR	VanR	PolR	EnvR	3rd Root	Priority vector
VanR	1.000	0.216	0.585	0.502	0.1492
PolR	4.634	1.000	1.000	1.666	0.4954
EnvR	1.709	1.000	1.000	1.195	0.3554
Sum up	7.344	2.216	2.585	3.364	1.000
Sum up x PV	1.096	1.098	0.919	**3.112**	

CI	0.056
CR	0.097

A1.27 Engineering risk factors

$$DesR - ConR = (2 \times 5 \times 1 \times \frac{1}{2})^{1/3} = 2.039$$

$$DesR - OpeR = (\frac{1}{2} \times 1 \times 3 \times 2)^{1/3} = 1.865$$

$$ConR - OpeR = (1 \times 5 \times 4 \times 5)^{1/3} = 2.464$$

Table A1.27 Aggregated pairwise comparisons for the sub-criteria (engineering risk)

Engineering risk

EngR	DesR	ConR	OpeR	3rd Root	Priority vector
DesR	1.000	0.694	1.442	1.000	0.293
ConR	1.442	1.000	4.634	1.882	0.551
OpeR	0.694	0.216	1.000	0.531	0.156
Sum up	3.135	1.909	7.076	3.414	1.000
Sum up x PV	0.918	1.053	1.101	**3.073**	

CI	0.036
CR	0.063

A1.28 Financial risk factors

$$AccR - ForR = (\frac{1}{6} \times \frac{1}{5} \times \frac{1}{4} \times 1)^{1/3} = 1.173$$

$$AccR - InfR = (\frac{1}{7} \times \frac{1}{3} \times 1 \times \frac{1}{3})^{1/3} = 1.218$$

$$ForR - InfR = (\frac{1}{2} \times \frac{1}{3} \times 1 \times \frac{1}{2})^{1/3} = 1.218$$

Table A1.28 Aggregated pairwise comparisons for the sub-criteria (financial risk)

Financial risk

Financial Risk	Accounting Risk	FOREX Risk	Inflation Risk	3rd Root	Priority vector
Accounting Risk	1.000	0.203	0.105	0.277	0.061
FOREXR	4.925	1.000	0.303	1.143	0.250
Inflation Risk	9.568	3.298	1.000	3.156	0.690
Sum up	15.493	4.501	1.408	4.576	1.000
Sum up x PV	0.938	1.124	0.971	**3.033**	

CI	0.017
CR	0.029

A1.29 Organisational risk factors

$$Lack\ of\ Fuctional\ \Pr oc.R - Staff\ unreliabilityR = (\frac{1}{5}\times\frac{1}{3}\times 1\times\frac{1}{4})^{1/3} = 1.212$$

$$Lack\ of\ Fuctional\ \Pr oc.R - Lack\ communicationR = (\frac{1}{2}\times\frac{1}{2}\times\frac{1}{4}\times 2)^{1/3} = 1.481$$

$$Staff\ unreliability.R - Lack\ communicationR = (5\times 2\times\frac{1}{2}\times 4)^{1/3} = 2.255$$

Table A1.29 Aggregated pairwise comparisons for the sub-criteria (organisational risk)

Organisational risk	Lack of functional procedure R	Staff unreliability Risk	Lack of coordination Risk	3rd Root	Priority vector
Lack of functional procedure	1.000	0.256	0.500	0.504	0.140
Staff unreliability	3.910	1.000	2.712	2.195	0.609
Lack of coordination R	1.999	0.369	1.000	0.903	0.251
Sum up	6.908	1.625	4.212	3.603	1.000
Sum up x PV	0.967	0.990	1.056	**3.013**	

A1.30 Pairwise comparison aggregation constructed by using the AHP assessment software

The pairwise matrices below are derived from the AHP Assessment tool to check the hand calculations. The pairwise comparisons will focus on aggregating the judgements of the four expert opinions. The two different aggregated pairwise comparisons constructed are i) for the main criteria (see Table 3.12 or A1.25) and ii) for the sub-criteria with respect to the individual main criterion (see Tables A1.26, A1.27, A1.28 and A1.29).

Table A1.30 Aggregated pairwise comparisons for the main criteria derived from section A 1.25

OWFD	ExtR	EngR	FinR	OrgR	4th Root	Priority vector	Normalized principal Eigenvector
ExtR	1.000	0.389	0.669	0.752	0.665	0.154	15.387
EngR	2.572	1.000	1.848	2.198	1.798	0.416	41.599
FinR	1.495	0.541	1.000	1.778	1.095	0.253	25.342
OrgR	1.330	0.455	0.562	1.000	0.764	0.177	17.671
Sum up	6.397	2.385	4.079	5.728	4.322	1.000	
Sum up x PV	0.984	0.992	1.034	1.012	4.022		

Normalised principal eigenvectors are external risk is 15.39%; engineering risk is 41.59%; financial risk is 25.34%; organisational risk is 17.67%. This table shall be used to apply ranking assessment (global ranking).

Table A1.31 Aggregated pairwise comparisons for the sub-criteria of external risk for the purpose of ranking

External risk

ExtR	VanR	PolR	EnvR
Criterion	External risk (PV)	Score or Global weight	Global Ranking
Option	0.154		
VanR	0.149	0.023	3
PolR	0.495	0.076	1
EnvR	0.355	0.055	2
		0.154	

Normalised principal Eigenvector are risk of vandalism/sabotage is 14.90%; political risk is 49.50%; Environmental risk is 35.50%.

Table A1.32 aggregated pairwise comparisons for the sub-criteria derived from software (engineering risk)

Engineering risk

EngR	DesR	ConR	OpeR
Criterion	Engineering risk	Score or Global weight	Global Ranking

Option	0.416		
DesR	0.293	0.122	2
ConR	0.551	0.229	1
OpeR	0.156	0.065	3
		0.416	

Normalised principal eigenvectors are design risk is 29.30%; construction risk is 55.10%; operational risk is 15.60%.

Table A1.33 Aggregated pairwise comparisons for the sub-criteria derived from software (financial risk)

Financial risk

Engineering Risk	Accounting Risk	FOREX Risk	Inflation Risk
Criterion	Financial risk	Score or Global weight	Global Ranking
Option	0.253		
Accounting Risk	0.10	0.025	3
FOREX Risk	0.29	0.073	2
Inflation Risk	0.61	0.155	1
		0.253	

Normalised principal eigenvectors are accounting risk is 10.00%; FOREX risk is 29.00%; inflation risk is 61.007%

Table A1.34 Aggregated pairwise comparisons for the sub-criteria derived from software (organisational risk)

Organisational risk	Lack of functional procedure R	Staff unreliability Risk	Lack of coordinatio n Risk
Criterion	Organisational risk	Score or Global weight	Global Ranking
Option	0.177		
Lack of functional procedure	0.18	0.032	3
Staff unreliability	0.54	0.096	1
Lack of coordination R	0.28	0.049	2
		0.177	

Normalised principal eigenvectors are risk of lack of functional procedure is 18.00%; risk of staff unreliability is 54.00%; risk of lack of coordination / communication is 28.00%.

The grand total of the weights of the parameters when summed together must be equal to 1.000.

Table A1.35 Global Ranking Process

Main criteria	Main criteria weights	Sub-criteria	Sub-criteria weights	Global weight	Global Ranking
ExtR	0.154	VanR	0.149	0.023	12
	0.154	PolR	0.495	0.076	5
	0.154	EnvR	0.355	0.055	8
EngR	0.416	DesR	0.293	0.122	3
	0.416	ConR	0.551	0.229	1
	0.416	OpeR	0.156	0.065	7
FinR	0.253	Accounting R	0.180	0.045	10
	0.253	FOREX R	0.542	0.137	2
	0.253	Inflation R	0.278	0.071	6
OrgR	0.177	Lack of functional procedure	0.180	0.032	11
	0.177	Staff unreliability	0.542	0.096	4
	0.177	Lack of coordination R	0.278	0.049	9
				1.000	

In order to obtain the global raking values, multiply the PVs of main criteria with those of sub-criteria and obtain the Global weights as indicated in Table A1.34 above.

Table A1.36 Final Global Rank of the Risk Parameters

Main criteria	Main criteria weights	Sub-criteria	Sub-criteria weights	Global weight	Global Ranking
		C11	0.149	0.023	12
C1	0.154	C12	0.495	0.076	5
		C13	0.355	0.055	8
		C21	0.293	0.122	3
C2	0.416	C22	0.551	0.229	1
		C23	0.156	0.065	7
		C31	0.180	0.045	10
C3	0.253	C32	0.542	0.137	2
		C33	0.278	0.071	6
		C41	0.180	0.032	11
C4	0.177	C42	0.542	0.096	4
		C43	0.278	0.049	9
				1.000	

A2.0 Calculating the Crisp Value for the Main Risk Associated with OWFD through the Implementation of the Mapping Process

A2.1 Vandalism/Sabotage Risk

The following fuzzy rules are developed based on the expert judgements from vandalism/sabotage to external risk factors presented in FigureA2.1:

- If the vandalism/sabotage risk is very low, then the external risk factors impacting on the offshore wind farm development are100% extremely low.
- If the vandalism/sabotage risk is low, then the external risk factors impacting on the offshore wind farm development are 50% fairly low, 50% extremely low.
- If the vandalism/sabotage risk is moderate, then the external risk factors impacting on the offshore wind farm development are 70% medium, 30% fairly low.
- If the vandalism/sabotage risk is high, then the external risk factors impacting on the offshore wind farm development are 90% fairly high, 10% medium.
- If the vandalism/sabotage risk is very high, then the external risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_{VS} = \{(VeryLow, 0), (Low, 0.5), (Moderate, 0.5), (High, 0), (VeryHigh, 0)\}$$

The fuzzy rules developed by the experts are transformed into quantitative values by application of the mapping process from vandalism/sabotage risk to external risk factor as show in FigureA2.1.

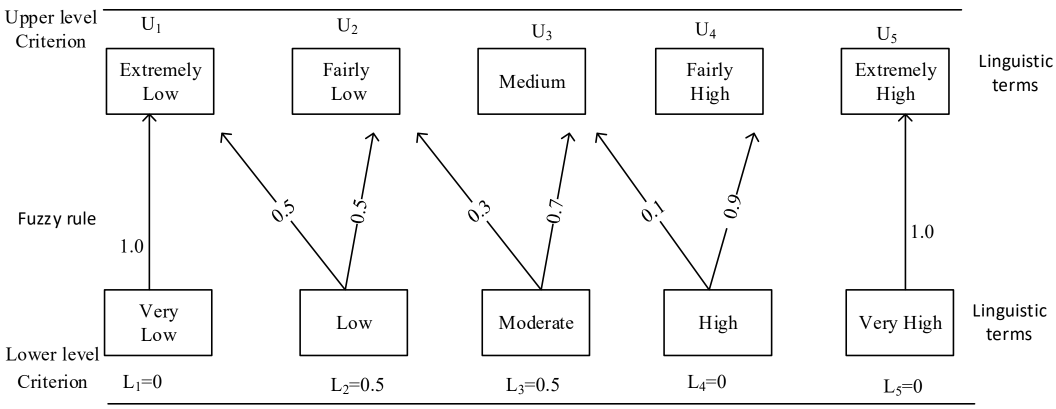


Figure A 2.1 Mapping vandalism/sabotage risk to external risk factor

Using equations 3.4, 3.5 and 3.6; the associated belief degrees of the linguistic terms of the upper level criterion (external risk factor) is transformed from the lower level criterion (vandalism/sabotage risk) into numerical quantities.

Hence,

$$U_1 = \{(0\times 1.0)+(0.5\times 0.5),\quad U_2 = (0.5\times 0.5)+(0.5\times 0.3),\quad U_3 = (0.5\times 0.7)+(0\times 0.9)\}$$

$$= 0.25, \qquad\qquad = 0.40, \qquad\qquad = 0.35,$$

Therefore, the fuzzy set out will be:

$$\widetilde{M}_{VSO} = \{(Extremely\ Low, 0.25), (Fairly\ Low, 0.40), (Medium, 0.35),\ (Fairly\ High, 0), (Extremely\ High, 0)\}$$

A2.2 Political Risk

The following fuzzy rules are developed based on the expert judgements from political risk to external risk factors presented in Figure A2.2.

- If the political risk is very low, then the external risk factors impacting on the offshore wind farm development are100% extremely low.
- If the political risk is low, then the external risk factors impacting on the offshore wind farm development are 50% fairly low, 50% extremely low.

- If the political risk is moderate, then the external risk factors impacting on the offshore wind farm development are 60% medium, 40% fairly low.
- If the political risk is high, then the external risk factors impacting on the offshore wind farm development are 90% extremely high, 10% fairly high.
- If the political risk is very high, then the external risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_P = \{(Very\ Low, 0), (Low, 0), (Moderate, 0.3), (High, 0.7), (Very\ High, 0)\}$$

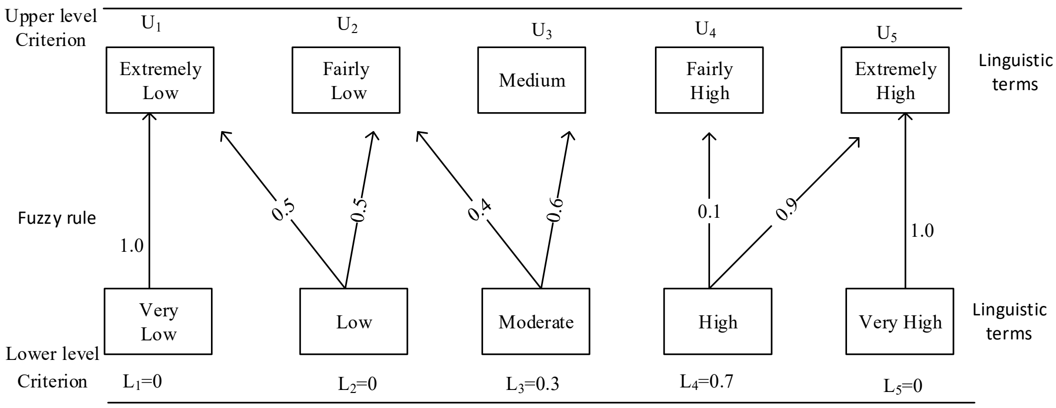


Figure A2.2 Mapping political risk to external risk factor

$$U_1 = \{(0),\ U_2 = (0 \times 0.5) + (0.3 \times 0.4),\ U_3 = (0.3 \times 0.6),\ (U_4 = (0.7 \times 0.1) + (0.7 \times 0.9), U_5(0)\}$$
$$U_1 = 0, \quad U_2 = 0.12, \quad U_3 = 0.18, \quad U_4 = 0.70, \quad U_5 = 0$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{PO} = \{(ExtremelyLow, 0), (FairlyLow, 0.12), (Medium, 0.18), (FairlyHigh, 0.7), (ExtremelyHigh, 0)\}$$

A2.3 Environmental Risk

The following fuzzy rules are developed based on the expert judgements from environmental risk to external risk factors presented in Figure A2.3.

- If the environmental risk is very low, then the external risk factors impacting on the offshore wind farm development are100% extremely low.
- If the environmental risk is low, then the external risk factors impacting on the offshore wind farm development are 60% fairly low, 40% extremely low.
- If the environmental risk is moderate, then the external risk factors impacting on the offshore wind farm development are 40% medium, 60% fairly high.
- If the environmental risk is high, then the external risk factors impacting on the offshore wind farm development are 90% extremely high, 10% fairly high.
- If the environmental risk is very high, then the external risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_E = \{(Very\,Low, 0), (Low, 0), (Moderate, 1.0), \ (High, 0), (Very\,High, 0)\}$$

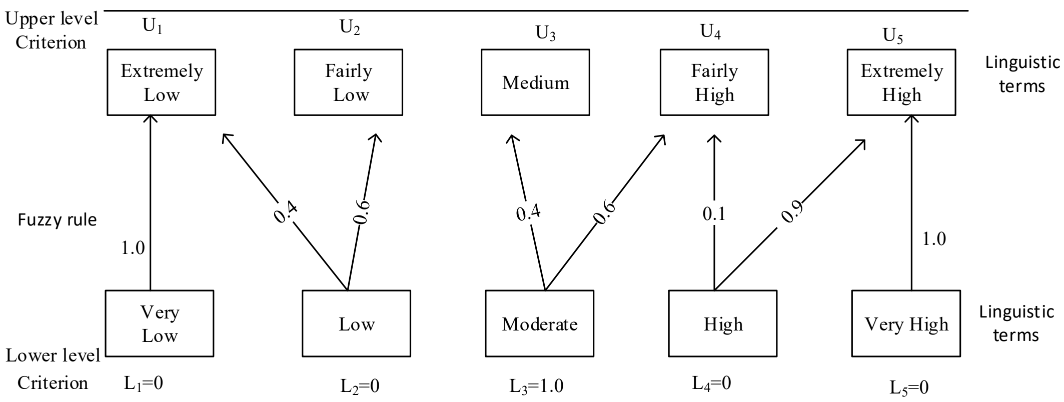


Figure A2.3 Mapping environmental risk to external risk factor

$$U_1 = \{(0), \ U_2 = (0), \ U_3 = (1.0 \times 0.4), \ (U_4 = (1.0. \times 0.6) + (0 \times 0.1), U_5(0)\}$$

$$U_1 = 0, \quad U_2 = 0 \quad U_3 = 0.40, \quad U_4 = 0.60, \quad U_5 = 0$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{EO} = \{(ExtremelyLow, 0), (FairlyLow, 0), (Medium, 0.4), \ (FairlyHigh, 0.6), (ExtremelyHigh, 0)\}$$

A2.4 Aggregation of External Risk Factors

Reference to the risk weights presented in Table 3.28 and the fuzzy set outputs presented in Table 3.29, the sub-criteria of the external risk factors values (M_{VS}, M_P and M_E) can be aggregated by computation using Intelligent Decision Making (IDS) software (see result in Table A2.1).

Table A2.1 Aggregation of external risk factors

External Risk	Extremely Low	Fairly Low	Medium	Fairly High	Extremely High
$\widetilde{M}_{VS}$	0.24	0.4	0.35	0	0
$\widetilde{M}_{P}$	0	0.12	0.18	0.7	0
$\widetilde{M}_{E}$	0	0	0.4	0.6	0
Result from Aggregation					

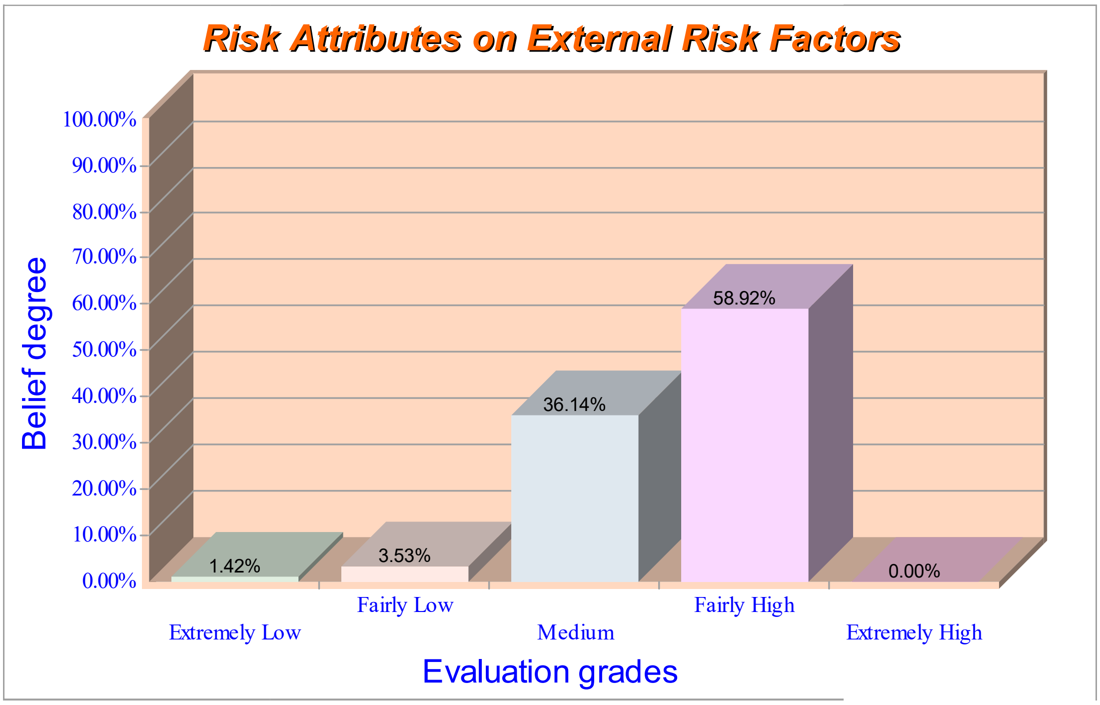


Figure2.4 External risk factor aggregation result chart

A2.5 Mapping from External Risk Factors to the Goal

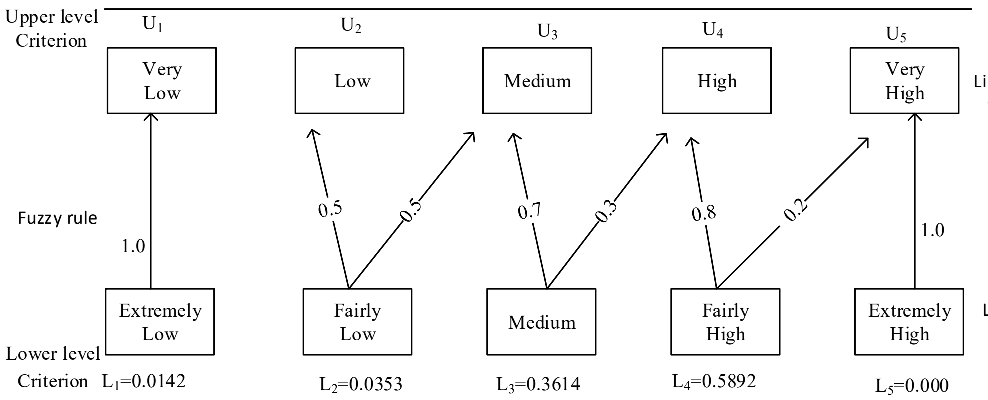
In order to evaluate the potential external risk factors affecting the offshore wind farm development (OWFD), the external risk factors will be transformed to the 'goal' using a mapping process.

The following fuzzy rules are developed based on the expert judgements from external risk factors to goal (OWFW Risk) presented in FigureA1.6.

- If the external risk factors are extremely low, then the risksimpacting on the offshore wind farm development (OWFW) are100% very low.
- If the external risk factors are fairly low, then the risks impacting on the offshore wind farm development (OWFW) are50% low, 50% medium.
- If the external risk factors are medium, then the risks impacting on the offshore wind farm development (OWFW) are 30% high, 70% medium.
- If the external risk factors are fairly high, then the risks impacting on the offshore wind farm development (OWFW) are 80% high, 20% very high.
- If the external risk factors extremely high, then the risks impacting on the offshore wind farm development (OWFW) are 100% very high.

Based on the derived input values of the sub-criteria of external risk factors, the fussy set inputs are as follows:

$$\widetilde{M}_{EX} = \{(Extremely\ High,0),(Fairly\ High,0),(Medium,0),\ (FairlyLow,0),(ExtremelyLow,0)\}$$



FigureA2.5 Mapping external risk to the goal (OWFD risk)

From the above mapping process in Figure A2.5, the output values are as follows:

$$U_1 = \{(0.0142 \times 1.0),\ \ U_2 = (0.0353 \times 0.5),\ \ U_3 = (0.0353 \times 0.5) + (0.3614 \times 0.7)$$

$$U_4 = (0.3614 \times 0.3) + (0.5892 \times 0.8),\ \ U_5 = (0.5892 \times 0.2) + (0.000 \times 1.0)\}$$

$$U_1 = 0.0142, \quad U_2 = 0.0177, \quad U_3 = 0.2706, \quad U_4 = 0.5798, \quad U_5 = 0.1178$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{EXO} = \{(VeryLow, 0.0142), (Low, 0.0177), (Medium, 0.2706), (High, 0.0.5798), (VeryHigh, 0.1178)\}$$

A2.6 Design Risk

The following fuzzy rules are developed based on the expert judgements from construction risk to engineering risk factors presented in Figure A2.6.

- If the design risk is very low, then the engineering risk factors impacting on the offshore wind farm development are100% extremely low.
- If the design risk is low, then the engineering risk factors impacting on the offshore wind farm development are 40% fairly low, 60% extremely low.
- If the design risk is moderate, then the engineering risk factors impacting on the offshore wind farm development are 30% medium, 70% fairly high.
- If the design risk is high, then the engineering risk factors impacting on the offshore wind farm development are 90% extremely high, 10% fairly high.
- If the design risk is very high, then the engineering risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_{D} = \{(Very\ Low, 0.6), (Low, 0.4), (Moderate, 0), (High, 0), (Very\ High, 0)\}$$

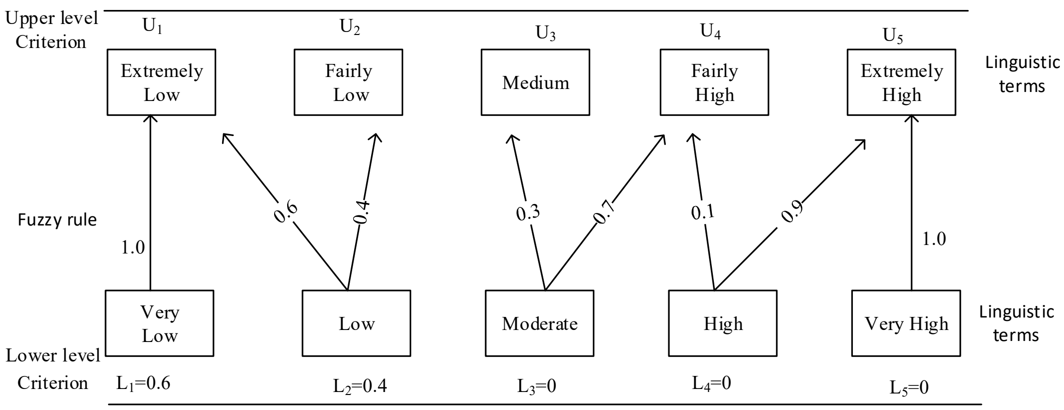


Figure A2.6 Mapping design risk to engineering risk factors

$$U_1 = \{(0.6 \times 1.0) + (0.4 \times 0.6), \quad U_2 = (0.4 \times 0.4), \quad U_3 = (0), \; (U_4 = (0) + (0)\}$$

$$U_1 = 0.84, \qquad U_2 = 0.16 \quad U_3 = 0, \quad U_4 = 0, \qquad U_5 = 0$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{DO} = \{(Extremely\ Low, 0.84), (Fairly\ Low, 0.16), (Medium, 0), \ (Fairly\ High, 0), (Extremely\ High, 0)\}$$

A2.7 Construction Risk

The following fuzzy rules are developed based on the expert judgements from construction risk to engineering risk factors presented in Figure A2.7.

- If the construction risk is very low, then the engineering risk factors impacting on the offshore wind farm development are100% extremely low.
- If the construction risk is low, then the engineering risk factors impacting on the offshore wind farm development are 20% fairly low, 80% extremely low.
- If the construction risk is moderate, then the engineering risk factors impacting on the offshore wind farm development are 20% medium, 80% fairly high.
- If the construction risk is high, then the engineering risk factors impacting on the offshore wind farm development are 90% extremely high, 10% fairly high.
- If the construction risk is very high, then the engineering risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_C = \{(Very\ Low, 0), (Low, 0), (Moderate, 0), \ (High, 1), (Very\ High, 0)\}$$

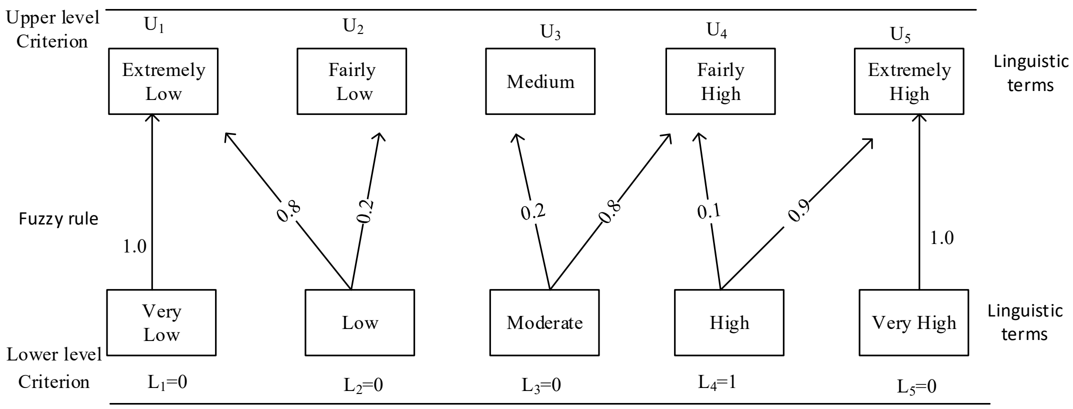


Figure A2.7 Mapping construction risk to engineering risk Factors

$$U_1 = \{(0),\ U_2 = (0),\ U_3 = (0), U_4 = (1), U_5 = 0)\}$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{CO} = \{(Extremely\,Low, 0), (Fairly\,Low, 0), (Medium, 0),\ (Fairly\,High, 1), (Extremely\,High, 0)\}$$

A2.8 Operational Risk

The following fuzzy rules are developed based on the expert judgements from operational risk to engineering risk factors presented in Figure A2.8.

- If the operational risk is very low, then the engineering risk factors impacting on the offshore wind farm development are 100% extremely low.
- If the operational risk is low, then the engineering risk factors impacting on the offshore wind farm development are 20% fairly low, 80% extremely low.
- If the operational risk is moderate, then the engineering risk factors impacting on the offshore wind farm development are 20% medium, 80% fairly high.
- If the operational risk is high, then the engineering risk factors impacting on the offshore wind farm development are 10% medium, 90% fairly high.
- If the operational risk is very high, then the engineering risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_O = \{(Very\ Low, 0), (Low, 0), (Moderate, 0.2), (High, 0.8), (Very\ High, 0)\}$$

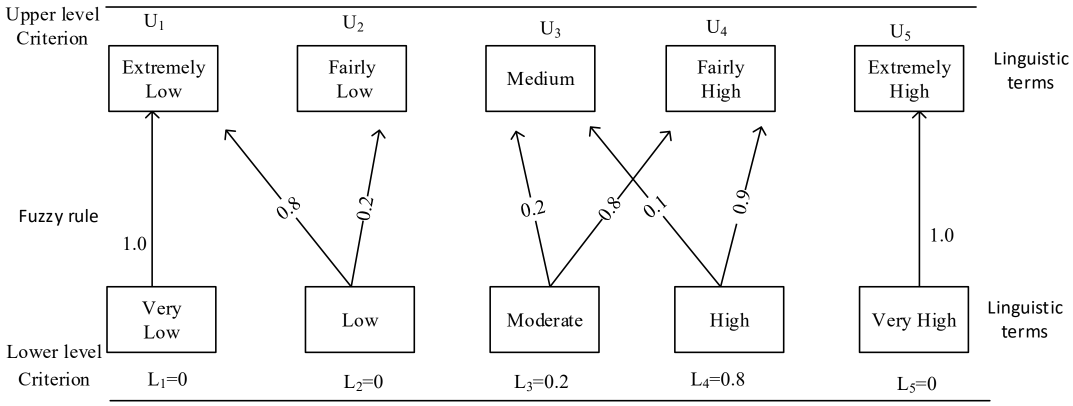


Figure A2.8 Mapping Operational Risk to Engineering Risk

$$U_1 = \{(0),\ \ U_2 = (0),\ \ U_3 = (0.2 \times 0.2) + (0.2 \times 0.8) + (0.8 \times 0.1),\ U_4 = (0.8 \times 0.9), U_5 = 0)\}$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{OO} = \{(Extremely\ Low, 0), (Fairly\ Low, 0), (Medium, 0.28), (Fairly\ High, 0.72), (Extremely\ High, 0)\}$$

Table A2.2 Aggregation of the sub-criteria with respect to external risk factors

External Risk	**Extremely Low**	**Fairly Low**	**Medium**	**Fairly High**	**Extremely High**
$\widetilde{M}_{DO}$	0.84	0.16	0.00	0.00	0.00
$\widetilde{M}_{CO}$	0.00	0.00	0.00	1.00	0.00
$\widetilde{M}_{OO}$	0	0	0.28	0.72	0.00
Result from Aggregation	0.2293	0.0437	0.0500	0.6770	0.0000

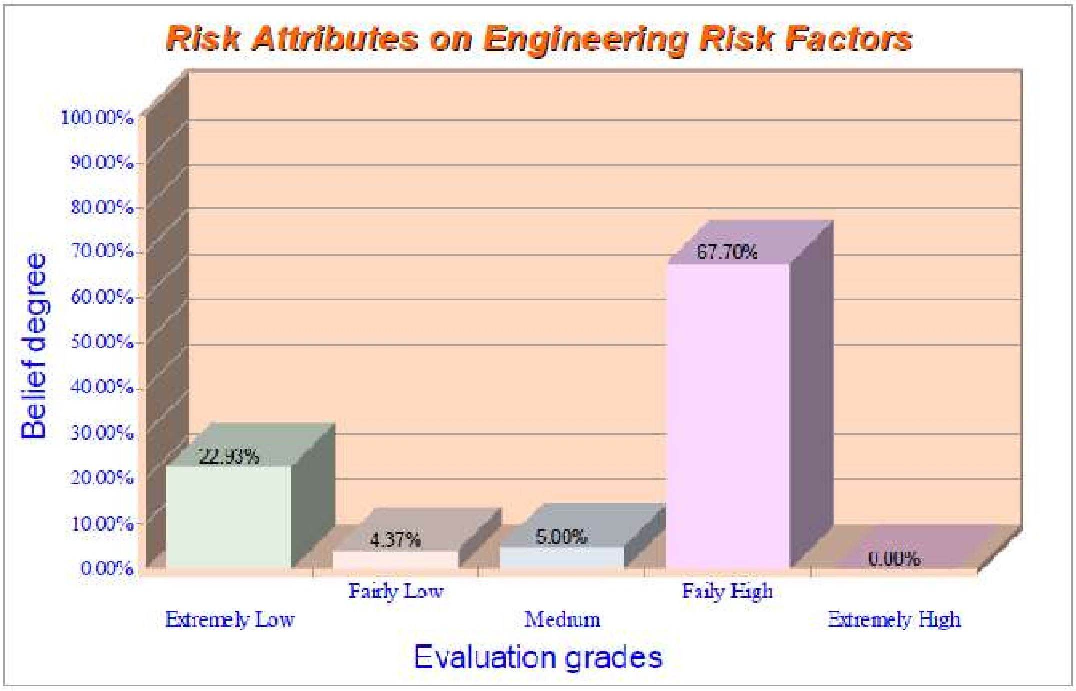


Figure 2.9 Engineering risk factors aggregation result chart

A2.9 Mapping from Engineering Risk Factors to the Goal

In order to evaluate the potential engineering risk factors affecting the offshore wind farm development (OWFD), the engineering risk factors will be transformed to the 'goal' using a mapping process.

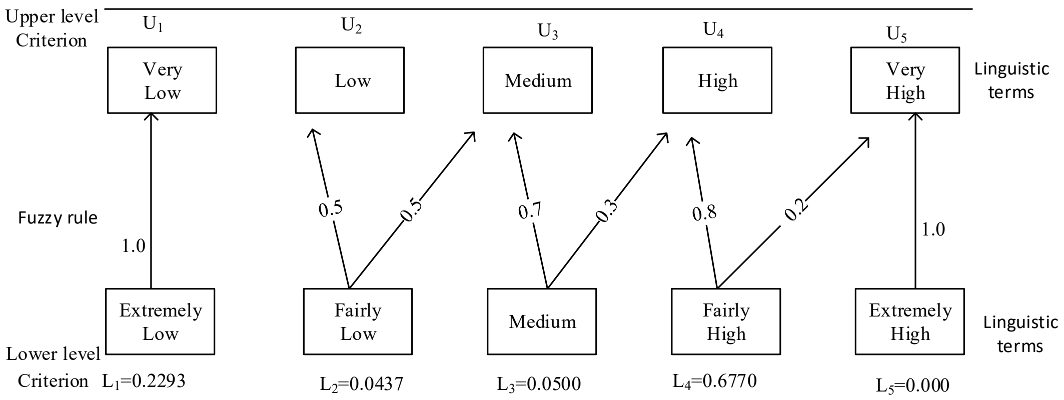
The following fuzzy rules are developed based on the expert judgements from engineering risk factors to goal (OWFW Risk) presented in FigureA2.10.

- If the engineering risk factors are extremely low, then the risks impacting on the offshore wind farm development (OWFW) are 100% very low.
- If the engineering risk factors are fairly low, then the risks impacting on the offshore wind farm development (OWFW) are 50% low, 50% medium.
- If the engineering risk factors are medium, then the risks impacting on the offshore wind farm development (OWFW) are 30% high, 70% medium.
- If the engineering risk factors are fairly high, then the risks impacting on the offshore wind farm development (OWFW) are 80% high, 20% very high.

- If the engineering risk factors extremely high, then the risks impacting on the offshore wind farm development (OWFW) are 100% very high.

Based on the derived input values of the sub-criteria of engineering risk factors, the fussy set inputs are as follows:

$$\widetilde{M}_{EN} = \{(Extremely\ High, 0), (Fairly\ High, 0), (Medium, 0), (FairlyLow, 0), (ExtremelyLow, 0)\}$$



FigureA2.10 Mapping engineering risk to the goal (OWFD Risk)

$$U_1 = \{(0.2293 \times 1.0),\ \ U_2 = (0.0437 \times 0.5),\ \ U_3 = (0.0437 \times 0.5) + (0.0500 \times 0.7),$$
$$(U_4 = (0.0500 \times 0.3) + (0.677 \times 0.8),\ U_5 = (0.6770 \times 0.2) + (0.0000 \times 1.0)\}$$

$$U_1 = 0.2293, \quad U_2 = 0.0219, \quad U_3 = 0.0569, \quad U_4 = 0.5566, \quad U_5 = 0.1354$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{ENO} = \{(VeryLow, 0.2293), (Low, 0.0219), (Medium, 0.0569), (High, 0.5566), (VeryHigh, 0.1354)\}$$

A2.10 Accounting Risk

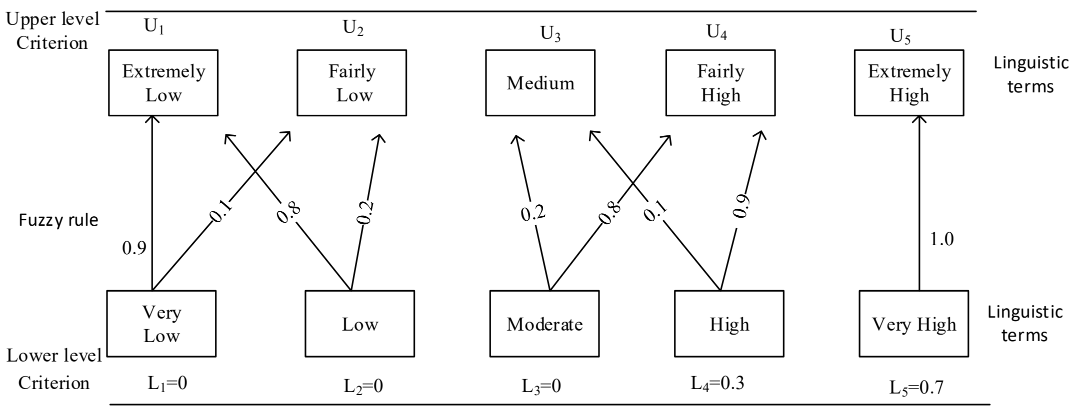
The following fuzzy rules are developed based on the expert judgements from accounting risk to financial risk factors presented in Figure A2.11.

- If the accounting risk is very low, then the financial risk factors impacting on the offshore wind farm development are 90% extremely low and 10% fairly low.
- If the accounting risk is low, then the financial risk factors impacting on the offshore wind farm development are 20% fairly low, 80% extremely low.

- If the accounting risk is moderate, then the financial risk factors impacting on the offshore wind farm development are 20% medium, 80% fairly high.
- If the accounting risk is high, then the financial risk factors impacting on the offshore wind farm development are 10% medium, 90% fairly high.
- If the accounting risk is very high, then the financial risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_{ACC} = \{(Very\ Low, 0), (Low, 0), (Moderate, 0), (High, 0.3), (Very\ High, 0.7)\}$$



FigureA2.11 Mapping accounting risk to financial risk factor

$$U_1 = \{(0),\ \ U_2 = (0),\ \ U_3 = (0.3 \times 0.1),\ (U_4 = (0.3. \times 0.9) + (0 \times 0.1), U_5(0.7 \times 1.0)\}$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{ACO} = \{(Extremely\ Low, 0), (Fairly\ Low, 0), (Medium, 0.03), (Fairly\ High, 0.27), (Extremely\ High, 0.7)\}$$

A2.11 FOREX Risk

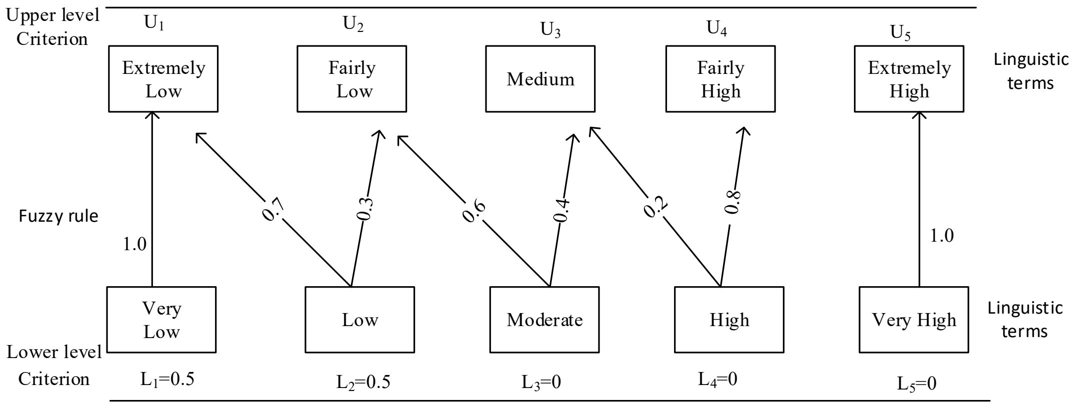
The following fuzzy rules are developed based on the expert judgements from FOREX risk to financial risk factors presented in Figure A2.12.

- If the FOREX risk is very low, then the financial risk factors impacting on the offshore wind farm development are 100% extremely low.

- If the FOREX risk is low, then the financial risk factors impacting on the offshore wind farm development are 30% fairly low, 70% extremely low.
- If the FOREX risk is moderate, then the financial risk factors impacting on the offshore wind farm development are 40% medium, 60% fairly low.
- If the FORE risk is high, then the financial risk factors impacting on the offshore wind farm development are 20% medium, 80% fairly high.
- If the FOREX risk is very high, then the financial risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_{FX} = \{(Very\,Low, 0.5), (Low, 0.5), (Moderate, 0), \ (High, 0), (Very\,High, 0)\}$$



FigureA2.12 Mapping accounting risk to financial risk factor

$$U_1 = \{(0), \ U_2 = (0), \ U_3 = (0.3 \times 0.1), \ (U_4 = (0.3. \times 0.9) + (0 \times 0.1), U_5(0.7 \times 1.0)\}$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{FXO} = \{(Extremely\,Low, 0.85), (Fairly\,Low, 0.15), (Medium, 0), \ (Fairly\,High, 0), (Extremely\,High, 0)\}$$

A.2.12 Inflation Risk

The following fuzzy rules are developed based on the expert judgements from inflation risk to financial risk factors presented in Figure A2.13.

- If the inflation risk is very low, then the financial risk factors impacting on the offshore wind farm development are100% extremely low.
- If the inflation risk is low, then the financial risk factors impacting on the offshore wind farm development are 60% fairly low, 40% medium.
- If the inflation risk is moderate, then the financial risk factors impacting on the offshore wind farm development are 40% medium, 60% fairly low.
- If the inflation risk is high, then the financial risk factors impacting on the offshore wind farm development are 20% fairly high, 80% extremely high.
- If the inflation risk is very high, then the financial risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_{INF} = \{(Very\ Low, 0), (Low, 0.4), (Moderate, 0.6), (High, 0), (Very\ High, 0)\}$$

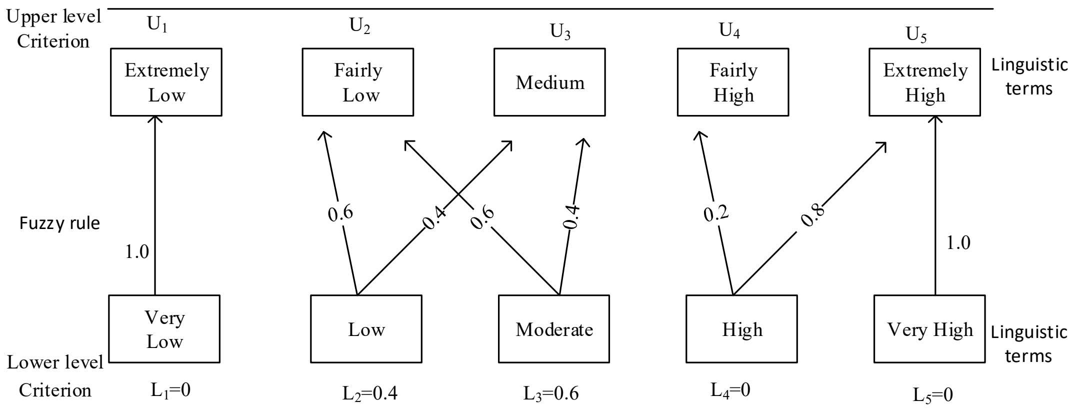


Figure A2.13 Mapping inflation risk to financial risk factor

$$U_1 = \{(0),\ U_2 = (0.4 \times 0.6) + (0.6 \times 0.6),\ U_3 = (0.4 \times 0.4) + (0.6 \times 0.4),\ U_4 = (0), U_5(0)\}$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{INO} = \{(Extremely\ Low, 0), (Fairly\ Low, 0.6), (Medium, 0.4), (Fairly\ High, 0), (Extremely\ High, 0)\}$$

Table A2.3 Aggregation of the sub-criteria with respect to financial risk factors

External Risk	Extremely Low	Fairly Low	Medium	Fairly High	Extremely High
$\widetilde{M}_{ACO}$	0.00	0.00	0.03	0.27	0.70
$\widetilde{M}_{FXO}$	0.85	0.15	0.00	0.00	0.00
$\widetilde{M}_{IFO}$	0	0.60	0.40	0.00	0.00
Result from Aggregation	0.2192	0.4747	0.2708	0.0098	0.0255

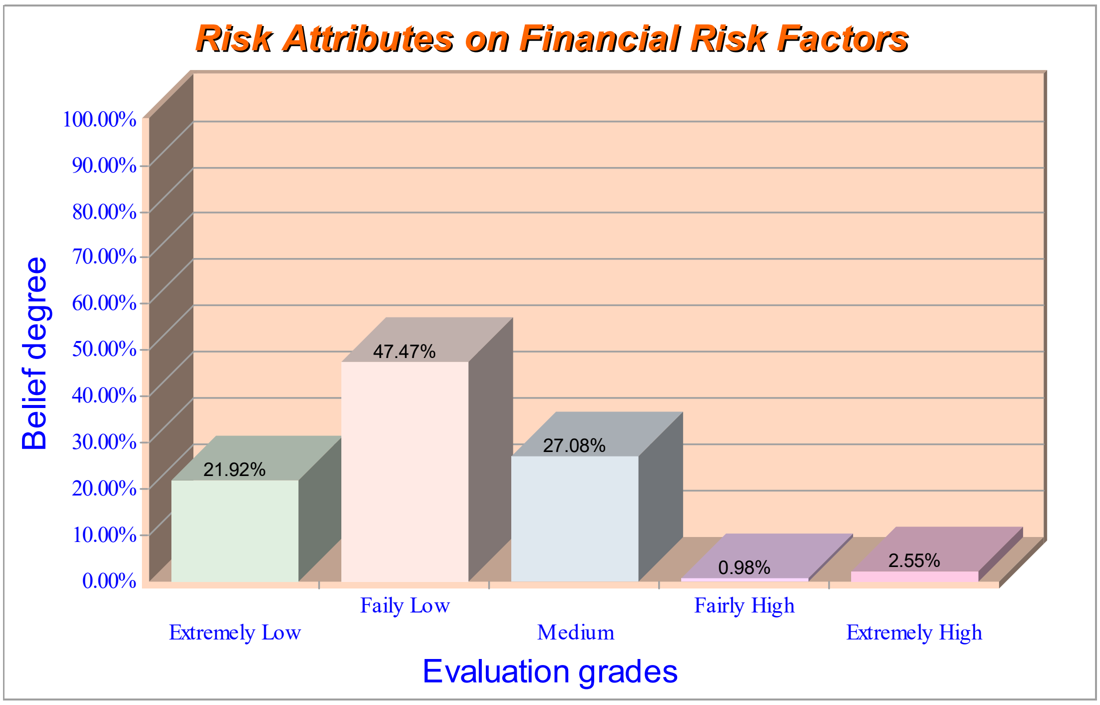


Figure A2.14 Financial risk factors aggregation result chart

A2.13 Mapping from Financial Risk Factors to the Goal

In order to evaluate the potential financial risk factors affecting the offshore wind farm development (OWFD), the financial risk factors will be transformed to the 'goal' using a mapping process.

The following fuzzy rules are developed based on the expert judgements from financial risk factors to goal (OWFW Risk) presented in Figure A2.15.

- If the financial risk factors are extremely low, then the risks impacting on the offshore wind farm development (OWFW) are 100% very low.
- If the financial risk factors are fairly low, then the risks impacting on the offshore wind farm development (OWFW) are 40% low, 60% very low.
- If the financial risk factors are medium, then the risks impacting on the offshore wind farm development (OWFW) are 20% high, 80% medium.
- If the financial risk factors are fairly high, then the risks impacting on the offshore wind farm development (OWFW) are 70% high, 30% very high.
- If the financial risk factors extremely high, then the risks impacting on the offshore wind farm development (OWFW) are 100% very high.

Based on the derived input values of the sub-criteria of engineering risk factors, the fussy set inputs are as follows:

$$\widetilde{M}_{FIN} = \{(Extremely\ High, 0.2192), (Fairly\ High, 0.4747), (Medium, 0.2708), (FairlyLow, 0.0098), (ExtremelyL\ ow, 0.0255)\}$$

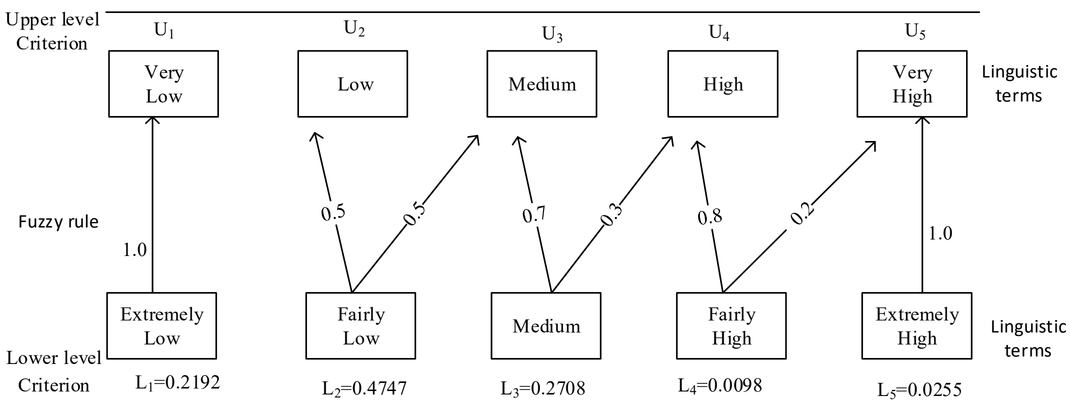


Figure A2.15 Mapping financial risk to the goal (OWFD risk)

$$U_1 = \{(0.2192 \times 1.0),\quad U_2 = (0.4747 \times 0.5),\quad U_3 = (0.4747 \times 0.5) + (0.2708 \times 0.7),$$
$$(U_4 = (0.2708 \times 0.3) + (0.0098 \times 0.8), U_5 (0.0098 \times 0.2) + (0.0255 \times 1.0)\}$$

$$U_1 = 0.2192,\qquad U_2 = 0.2374,\quad U_3 = 0.4269,\qquad U_4 = 0.0891,\qquad U_5 = 0.0255$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{FIO} = \{(VeryLow, 0.2192), (Low, 0.2374), (Medium, 0.4269), (High, 0.0891), (VeryHigh, 0.0255)\}$$

A2.14 Lack of Functional Procedure Risk

The following fuzzy rules are developed based on the expert judgements from lack of functional procedure risk to organisational risk factors presented in Figure A2.16.

- If the lack of functional procedure risk is very low, then the external risk factors impacting on the offshore wind farm development are100% extremely low.
- If the lack of functional procedure risk is low, then the external risk factors impacting on the offshore wind farm development are 50% fairly low, 50% extremely low.
- If the lack of functional procedure risk is moderate, then the external risk factors impacting on the offshore wind farm development are 40% medium, 60% fairly low.
- If the lack of functional procedure risk is high, then the external risk factors impacting on the offshore wind farm development are 70% fairly high, 30% medium.
- If the lack of functional procedure risk is very high, then the external risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_{LFP} = \{(Very\ Low, 0), (Low, 1.0), (Moderate, 0), (High, 0), (Very\ High, 0)\}$$

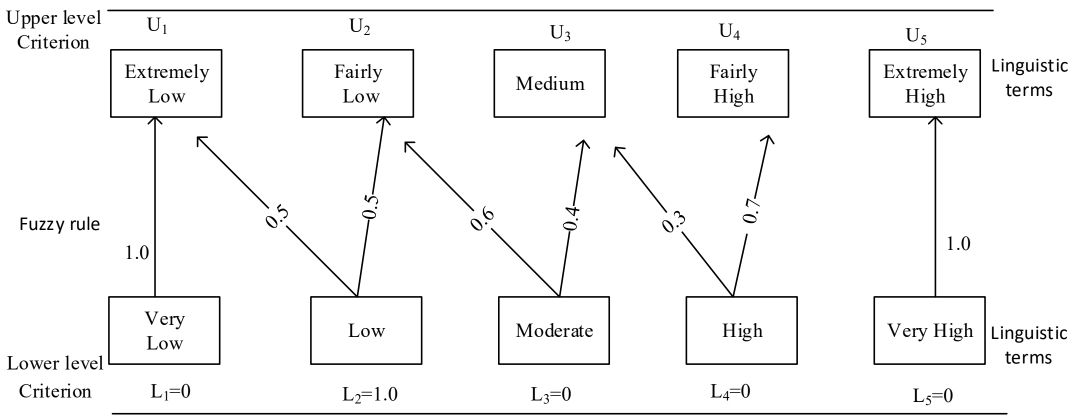


Figure A2.16 Mapping lack of functional procedure to organisational risk factor

$$U_1 = \{(0 \times 1.0) + (1.0 \times 0.5),\ U_2 = (1.0 \times 0.5) + (0 \times 0.6),\ U_3 = (0),\ U_4 = (0), U_5(0)\}$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{LFO} = \{(Extremely\ Low, 0.5), (Fairly\ Low, 0.5), (Medium, 0),\ (Fairly\ High, 0), (Extremely\ High, 0)\}$$

A2.15 Staff Unreliability Risk

The following fuzzy rules are developed based on the expert judgements from staff unreliability risk procedure risk to organisational risk factors presented in Figure A2.17.

- If the staff unreliability risk is very low, then the external risk factors impacting on the offshore wind farm development are 60% extremely low and 40% fairly low.
- If the staff unreliability risk is low, then the external risk factors impacting on the offshore wind farm development are 80% fairly low, 20% extremely low.
- If the staff unreliability risk is moderate, then the external risk factors impacting on the offshore wind farm development are 50% medium, 50% fairly low.
- If the staff unreliability risk is high, then the external risk factors impacting on the offshore wind farm development are 90% fairly high, 10% medium.
- If the staff unreliability risk is very high, then the external risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_{SU} = \{(Very\ Low, 0), (Low, 0.3), (Moderate, 0.7), (High, 0), (Very\ High, 0)\}$$

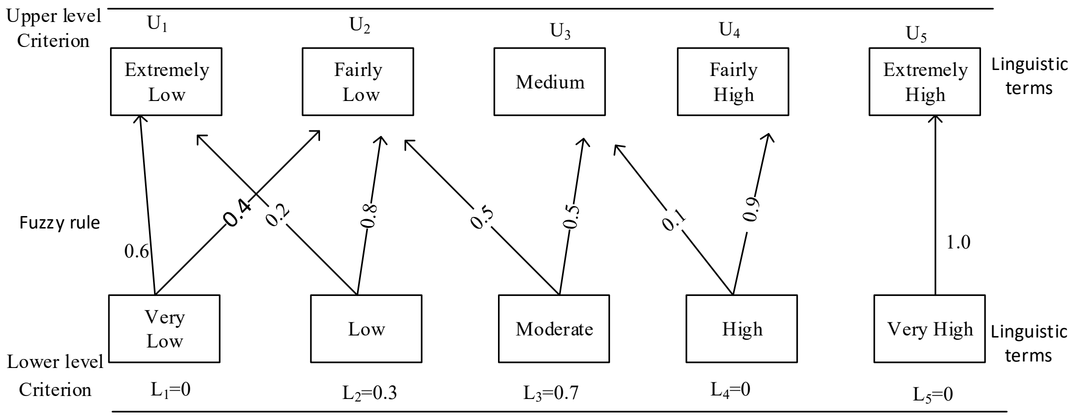


Figure A2.17 Mapping staff unreliability risk to organisational risk factor

$$U_1 = \{(0 \times 0.6) + (0.3 \times 0.2), U_2 = (0 \times 0.4) + (0.3 \times 0.8) + (0.7 \times 0.5), U_3 = (0.7 \times 0.5) + (0 \times 0.1), U_4 = (0), U_5(0)\}$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{SUO} = \{(Extremely Low, 0.06), (Fairly Low, 0.59), (Medium, 0.35), (Fairly High, 0), (Extremely High, 0)\}$$

A2.16 Lack of Communication/Coordination Risk

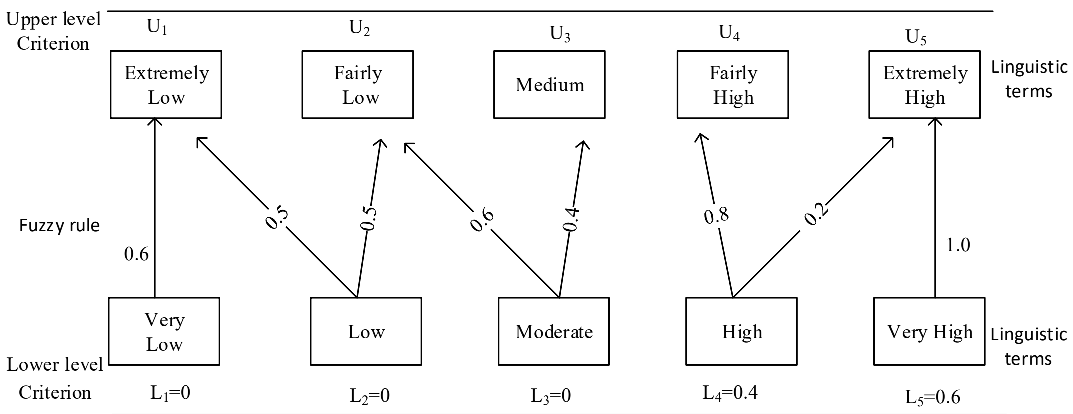
The following fuzzy rules are developed based on the expert judgements from lack of communication/coordination risk procedure risk to organisational risk factors presented in Figure A2.18.

- If the lack of communication/coordination risk is very low, then the external risk factors impacting on the offshore wind farm development are 100% extremely low.
- If the lack of communication/coordination risk is low, then the external risk factors impacting on the offshore wind farm development are 50% fairly low, 50% extremely low.

- If the lack of communication/coordination risk is moderate, then the external risk factors impacting on the offshore wind farm development are 40% medium, 60% fairly low.
- If the lack of communication/coordination risk is high, then the external risk factors impacting on the offshore wind farm development are 80% fairly high, 20% extremely high.
- If the lack of communication/coordination risk is very high, then the external risk factors impacting on the offshore wind farm development are 100% extremely high.

Based on the expert judgements, some input values are assigned to the fuzzy set input as follows:

$$\widetilde{M}_{LCC} = \{(Very\ Low, 0), (Low, 0), (Moderate, 0), \ (High, 0.4), (Very\ High, 0.6)\}$$



FigureA2.18 Mapping lack of communication/coordination risk to organisational risk factor

$$U_1 = \{(0 \times 0.6) + (0.3 \times 0.2), U_2 = (0 \times 0.4) + (0.3 \times 0.8) + (0.7 \times 0.5), U_3 = (0.7 \times 0.5) + (0 \times 0.1), U_4 = (0), U_5(0)\}$$

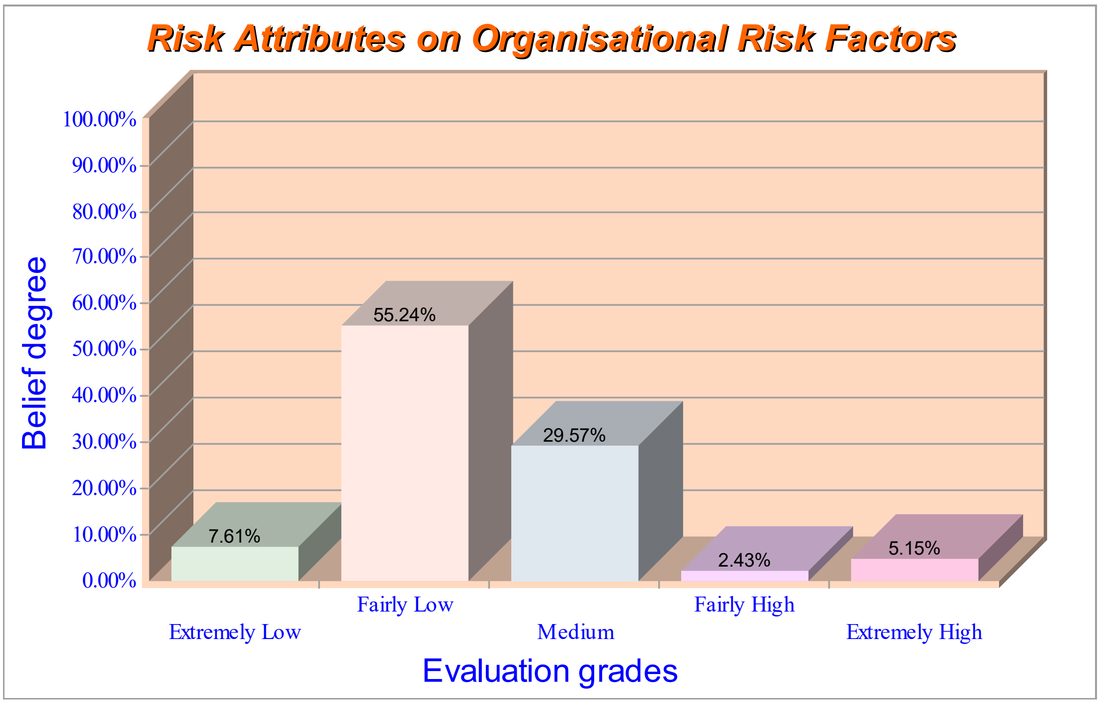
Therefore, the fuzzy set output will be:

$$\widetilde{M}_{LCO} = \{(ExtremelyLow, 0), (FairlyLow, 0), (Medium, 0), \ (FairlyHigh, 0.32), (ExtremelyHigh, 0.68)\}$$

Table A2.4 Aggregation of the sub-criteria with respect to organisational risk factors

External	Extremely	Fairly	Medium	Fairly	Extremely

Risk	Low	Low		High	High
$\widetilde{M}_{LFO}$	0.50	0.50	0.00	0.00	0.00
$\widetilde{M}_{SUO}$	0.06	0.59	0.35	0.00	0.00
$\widetilde{M}_{LCO}$	0.00	0.00	0.00	0.32	0.68
Result from Aggregation	0.0761	0.5524	0.2957	0.0243	0.0515



FigureA2.19 Organisational risk factors aggregation result chart

A2.17 Mapping from Organisational Risk Factors to the Goal

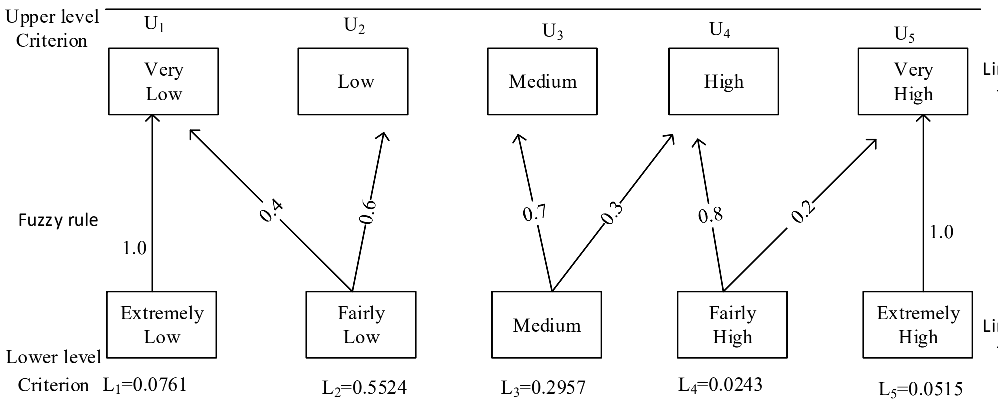
In order to evaluate the potential Organisational risk factors affecting the offshore wind farm development (OWFD), the Organisational risk factors will be transformed to the 'goal' using a mapping process.

The following fuzzy rules are developed based on the expert judgements from financial risk factors to goal (OWFW Risk) presented in Figure A2.20.

- If the Organisational risk factors are extremely low, then the risks impacting on the offshore wind farm development (OWFW) are 100% very low.
- If the Organisational risk factors are fairly low, then the risks impacting on the offshore wind farm development (OWFW) are 60% low, 40% very low.
- If the Organisational risk factors are medium, then the risks impacting on the offshore wind farm development (OWFW) are 30% high, 70% medium.
- If the Organisational risk factors are fairly high, then the risks impacting on the offshore wind farm development (OWFW) are 80% high, 20% very high.
- If the Organisational risk factors extremely high, then the risks impacting on the offshore wind farm development (OWFW) are 100% very high.

Based on the derived input values of the sub-criteria of engineering risk factors, the fussy set inputs are as follows:

$$\widetilde{M}_{ORG} = \{(Extremely\ High, 0.0761), (Fairly\ High, 0.5524), (Medium, 0.2957), (FairlyLow, 0.0243), (ExtremelyL\ ow, 0.0515)\}$$



FigureA2.20 Mapping organisational risk to the goal (OWFD Risk)

$$U_1 = \{(0.0761 \times 1.0) + (0.5524 \times 0.4),\ \ U_2 = (0.5524 \times 0.6),\ \ U_3 = (0.2957 \times 0.7),$$
$$(U_4 = (0.2957 \times 0.3) + (0.0243 \times 0.8), U_5 (0.0243 \times 0.2) + (0.0515 \times 1.0)\}$$

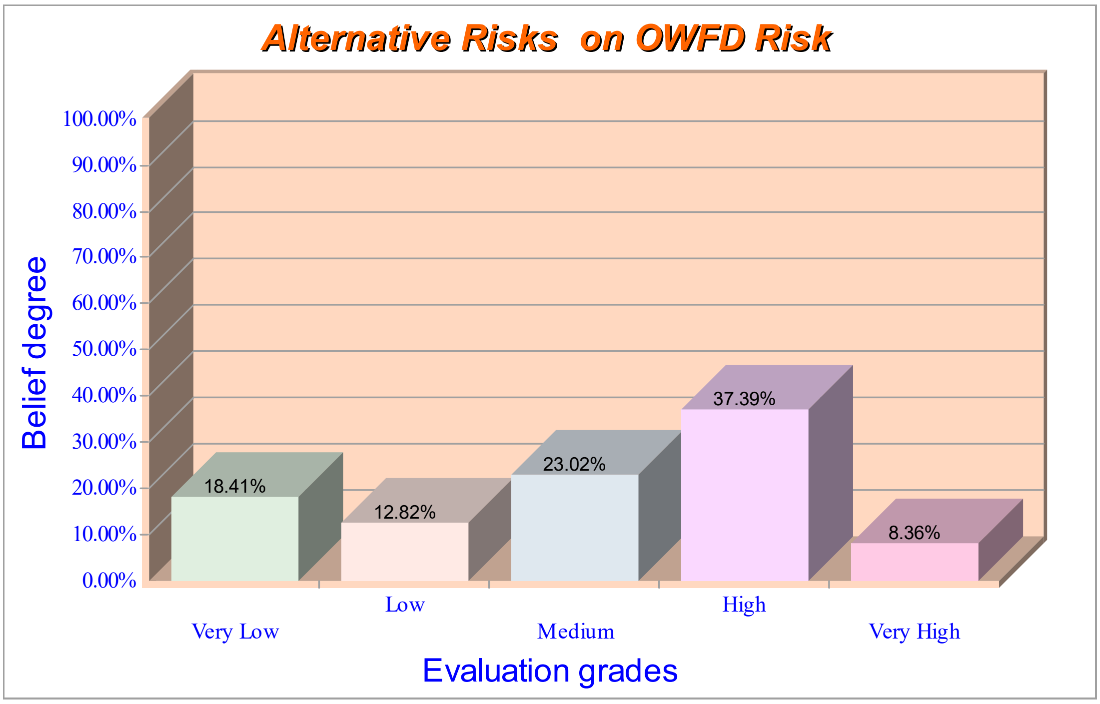
$$U_1 = 0.2971, \quad U_2 = 0.3314, \quad U_3 = 0.2069, \quad U_4 = 0.1082, \quad U_5 = 0.0564$$

Therefore, the fuzzy set output will be:

$$\widetilde{M}_{ORO} = \{(VeryLow, 0.2971), (Low, 0.3314), (Medium, 0.2069), (High, 0.1082), (VeryHigh, 0.0564)\}$$

A2.18 Mapping of the Main Risk Criteria to the Goal

This is achieved by computation of the weights of the main criteria as shown in Table 3.18 and the aggregated values in Table 3.30 into the IDS software.



FigureA2.21 Main risk criteria aggregation on OWFD

Appendix 2: Solution to Test Case of Chapter Four

A2.0 A Bayesian Network Approach to Offshore Wind Farm (OWF) Development Risk Analysis

Table A.21 Condition probability table (CPT) for C_2

	C_2 (Y)				C_2 (N)			
	C_{21}		C_{23}		C_{23}		C_{21}	
	C_{22}	C_{23}	C_{21}	C_{22}	C_{22}	C_{21}	C_{23}	C_{22}
Ω (L)	1	84.4	44.9	29.3	70.7	55.1	15.6	0
Ω (U)	0	15.6	55.1	70.7	29.3	44.9	84.4	1

In Table A2.1, Y denotes Yes and
N denotes No;
L and U denotes Likely and Unlikely respectively.

$$\Omega(L) = P(Engineering\ Risk\ Factors = likely \mid C21, C22, C23)$$

$$\Omega(\neg U) = P(Engineering\ Risk\ Factors = unlikely \mid C21, C22, C23)$$

Bayes Chain Rule proposes that the marginal probabilities of the likelihood of Engineering Risk Factors are mathematically represented as follows (Zhou *et al.*, 2011 and Riahi, 2010):

$$P(Engineering\ Risk\ Factors = likely) = 0.5$$

$$P(Engineering\ Risk\ Factors = unlikely) = 0.5$$

The above expression is based on the modelling principles of NETICA software, which describes the likelihood of input data as 50% and the unlikelihood as 50% based on symmetrical approach. The outcome of the output of the Engineering Risk Factor is either 'Yes' or 'No' and 'Likely' or 'Unlikely'. Hence, the probability of the occurrence remains 50% as supported by the experts and the input data on NETICA software. For example, if a person is uncertain about the existence and non-existence of a child's parents, he/she should remain uncertain about the existence and non-existence of their child. In order to effectively apply this modelling technique, it is important to first define the input variables (i.e. starting nodes) by using their probability distributions, which describe the current conditions of the system under investigation.

Table A2.2 Condition probability table (CPT) for C_1

	$C_1(Y)$		$C_1(N)$	
	C_{12}	C_{13}	C_{13}	C_{12}
Ω (L)	100	58.2	41.8	0
Ω (U)	0	41.8	58.2	100

Table A2.3 Condition probability table (CPT) for C_3

	$C_3(Y)$		$C_3(N)$	
	C_{32}	C_{33}	C_{32}	C_{33}
Ω (L)	100	66.1	33.9	0
Ω (U)	0	33.9	66.1	100

Table A2.4 Condition probability table (CPT) for C_4

	$C_4(Y)$		$C_4(N)$	
	C32	C33	C32	C33
Ω (L)	100	66.1	33.9	0
Ω (U)	0	33.9	66.1	100

Table A2.5 The effect of increasing and decreasing the target node (OWFD) input value to 100%

ORIGINAL VALUES (%)		100% NO & 0% YES WRT TARGET NODE (OWFD)		CHANGES DUE TO TARGET NODE (%)	0% NO & 100% YES WRT TARGET NODE (OWFD)		CHANGES DUE TO TARGET NODE (%)
C21		C21			C21		
Likely	29.3	Likely	34.8	5.5	Likely	24.1	-5.2
Unlikely	70.7	Unlikely	65.2	-5.5	Unlikely	75.9	5.2
C22		C22			C22		
Likely	55.1	Likely	67.5	12.4	Likely	43.4	-11.7
Unlikely	44.9	Unlikely	32.5	-12.4	Unlikely	56.6	11.7
C23		C23			C23		
Likely	15.6	Likely	17.5	1.9	Likely	13.8	-1.8
Unlikely	84.4	Unlikely	82.5	-1.9	Unlikely	86.2	1.8
C42		C42			C42		
Likely	66.1	Likely	70.7	4.6	Likely	61.7	-4.4
Unlikely	33.9	Unlikely	29.3	-4.6	Unlikely	38.3	4.4
C43		C43		0	C43		
Likely	33.9	Likely	36.3	2.4	Likely	31.7	-2.2
Unlikely	66.1	Unlikely	63.7	-2.4	Unlikely	68.3	2.2
C12		C12			C12		
Likely	58.2	Likely	63.5	5.3	Likely	53.3	-4.9
Unlikely	41.8	Unlikely	36.5	-5.3	Unlikely	46.7	4.9
C13		C13			C13		
Likely	41.8	Likely	45.6	3.8	Likely	38.2	-3.6
Unlikely	58.2	Unlikely	54.4	-3.8	Unlikely	61.8	3.6
C32		C32			C32		
Likely	66.1	Likely	73.1	7	Likely	59.6	-6.5
Unlikely	33.9	Unlikely	26.9	-7	Unlikely	40.4	6.5
C33		C33			C33		
Likely	33.9	Likely	37.5	3.6	Likely	30.5	-3.4
Unlikely	66.1	Unlikely	62.5	-3.6	Unlikely	69.5	3.4
C1		C1			C1		
Likely	51.3	Likely	60.6	9.3	Likely	42.6	-8.7
Unlikely	48.7	Unlikely	39.4	-9.3	Unlikely	57.4	8.7
C2		C2			C2		

Likely	41.4
Unlikely	58.6

Likely	63.5	22.1
Unlikely	36.5	-22.1

Likely	20.6	-20.8
Unlikely	79.4	20.8

C3	
Likely	55.2
Unlikely	44.8

C3		
Likely	66.8	11.6
Unlikely	33.2	-11.6

C3		
Likely	44.3	-10.9
Unlikely	55.7	10.9

C4	
Likely	55.2
Unlikely	44.8

C4		
Likely	62.9	7.7
Unlikely	37.1	-7.7

C4		
Likely	47.9	-7.3
Unlikely	52.1	7.3

Appendix 3: Solution to Test Case of Chapter Five

A3.0 Survey Questionnaire for Chapter Five

A3.1 Questionnaire for Determination of Scale of Linguistic Assessments

Introduction

The fundamental goal of this research study bothers on the selection of the most appropriate risk management technique for offshore wind farm development. The decision alternatives and evaluation criteria listed in Table 1 are the parameters that need to be considered and evaluated using "*fuzzy Linguistic variables scale*" techniques.

Table A3.1 List of decision alternatives and evaluation criteria

Decision Alternatives	Evaluation Criteria
Structured Brain Storming and evaluation (SBS) Probability-Impact Calculations (PIC) Informal Direct Assessment of risks (IDA) Checklists Method (CLM)	Reliability Operability Maintainability Availability Cost Safety

Reliability *may be described as the consistent measurement of the quality of performance of the system. It is the degree to which the outcome of a measurement and specification are depend dent upon to be accurate. In the context of offshore wind farm development, reliability is the ability of the wind farm systems to operate efficiently for a specific period of time under predetermined conditions (Patrick and O'Connor, 2002). Reliability is also known as dependability, which can be* *described as the probability of success in simple terms (Saleh et al., 2006).*

Operability *is the ability of equipment or a system to operate in safe and reliable conditions in accordance with the predetermined operational requirements. In other words, operability is achieved when the system has the capability to perform safely, efficiently and profitably under the predefined operational conditions (Lawley, 1974).*

Maintainability *is the ability of a system or plant to maintain or restore a functional state of quality performance under the predefined conditions, when maintenance is carried out in accordance with prescribed procedures and resources (Stapelberg, 2009).*

Availability *is the probability of a system to be available for use at a specified time (Stapelberg, 2009). It is a function of reliability and maintainability expressed as operating time divided by the time, which is the available time per day minus the planned downtime.*

Cost *is may be defined for accounting purpose as cash amount or the equivalent forfeited for an asset. Associated costs include all those costs necessary to have an asset in place and ready for use (Didkovskaya et al., 2016). This includes comprehensive breakdown of all costs to be incurred on a project. The process of such cost analysis may vary from one organisation to the other (Mamayeva, 2014). Costs are analysed in different forms such as the soft costs and hard costs. Soft cost is a construction industry term used to identify those costs that are not directly related to the construction activities. These include engineering costs, architectural costs, financing costs, legal fees, and costs of permits, insurance, taxes and other pre or post constructions* *expenditure (Didkovskaya et al., 2016). Hard costs are the tangible assets or expenses that are directly linked to the construction activities.*

Safety *in occupational health context is the act of protecting equipment and personnel against harm from physical, psychological, occupational activities, mechanical failure, accident, death, injury, or any such undesirable damage. It can also be described as a situation where there is positive control of known hazards in order to manage an acceptable degree of calculated risk such as a permissible exposure limit (Wang and Trbojevic, 2007),. Therefore, the plant or equipment must be designed, manufactured, constructed and operated for its intended purpose at all times by suitably qualified and experienced personnel who are trained to do so in order to minimise accidents and injuries caused due to neglect or misuse of the plant. A well designed and properly installed plant is likely to be easily maintained and as such will operate efficiently. An adequately maintained plant or system is less likely to breakdown or cause damage or harm (Collins et al., 2009). Besides, the efficiency and the overall life cycle of the system are improved.*

To proceed with the "*Fuzzy Linguistic variables scale*" technique, an expert needs to have a good knowledge of the linguistic variables and their corresponding trapezoidal fuzzy scales used for measurement in this study as represented in Tables 2. The Tables describe the numerical assessment together with the linguistic meaning of each variable.

Table A3.2 Fuzzy linguistic values of triangular FNs for alternatives (Alidoosti *et al,* 2012) and (Junior *et al*, 2014)

Linguistics term	Triangular FN
Very Low (VL)	(0.00, 0.00, 0.25)
Low (L)	(0.00, 0.25, 0.50)
Medium (M)	(0.25, 0.50, 0.75)
High (H)	(0.50, 0.75, 1.00)
Very High (VH)	(0.75, 1.00, 1.00)

With reference to Table A3.2, an expert is required to give a possible judgement to all question based on his/her experience and expertise in the renewable energy and most specifically the offshore wind farm development. The expert judgement process will be based on achieving the goal of each decision alternative with respect to the evaluation criteria. In order to do so, only one of the five linguistic variables is to be selected against each of the decision alternatives with respect to the evaluation criteria in the column as presented in Table A3.3.

Table A3.3 Example Expert Opinion Survey

	DECISION ALTERNATIVES			
EVALUATION CRITERIA (EC)	Structural Brain Storming and Evaluation (SBS)	Probability-Impact Calculations (PIC)	Informal Direct Assessment (IDA)	Checklist Method (CLM)
Reliability	VH			
Operability	H			
Maintainability	M			
Availability	L			
Cost	VL			
Safety	L			

A3.2 Explanation:

Linguistic assessment variable: VH = Very High, VL = Very Low, M = Medium, L = Low, H = High.

- From the second column, row 3; with (SBS), reliability of the offshore wind farm is considered to be Very High.
- From the second column, row 4; with (SBS), Operability of the offshore wind farm is considered to be High.

- From the second column, row 5; with (SBS), Maintainability of the offshore wind farm is considered to be Medium.
- From the second column, row 6; with (SBS), Availability of the offshore wind farm is considered to be Low.
- From the second column, row 7; with (SBS), associated Cost of the offshore wind farm is considered to be Very Low.
- From the second column, row 8; with (SBS), Safety of the offshore wind farm is considered to be Low.

A3.3 Questionnaire

"I have read the information sheet provided and I am happy to participate. I understand that by completing and returning this questionnaire I am consenting to be part of this research study and for my data to be used as described in the information sheet provided"

How to complete the questionnaire:

This questionnaire is divided into two sections A and B. Section A is using the fuzzy linguistic variables to determine decision alternation based on the evaluation criteria while Section B is about the expert's experiences and academic qualifications. Now, please complete the two sections of the questionnaire as instructed.

A3.3.1 Section A

Use the five linguistics variables VL, L, M, H, and VH to fill in the empty cells corresponding to each of the decision alternative and the evaluation criteria.

Table A3.4 Example expert opinion survey

DECISION ALTERNATIVES				
EVALUATION CRITERIA (EC)	Structural Brain Storming and Evaluation (SBS)	Probability-Impact Calculations (PIC)	Informal Direct Assessment (IDA)	Checklist Method (CLM)
Reliability				
Operability				
Maintainability				
Availability				
Cost				
Safety				

A3.3.2 Section B

Question 1

Choose from letter A-E, one that best describe your experience in the field of expertise (*please tick the appropriate box*).

(A) □ 1-5 years

(B) □ 6-10 years

(C) □ 11-25 years

(D) □ Over 25 years

(E) □ None of the above

Question 2

Please give your industry position and highest academic qualification in the appropriate box.

<u>Industry position</u>

<u>Highest academic qualification</u>

Appendix 4: A Test Case Illustrating Applicability of FAHP-FTOPSIS

A4.1 Evaluation of Decision Alternatives with respect to Corresponding Evaluation Criteria by Application of Linguistic Assessments

Table A4.1 Linguistic values of triangular FNs for alternatives (Alidoosti *et al.,* 2012) and (Junior *et al.,* 2014)

Linguistics term	Triangular FN
Very Low (VL)	(0.00, 0.00, 0.25)
Low (L)	(0.00, 0.25, 0.50)
Medium (M)	(0.25, 0.50, 0.75)
High (H)	(0.50, 0.75, 1.00)
Very High (VH)	(0.75, 1.00, 1.00)

Table A4.2 Evaluation criteria properties of the case study

Attributes	Type of assessment	Category of attribute	Judgement
Reliability	Linguistic term	Benefit	Subjective
Operability	Linguistic term	Benefit	Subjective
Maintainability	Linguistic term	Benefit	Subjective
Availability	Linguistic term	Cost	Subjective
Cost and	Linguistic term	Cost	Subjective
Safety	Linguistic term	Benefit	Subjective

Table A4.3 Decision alternatives and evaluation criteria

	Key	Description
Decision alternatives	AT1	Structured brainstorming and evaluation
	AT2	Probability-Impact calculations
	AT3	Informal direct assessment
	AT4	Checklists method
Evaluation Criteria	EC1	Reliability
	EC2	Operability
	EC3	Maintainability
	EC4	Availability
	EC5	Cost and
	EC6	Safety

Table A4.4 Linguistic assessment of the alternatives with respect to criteria completed by expert no.1

DM1				
EVALUATION CRITERIA (EC)	**SBS**	**PIC**	**IDA**	**CLM**
Reliability	VH	H	H	M
Operability	H	M	H	H
Maintainability	H	M	H	H
Availability	VH	M	M	M
Cost	H	L	M	VL
Safety	H	M	M	M

Table A4.5 Linguistic assessment of the alternatives with respect to criteria completed by expert no. 2

DM2				
EVALUATION CRITERIA (EC)	**SBS**	**PIC**	**IDA**	**CLM**
Reliability	VH	H	H	M
Operability	H	M	M	H
Maintainability	H	M	M	H
Availability	VH	H	H	L
Cost and	H	VL	M	M
Safety	H	H	H	M

Table A4.6 Linguistic assessment of the alternatives with respect to criteria completed by expert no. 3

No. 3 Expert				
EVALUATION CRITERIA (EC)	**SBS**	**PIC**	**IDA**	**CLM**
Reliability	H	VH	H	L
Operability	H	L	H	H
Maintainability	H	L	H	VH
Availability	H	H	H	L
Cost and	VH	H	L	VL
Safety	VH	H	H	L

Table A4.7 Fuzzy numbers for alternatives with respect to criteria completed by expert no. 1 (DM1)

DM1				
EC	**DA1**	**DA2**	**DA3**	**DA4**
EC1	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)
EC2	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
EC3	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
EC4	(0.75, 1.00, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)
EC5	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)	(0.25, 0.50, 0.75)	(0.00, 0.00, 0.25)
EC6	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)

Table A4.8 Fuzzy numbers for alternatives with respect to criteria completed by expert no. 2 (DM2)

DM2				
EC	**DA1**	**DA2**	**DA3**	**DA4**

EC1	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)
EC2	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)
EC3	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)
EC4	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)
EC5	(0.50, 0.75, 1.00)	(0.00, 0.00, 0.25)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)
EC6	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)

Table A4.9 Fuzzy numbers for alternatives with respect to criteria completed by expert no. 3 (DM3)

DM3				
EC	**DA1**	**DA2**	**DA3**	**DA4**
EC1	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)
EC2	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
EC3	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)
EC4	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)
EC5	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)	(0.00, 0.00, 0.25)
EC6	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.25, 0.50)

A4.2 Aggregation of Each Decision Alternatives with Respect to the Evaluation Criteria

Table A4.10 Aggregation computation for reliability with respect to SBS

Decision Maker (DM)	**Linguistic Assessment**	**FNs for alternatives**	**Answer**
DM1	VH	(0.75, 1.00, 1.00)	
DM2	VH	(0.75, 1.00, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)		$1-\frac{(0.75-0.75)+(1-1)+(1-1)}{3}$	1.000
S(DM1 & 3)		$1-\frac{(0.75-0.5)+(1-0.75)+(1-1)}{3}$	0.833
S(DM2 & 3)		$1-\frac{(0.75-0.5)+(1-0.75)+(1-1)}{3}$	0.833
AA(DM1)		$\frac{1+0.833}{2}$	0.917
AA(DM2)		$\frac{1+0.833}{2}$	0.917
AA(DM3)		$\frac{0.833+0.833}{2}$	0.833
RA(DM1)		$\frac{0.917}{0.917+0.917+0.833}$	0.344
RA(DM2)		$\frac{0.917}{0.917+0.917+0.833}$	0.344
RA(DM3)		$\frac{0.833}{0.917+0.917+0.833}$	0.312
AGGREGATED RESULT		$\widetilde{R}_{AGG}=0.344(0.75,1,1)+0.344(0.75,1,1)+0.312(0.5,0.75,1)$	
		$\widetilde{R}_{AGG}=0.344(0.75)+0.344(0.75)+0.312(0.5)$	0.672
		$\widetilde{R}_{AGG}=0.344(1)+0.344(1)+0.312(0.75)$	0.922
		$\widetilde{R}_{AGG}=0.344(1)+0.344(1)+0.312(1)$	1.000
		$\widetilde{R}_{AG}$	(0.672, 0.922, 1.000)

Table A4.11 Aggregation computation for operability with respect to SBS

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM2 & 3)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
AA(DM1)	$\frac{1+1}{2}$		1.000
AA(DM2)	$\frac{1+1}{2}$		1.000
AA(DM3)	$\frac{1+1}{2}$		1.000
RA(DM1)	$\frac{1}{1+1+1}$		0.333
RA(DM2)	$\frac{1}{1+1+1}$		0.333
RA(DM3)	$\frac{1}{1+1+1}$		0.333
AGGREGATED RESULT	$\tilde{R}_{AGG}=0.333(0.50,0.75,1.00)+0.333(0.50,0.75,1.00)+0.333(0.50,0.75,1.00)$		
	$\tilde{R}_{AGG}=0.333(0.5)+0.333(0.5)+0.333(0.5)$		0.500
	$\tilde{R}_{AGG}=0.333(0.75)+0.333(0.75)+0.333(0.75)$		0.749
	$\tilde{R}_{AGG}=0.333(1)+0.333(1)+0.333(1)$		0.999
		$\tilde{R}_{AG}$	(0.500, 0.749, 0.999)

Table A4.12 Aggregation computation for maintainability with respect to SBS

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM2 & 3)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
AA(DM1)	$\frac{1+1}{2}$		1.000
AA(DM2)	$\frac{1+1}{2}$		1.000
AA(DM3)	$\frac{1+1}{2}$		1.000
RA(DM1)	$\frac{1}{1+1+1}$		0.333
RA(DM2)	$\frac{1}{1+1+1}$		0.333
RA(DM3)	$\frac{1}{1+1+1}$		0.333
AGGREGATED RESULT	$\tilde{R}_{AGG}=0.333(0.50,0.75,1.00)+0.333(0.50,0.75,1.00)+0.333(0.50,0.75,1.00)$		
	$\tilde{R}_{AGG}=0.333(0.5)+0.333(0.5)+0.333(0.5)$		0.500
	$\tilde{R}_{AGG}=0.333(0.75)+0.333(0.75)+0.333(0.75)$		0.749
	$\tilde{R}_{AGG}=0.333(1)+0.333(1)+0.333(1)$		0.999
		$\tilde{R}_{AG}$	(0.500, 0.749, 0.999)

Table A4.13 Aggregation computation for availability with respect to SBS

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	VH	(0.75, 1.00, 1.00)	
DM2	VH	(0.75, 1.00, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.75-0.75)+(1-1)+(1-1)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.75-0.5)+(1-0.75)+(1-1)}{3}$		0.833
S(DM2 & 3)	$1-\frac{(0.75-0.5)+(1-0.75)+(1-1)}{3}$		0.833
AA(DM1)	$\frac{1+0.833}{2}$		0.917
AA(DM2)	$\frac{1+0.833}{2}$		0.917
AA(DM3)	$\frac{0.833+0.833}{2}$		0.833
RA(DM1)	$\frac{0.917}{0.917+0.917+0.833}$		0.344
RA(DM2)	$\frac{0.917}{0.917+0.917+0.833}$		0.344
RA(DM3)	$\frac{0.833}{0.917+0.917+0.833}$		0.312
AGGREGATED RESULT	$\widetilde{R}_{AGG}=0.344(0.75,1.00,1.00)+0.344(0.75,1.00,1.00)+0.312(0.5,0.75,1.00)$		
	$\widetilde{R}_{AGG}=0.344(0.75)+0.344(0.75)+0.312(0.5)$		0.672
	$\widetilde{R}_{AGG}=0.344(1)+0.344(1)+0.312(0.75)$		0.922
	$\widetilde{R}_{AGG}=0.344(1)+0.344(1)+0.312(1)$		1.000
		$\widetilde{R}_{AG}$	(0.672, 0.922, 1.000)

Table A4.14 Aggregation computation for cost with respect to SBS

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	VH	(0.75, 1.00, 1.00)	
S(DM1 & 2)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.50-0.75)+(0.75-1)+(1-1)}{3}$		1.167
S(DM2 & 3)	$1-\frac{(0.50-0.75)+(0.75-1)+(1-1)}{3}$		1.167
AA(DM1)	$\frac{1+1}{2}$		1.000
AA(DM2)	$\frac{1+1.167}{2}$		1.084
AA(DM3)	$\frac{1.167+1.167}{2}$		1.167
RA(DM1)	$\frac{1.000}{1.000+1.084+1.167}$		0.308
RA(DM2)	$\frac{1.084}{1.000+1.084+1.167}$		0.333
RA(DM3)	$\frac{1.167}{1.000+1.084+1.167}$		0.359
AGGREGATED RESULT	$\widetilde{R}_{AGG}=0.308(0.50,\ 0.75,\ 1.00)+0.333(0.50\ ,0.75,\ 1.00)+0.359(0.75\ ,1.00,\ 1.00)$		
	$\widetilde{R}_{AGG}=0.308(0.50)+0.333(0.50)+0.359(0.75)$		0.590
	$\widetilde{R}_{AGG}=0.308(0.75)+0.333(0.75)+0.359(1.00)$		0.840
	$\widetilde{R}_{AGG}=0.308(1.00)+0.333(1.00)+0.359(1.00)$		1.000
		$\widetilde{R}_{AG}$	(0.590, 0.840, 1.0000)

Table A4.15 Aggregation computation for safety with respect to SBS

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	VH	(0.75, 1.00, 1.00)	
S(DM1 & 2)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.50-0.75)+(0.75-1)+(1-1)}{3}$		1.167
S(DM2 & 3)	$1-\frac{(0.50-0.75)+(0.75-1)+(1-1)}{3}$		1.167
AA(DM1)	$\frac{1+1}{2}$		1.000
AA(DM2)	$\frac{1+1.167}{2}$		1.084
AA(DM3)	$\frac{1.167+1.167}{2}$		1.167
RA(DM1)	$\frac{1.000}{1.000+1.084+1.167}$		0.308
RA(DM2)	$\frac{1.084}{1.000+1.084+1.167}$		0.333
RA(DM3)	$\frac{1.167}{1.000+1.084+1.167}$		0.359
AGGREGATED RESULT	$\tilde{R}_{AGG}=0.308(0.50,0.75,1.00)+0.333(0.50,0.75,1.00)+0.359(0.75,1.00,1.00)$		
	$\tilde{R}_{AGG}=0.308(0.50)+0.333(0.50)+0.359(0.75)$		0.590
	$\tilde{R}_{AGG}=0.308(0.75)+0.333(0.75)+0.359(1.00)$		0.840
	$\tilde{R}_{AGG}=0.308(1.00)+0.333(1.00)+0.359(1.00)$		1.000
		$\tilde{R}_{AGG}$	(0.590, 0.840, 1.000)

Table A4.16 Aggregation computation for reliability with respect to PIC

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	VH	(0.75, 1.00, 1.00)	
S(DM1 & 2)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.50-0.75)+(0.75-1)+(1-1)}{3}$		1.167
S(DM2 & 3)	$1-\frac{(0.50-0.75)+(0.75-1)+(1-1)}{3}$		1.167
AA(DM1)	$\frac{1+1.167}{2}$		1.084
AA(DM2)	$\frac{1+1.167}{2}$		1.084
AA(DM3)	$\frac{1.167+1.167}{2}$		1.167
RA(DM1)	$\frac{1.084}{1.084+1.084+1.167}$		0.325
RA(DM2)	$\frac{1.084}{1.084+1.084+1.167}$		0.325
RA(DM3)	$\frac{1.167}{1.084+1.084+1.167}$		0.350
AGGREGATED RESULT	$\tilde{R}_{AGG}=0.325(0.50,0.75,1.00)+0.325(0.50,0.75,1.00)+0.350(0.75,1.00,1.00)$		
	$\tilde{R}_{AGG}=0.325(0.50)+0.325(0.50)+0.350(0.75)$		0.588
	$\tilde{R}_{AGG}=0.325(0.75)+0.325(0.75)+0.350(1.00)$		0.838
	$\tilde{R}_{AGG}=0.325(1.00)+0.325(1.00)+0.350(1.00)$		1.000
		$\tilde{R}_{AGG}$	(0.588, 0.838, 1.000)

Table A4.17 Aggregation computation for operability with respect to PIC

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	M	(0.25, 0.50, 0.75)	
DM3	L	(0.00, 0.25, 0.50)	
S(DM1 & 2)	$1-\frac{(0.25-0.25)+(0.50-0.50)+(0.75-0.75)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
S(DM2 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
AA(DM1)	$\frac{1.00+0.75}{2}$		0.875
AA(DM2)	$\frac{1.00+0.75}{2}$		0.875
AA(DM3)	$\frac{0.75+0.75}{2}$		0.750
RA(DM1)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM2)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM3)	$\frac{0.750}{0.875+0.875+0.750}$		0.300
AGGREGATED RESULT	$\tilde{R}_{AGG}=\tilde{R}_{AGG}=0.350(0.25, 0.50, 0.75)+0.350(0.25, 0.50, 0.75)+0.300(0.00, 0.25, 0.50)$		
	$\tilde{R}_{AGG}=0.350(0.25)+0.350(0.25)+0.300(0.00)$		0.175
	$\tilde{R}_{AGG}=0.350(0.50)+0.350(0.50)+0.300(0.25)$		0.425
	$\tilde{R}_{AGG}=0.350(0.75)+0.350(0.75)+0.300(0.50)$		0.675
		$\tilde{R}_{AGG}$	(0.175, 0.425, 0.675)

Table A4.18 Aggregation computation for maintainability with respect to PIC

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	M	(0.25, 0.50, 0.75)	
DM3	L	(0.00, 0.25, 0.50)	
S(DM1 & 2)	$1-\frac{(0.25-0.25)+(0.50-0.50)+(0.75-0.75)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
S(DM2 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
AA(DM1)	$\frac{1.00+0.75}{2}$		0.875
AA(DM2)	$\frac{1.00+0.75}{2}$		0.875
AA(DM3)	$\frac{0.75+0.75}{2}$		0.750
RA(DM1)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM2)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM3)	$\frac{0.750}{0.875+0.875+0.750}$		0.300
AGGREGATED RESULT	$\tilde{R}_{AGG}=\tilde{R}_{AGG}=0.350(0.25, 0.50, 0.75)+0.350(0.25, 0.50, 0.75)+0.300(0.00, 0.25, 0.50)$		
	$\tilde{R}_{AGG}=0.350(0.25)+0.350(0.25)+0.300(0.00)$		0.175
	$\tilde{R}_{AGG}=0.350(0.50)+0.350(0.50)+0.300(0.25)$		0.425
	$\tilde{R}_{AGG}=0.350(0.75)+0.350(0.75)+0.300(0.50)$		0.675
		$\tilde{R}_{AGG}$	(0.175, 0.425, 0.675)

Table A4.19 Aggregation computation for availability with respect to PIC

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.25-0.50)+(0.50-0.75)+(0.75-1.00)}{3}$		1.250
S(DM1 & 3)	$1-\frac{(0.25-0.50)+(0.50-0.75)+(0.75-1.00)}{3}$		1.250
S(DM2 & 3)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1.00-1.00)}{3}$		1.000
AA(DM1)	$\frac{1.250 + 1.250}{2}$		1.250
AA(DM2)	$\frac{1.250 + 1.00}{2}$		1.125
AA(DM3)	$\frac{1.250 + 1.00}{2}$		1.125
RA(DM1)	$\frac{1.250}{1.250 + 1.125 + 1.125}$		0.357
RA(DM2)	$\frac{1.125}{1.250 + 1.125 + 1.125}$		0.321
RA(DM3)	$\frac{1.125}{1.250 + 1.125 + 1.125}$		0.321
AGGREGATED RESULT	$\tilde{R}_{AGG} = 0.357\,(0.25,\ 0.50,\ 0.75) + 0.321(0.50\ ,0.75,\ 1.00) + 0.312(0.5,\ 0.75,\ 1.00)$		
	$\tilde{R}_{AGG} = 0.357\,(0.25) + 0.321\,(0.50) + 0.321\,(0.5)$		0.410
	$\tilde{R}_{AGG} = 0.357\,(0.50) + 0.321\,(0.75) + 0.321\,(0.75)$		0.660
	$\tilde{R}_{AGG} = 0.357\,(0.75) + 0.321\,(1.00) + 0.321\,(1.00)$		0.910
		$\tilde{R}_{AGG}$	(0.410, 0.660, 0.910)

Table A4.20 Aggregation computation for cost with respect to PIC

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	L	(0.00, 0.25, 0.50)	
DM2	VL	(0.00, 0.00, 0.25)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.00-0.00)+(0.25-0.00)+(0.50-0.25)}{3}$		0.833
S(DM1 & 3)	$1-\frac{(0.00-0.00)+(0.25-0.75)+(0.50-1.0)}{3}$		1.333
S(DM2 & 3)	$1-\frac{(0.00-0.50)+(0.00-0.75)+(0.25-1.00)}{3}$		1.667
AA(DM1)	$\frac{0.833 + 1.333}{2}$		1.083
AA(DM2)	$\frac{0.833 + 1.667}{2}$		1.250
AA(DM3)	$\frac{1.333 + 1.1667}{2}$		1.500
RA(DM1)	$\frac{1.083}{1.083 + 1.250 + 1.500}$		0.283
RA(DM2)	$\frac{1.250}{1.083 + 1.250 + 1.500}$		0.326
RA(DM3)	$\frac{1.500}{1.083 + 1.250 + 1.500}$		0.391
AGGREGATED RESULT	$\tilde{R}_{AGG} = 0.283\,(0.00,\ 0.25,\ 0.50) + 0.326(0.00\ ,0.00,\ 0.25) + 0.391(0.50\ ,0.75,\ 1.00)$		
	$\tilde{R}_{AGG} = 0.283\,(0.00) + 0.326\,(0.00) + 0.391\,(0.50)$		0.196
	$\tilde{R}_{AGG} = 0.283\,(0.25) + 0.326\,(0.00) + 0.391\,(0.75)$		0.364
	$\tilde{R}_{AGG} = 0.283\,(0.50) + 0.326\,(0.25) + 0.391\,(1.00)$		0.614
		$\tilde{R}_{AGG}$	(0.196, 0.364, 0.614)

Table A4.21 Aggregation computation for safety with respect to PIC

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.25-0.50)+(0.50-0.75)+(0.75-1.00)}{3}$		1.250
S(DM1 & 3)	$1-\frac{(0.25-0.50)+(0.50-0.75)+(0.75-1.00)}{3}$		1.250
S(DM2 & 3)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1.00-1.00)}{3}$		1.000
AA(DM1)	$\frac{1.250+1.250}{2}$		1.250
AA(DM2)	$\frac{1.250+1.00}{2}$		1.125
AA(DM3)	$\frac{1.250+1.00}{2}$		1.125
RA(DM1)	$\frac{1.250}{1.250+1.125+1.125}$		0.357
RA(DM2)	$\frac{1.125}{1.250+1.125+1.125}$		0.321
RA(DM3)	$\frac{1.125}{1.250+1.125+1.125}$		0.321
AGGREGATED RESULT	$\widetilde{R}_{AGG} = 0.357\,(0.25, 0.50, 0.75) + 0.321(0.50, 0.75, 1.00) + 0.312(0.5, 0.75, 1.00)$		
	$\widetilde{R}_{AGG} = 0.357\,(0.25) + 0.321\,(0.50) + 0.321\,(0.5)$		0.410
	$\widetilde{R}_{AGG} = 0.357\,(0.50) + 0.321\,(0.75) + 0.321\,(0.75)$		0.660
	$\widetilde{R}_{AGG} = 0.357\,(0.75) + 0.321\,(1.00) + 0.321\,(1.00)$		0.910
		$\widetilde{R}_{AGG}$	(0.410, 0.660, 0.910)

Table A4.22 Aggregation computation for reliability with respect to IDA

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM2 & 3)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
AA(DM1)	$\frac{1+1}{2}$		1.000
AA(DM2)	$\frac{1+1}{2}$		1.000
AA(DM3)	$\frac{1+1}{2}$		1.000
RA(DM1)	$\frac{1}{1+1+1}$		0.333
RA(DM2)	$\frac{1}{1+1+1}$		0.333
RA(DM3)	$\frac{1}{1+1+1}$		0.333
AGGREGATED RESULT	$\widetilde{R}_{AGG} = 0.333(0.50, 0.75, 1.00) + 0.333(0.50, 0.75, 1.00) + 0.333(0.50, 0.75, 1.00)$		
	$\widetilde{R}_{AGG} = 0.333\,(0.5) + 0.333\,(0.5) + 0.333\,(0.5)$		0.500
	$\widetilde{R}_{AGG} = 0.333\,(0.75) + 0.333\,(0.75) + 0.333\,(0.75)$		0.749
	$\widetilde{R}_{AGG} = 0.333\,(1) + 0.333\,(1) + 0.333\,(1)$		0.999
		$\widetilde{R}_{AG}$	(0.500, 0.749, 0.999)

Table A4.23 Aggregation computation for operability with respect to IDA

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	M	(0.25, 0.50, 0.75)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.50-0.25)+(0.75-0.50)+(1.00-0.75)}{3}$		0.750
S(DM1 & 3)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1.00-1.00)}{3}$		1.000
S(DM2 & 3)	$1-\frac{(0.25-0.50)+(0.50-0.75)+(0.75-1.00)}{3}$		1.250
AA(DM1)	$\frac{0.750+1.000}{2}$		0.875
AA(DM2)	$\frac{0.750+1.250}{2}$		1.000
AA(DM3)	$\frac{1.000+1.250}{2}$		1.125
RA(DM1)	$\frac{0.875}{0.875+1.000+1.125}$		0.292
RA(DM2)	$\frac{1.000}{0.875+1.000+1.125}$		0.333
RA(DM3)	$\frac{1.125}{0.875+1.000+1.125}$		0.375
AGGREGATED RESULT	$\widetilde{R}_{AGG} = 0.292(0.50,\ 0.75,\ 1.00) + 0.333(0.25\ ,\ 0.50,\ 0.750) + 0.375(0.50\ ,\ 0.75,\ 1.00)$		
	$\widetilde{R}_{AGG} = 0.292(0.50) + 0.333(0.25) + 0.375(0.50)$		0.417
	$\widetilde{R}_{AGG} = 0.292(0.75) + 0.333(0.50) + 0.375(0.75)$		0.667
	$\widetilde{R}_{AGG} = 0.292(1.00) + 0.333(0.75) + 0.375(1.00)$		0.917
		$\widetilde{R}_{AGG}$	(0.417, 0.667, 0.917)

Table A4.24 Aggregation computation for maintainability with respect to IDA

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	M	(0.25, 0.50, 0.75)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.50-0.25)+(0.75-0.50)+(1.00-0.75)}{3}$		0.750
S(DM1 & 3)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1.00-1.00)}{3}$		1.000
S(DM2 & 3)	$1-\frac{(0.25-0.50)+(0.50-0.75)+(0.75-1.00)}{3}$		1.250
AA(DM1)	$\frac{0.75+1.00}{2}$		0.875
AA(DM2)	$\frac{0.75+1.250}{2}$		1.000
AA(DM3)	$\frac{1.00+1.250}{2}$		1.125
RA(DM1)	$\frac{0.875}{0.875+1.000+1.125}$		0.292
RA(DM2)	$\frac{1.000}{0.875+1.000+1.125}$		0.333
RA(DM3)	$\frac{1.125}{0.875+1.000+1.125}$		0.375
AGGREGATED RESULT	$\widetilde{R}_{AGG} = \widetilde{R}_{AGG} = 0.292(0.50,\ 0.75,\ 1.00) + 0.333(0.25\ ,\ 0.50,\ 0.75) + 0.300(0.50\ ,\ 0.75,\ 1.00)$		
	$\widetilde{R}_{AGG} = 0.292(0.50) + 0.333(0.25) + 0.375(0.50)$		0.417
	$\widetilde{R}_{AGG} = 0.292(0.75) + 0.333(0.50) + 0.375(0.75)$		0.667
	$\widetilde{R}_{AGG} = 0.292(1) + 0.333(0.75) + 0.375(1)$		0.917
		$\widetilde{R}_{AGG}$	(0.417, 0.667, 0.917)

Table A4.25 Aggregation computation for availability with respect to IDA

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.25-0.50)+(0.50-0.75)+(0.75-1.00)}{3}$		1.250
S(DM1 & 3)	$1-\frac{(0.25-0.50)+(0.50-0.75)+(0.75-1.00)}{3}$		1.250
S(DM2 & 3)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1.00-1.00)}{3}$		1.000
AA(DM1)	$\frac{1.250+1.250}{2}$		1.250
AA(DM2)	$\frac{1.250+1.00}{2}$		1.125
AA(DM3)	$\frac{1.250+1.00}{2}$		1.125
RA(DM1)	$\frac{1.250}{1.250+1.125+1.125}$		0.357
RA(DM2)	$\frac{1.125}{1.250+1.125+1.125}$		0.321
RA(DM3)	$\frac{1.125}{1.250+1.125+1.125}$		0.321
AGGREGATED RESULT	$\tilde{R}_{AGG} = 0.357\,(0.25,\ 0.50,\ 0.75) + 0.321(0.50\ ,\ 0.75,\ 1.00) + 0.312(0.5,\ 0.75,\ 1.00)$		
	$\tilde{R}_{AGG} = 0.357\,(0.25) + 0.321\,(0.50) + 0.321\,(0.5)$		0.410
	$\tilde{R}_{AGG} = 0.357\,(0.50) + 0.321\,(0.75) + 0.321\,(0.75)$		0.660
	$\tilde{R}_{AGG} = 0.357\,(0.75) + 0.321\,(1.00) + 0.321\,(1.00)$		0.910
		$\tilde{R}_{AGG}$	(0.410, 0.660, 0.910)

Table A4.26 Aggregation computation for cost with respect to IDA

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	M	(0.25, 0.50, 0.75)	
DM3	L	(0.00, 0.25, 0.50)	
S(DM1 & 2)	$1-\frac{(0.25-0.25)+(0.50-0.50)+(0.75-0.75)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
S(DM2 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
AA(DM1)	$\frac{1.00+0.75}{2}$		0.875
AA(DM2)	$\frac{1.00+0.75}{2}$		0.875
AA(DM3)	$\frac{0.75+0.75}{2}$		0.750
RA(DM1)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM2)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM3)	$\frac{0.750}{0.875+0.875+0.750}$		0.300
AGGREGATED RESULT	$\tilde{R}_{AGG} = \tilde{R}_{AGG} = 0.350(0.25, 0.50, 0.75) + 0.350(0.25, 0.50, 0.75) + 0.300(0.00, 0.25, 0.50)$		
	$\tilde{R}_{AGG} = 0.350\,(0.25) + 0.350\,(0.25) + 0.300\,(0.00)$		0.175
	$\tilde{R}_{AGG} = 0.350\,(0.50) + 0.350\,(0.50) + 0.300\,(0.25)$		0.425
	$\tilde{R}_{AGG} = 0.350\,(0.75) + 0.350\,(0.75) + 0.300\,(0.50)$		0.675
		$\tilde{R}_{AGG}$	(0.175, 0.425, 0.675)

Table A4.27 Aggregation computation for safety with respect to SBS

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)			1.250
S(DM1 & 3)	$1-\frac{(0.25-0.50)+(0.50-0.75)+(0.75-1.00)}{3}$		1.250
S(DM2 & 3)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1.00-1.00)}{3}$		1.000
AA(DM1)	$\frac{1.250+1.250}{2}$		1.250
AA(DM2)	$\frac{1.250+1.00}{2}$		1.125
AA(DM3)	$\frac{1.250+1.00}{2}$		1.125
RA(DM1)	$\frac{1.250}{1.250+1.125+1.125}$		0.357
RA(DM2)	$\frac{1.125}{1.250+1.125+1.125}$		0.321
RA(DM3)	$\frac{1.125}{1.250+1.125+1.125}$		0.321
AGGREGATED RESULT	$\tilde{R}_{AGG} = 0.357(0.25, 0.50, 0.75) + 0.321(0.50, 0.75, 1.00) + 0.312(0.5, 0.75, 1.00)$		
	$\tilde{R}_{AGG} = 0.357(0.25) + 0.321(0.50) + 0.321(0.5)$		0.410
	$\tilde{R}_{AGG} = 0.357(0.50) + 0.321(0.75) + 0.321(0.75)$		0.660
	$\tilde{R}_{AGG} = 0.357(0.75) + 0.321(1.00) + 0.321(1.00)$		0.910
		$\tilde{R}_{AGG}$	(0.410, 0.660, 0.910)

Table A4.28 Aggregation computation for reliability with respect to CLM

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	M	(0.25, 0.50, 0.75)	
DM3	L	(0.00, 0.25, 0.50)	
S(DM1 & 2)	$1-\frac{(0.25-0.25)+(0.50-0.50)+(0.75-0.75)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
S(DM2 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		1.167
AA(DM1)	$\frac{1.00+0.75}{2}$		0.875
AA(DM2)	$\frac{1.00+0.75}{2}$		0.875
AA(DM3)	$\frac{0.75+0.75}{2}$		0.750
RA(DM1)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM2)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM3)	$\frac{0.750}{0.875+0.875+0.750}$		0.300
AGGREGATED RESULT	$\tilde{R}_{AGG} = \tilde{R}_{AGG} = 0.350(0.25, 0.50, 0.75) + 0.350(0.25, 0.50, 0.75) + 0.300(0.00, 0.25, 0.50)$		
	$\tilde{R}_{AGG} = 0.350(0.25) + 0.350(0.25) + 0.300(0.00)$		0.175
	$\tilde{R}_{AGG} = 0.350(0.50) + 0.350(0.50) + 0.300(0.25)$		0.425
	$\tilde{R}_{AGG} = 0.350(0.75) + 0.350(0.75) + 0.300(0.50)$		0.675
		$\tilde{R}_{AGG}$	(0.175, 0.425, 0.675)

Table A4.29 Aggregation computation for operability with respect to CLM

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	H	(0.50, 0.75, 1.00)	
S(DM1 & 2)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM2 & 3)	$1-\frac{(0.5-0.5)+(0.75-0.75)+(1-1)}{3}$		1.000
AA(DM1)	$\frac{1+1}{2}$		1.000
AA(DM2)	$\frac{1+1}{2}$		1.000
AA(DM3)	$\frac{1+1}{2}$		1.000
RA(DM1)	$\frac{1}{1+1+1}$		0.333
RA(DM2)	$\frac{1}{1+1+1}$		0.333
RA(DM3)	$\frac{1}{1+1+1}$		0.333
AGGREGATED RESULT	$\widetilde{R}_{AGG}=0.333(0.50, 0.75, 1.00)+0.333(0.50, 0.75, 1.00)+0.333(0.50, 0.75, 1.00)$		
	$\widetilde{R}_{AGG}=0.333(0.5)+0.333(0.5)+0.333(0.5)$		0.500
	$\widetilde{R}_{AGG}=0.333(0.75)+0.333(0.75)+0.333(0.75)$		0.749
	$\widetilde{R}_{AGG}=0.333(1)+0.333(1)+0.333(1)$		0.999
		$\widetilde{R}_{AGG}$	(0.500, 0.749, 0.999)

Table A4.30 Aggregation computation for maintainability with respect to CLM

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	H	(0.50, 0.75, 1.00)	
DM2	H	(0.50, 0.75, 1.00)	
DM3	VH	(0.75, 1.00, 1.00)	
S(DM1 & 2)	$1-\frac{(0.50-0.50)+(0.75-0.75)+(1-1)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.50-0.75)+(0.75-1)+(1-1)}{3}$		1.167
S(DM2 & 3)	$1-\frac{(0.50-0.75)+(0.75-1)+(1-1)}{3}$		1.167
AA(DM1)	$\frac{1+1}{2}$		1.000
AA(DM2)	$\frac{1+1.167}{2}$		1.084
AA(DM3)	$\frac{1.167+1.167}{2}$		1.167
RA(DM1)	$\frac{1.000}{1.000+1.084+1.167}$		0.308
RA(DM2)	$\frac{1.084}{1.000+1.084+1.167}$		0.333
RA(DM3)	$\frac{1.167}{1.000+1.084+1.167}$		0.359
AGGREGATED RESULT	$\widetilde{R}_{AGG}=0.308(0.50, 0.75, 1.00)+0.333(0.50, 0.75, 1.00)+0.359(0.75, 1.00, 1.00)$		
	$\widetilde{R}_{AGG}=0.308(0.50)+0.333(0.50)+0.359(0.75)$		0.590
	$\widetilde{R}_{AGG}=0.308(0.75)+0.333(0.75)+0.359(1.00)$		0.840
	$\widetilde{R}_{AGG}=0.308(1.00)+0.333(1.00)+0.359(1.00)$		1.000
		$\widetilde{R}_{AGG}$	(0.590, 0.840, 1.0000)

Table A4.31 Aggregation computation for availability with respect to CLM

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	L	(0.00, 0.25, 0.50)	
DM3	L	(0.00, 0.25, 0.50)	
S(DM1 & 2)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
S(DM1 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
S(DM2 & 3)	$1-\frac{(0.00-0.00)+(0.25-0.25)+(0.50-0.50)}{3}$		1.000
AA(DM1)	$\frac{0.75+0.75}{2}$		0.750
AA(DM2)	$\frac{0.75+1.00}{2}$		0.875
AA(DM3)	$\frac{0.75+1.00}{2}$		0.875
RA(DM1)	$\frac{0.750}{0.750+0.875+0.875}$		0.300
RA(DM2)	$\frac{0.875}{0.750+0.875+0.875}$		0.350
RA(DM3)	$\frac{0.875}{0.750+0.875+0.875}$		0.350
AGGREGATED RESULT	$\tilde{R}_{AGG}=0.300(0.25,\ 0.50,\ 0.75)+0.350(0.00,\ 0.25,\ 0.50)+0.350(0.00,\ 0.25,\ 0.50)$		
	$\tilde{R}_{AGG}=0.300(0.25)+0.350(0.00)+0.350(0.00)$		0.075
	$\tilde{R}_{AGG}=0.300(0.50)+0.350(0.25)+0.350(0.25)$		0.325
	$\tilde{R}_{AGG}=0.300(0.75)+0.350(0.50)+0.350(0.50)$		0.575
		$\tilde{R}_{AGG}$	(0.075, 0.325, 0.575)

Table A4.32 Aggregation computation for cost with respect to CLM

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	VL	(0.00, 0.00, 0.25)	
DM2	M	(0.25, 0.50, 0.75)	
DM3	VL	(0.00, 0.00, 0.25)	
S(DM1 & 2)	$1-\frac{(0.00-0.25)+(0.00-0.50)+(0.25-0.75)}{3}$		1.417
S(DM1 & 3)	$1-\frac{(0.00-0.00)+(0.00-0.00)+(0.25-0.25)}{3}$		1.000
S(DM2 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.00)+(0.75-0.25)}{3}$		0.583
AA(DM1)	$\frac{1.417+1.000}{2}$		1.209
AA(DM2)	$\frac{1.417+0.583}{2}$		1.000
AA(DM3)	$\frac{1.00+0.583}{2}$		0.792
RA(DM1)	$\frac{1.209}{1.209+1.000+0.792}$		0.403
RA(DM2)	$\frac{1.000}{1.209+1.000+0.792}$		0.333
RA(DM3)	$\frac{0.792}{1.209+1.000+0.792}$		0.264
AGGREGATED RESULT	$\tilde{R}_{AGG}=0.403(0.00,\ 0.00,\ 0.25)+0.333(0.25,\ 0.50,\ 0.75)+0.264(0.00,\ 0.00,\ 0.25)$		
	$\tilde{R}_{AGG}=0.403(0.00)+0.333(0.25)+0.264(0.00)$		0.083
	$\tilde{R}_{AGG}=0.403(0.00)+0.333(0.50)+0.264(0.00)$		0.167
	$\tilde{R}_{AGG}=0.403(0.25)+0.333(0.75)+0.264(0.25)$		0.417
		$\tilde{R}_{AGG}$	(0.083,0.167,0.417)

Table A4.33 Aggregation computation for safety with respect to CLM

Decision Maker (DM)	Linguistic Assessment	FNs for alternatives	Answer
DM1	M	(0.25, 0.50, 0.75)	
DM2	M	(0.25, 0.50, 0.75)	
DM3	L	(0.00, 0.25, 0.50)	
S(DM1 & 2)	$1-\frac{(0.25-0.25)+(0.50-0.50)+(0.75-0.75)}{3}$		1.000
S(DM1 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		0.750
S(DM2 & 3)	$1-\frac{(0.25-0.00)+(0.50-0.25)+(0.75-0.50)}{3}$		1.167
AA(DM1)	$\frac{1.00+0.75}{2}$		0.875
AA(DM2)	$\frac{1.00+0.75}{2}$		0.875
AA(DM3)	$\frac{0.75+0.75}{2}$		0.750
RA(DM1)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM2)	$\frac{0.875}{0.875+0.875+0.750}$		0.350
RA(DM3)	$\frac{0.750}{0.875+0.875+0.750}$		0.300
AGGREGATED RESULT	$\widetilde{R}_{AGG} = \widetilde{R}_{AGG} = 0.350(0.25, 0.50, 0.75) + 0.350(0.25, 0.50, 0.75) + 0.300(0.00, 0.25, 0.50)$		
	$\widetilde{R}_{AGG} = 0.350(0.25) + 0.350(0.25) + 0.300(0.00)$		0.175
	$\widetilde{R}_{AGG} = 0.350(0.50) + 0.350(0.50) + 0.300(0.25)$		0.425
	$\widetilde{R}_{AGG} = 0.350(0.75) + 0.350(0.75) + 0.300(0.50)$		0.675
		$\widetilde{R}_{AGG}$	(0.175, 0.425, 0.675)

A4.3 Decision Making Aggregation Computation

Table A4.34 Decision matrix

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	(0.672, 0.922, 1.000)	(0.500, 0.749, 0.999)	(0.500, 0.749, 0.999)	(0.672, 0.922, 1.000)	(0.590, 0.840, 1.0000)	(0.590, 0.840, 1.000)
DA2	(0.588, 0.838, 1.000)	(0.497, 0.747, 0.913)	(0.175, 0.425, 0.675)	(0.410, 0.660, 0.910)	(0.196, 0.364, 0.614)	(0.410, 0.660, 0.910)
DA3	(0.500, 0.749, 0.999)	(0.417, 0.667, 0.917)	(0.417, 0.667, 0.917)	(0.410, 0.660, 0.910)	(0.175, 0.425, 0.675)	(0.410, 0.660, 0.910)
DA4	(0.175, 0.425, 0.675)	(0.500, 0.749, 0.999)	(0.590, 0.840, 1.0000)	(0.075, 0.325, 0.575)	(0.083, 0.167, 0.417)	(0.175, 0.425, 0.675)

Table A4.35 Fuzzy TOPSIS decision matrix

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	0.865	0.749	0.749	0.810	0.810	0.810
DA2	0.809	0.719	0.425	0.660	0.391	0.660
DA3	0.749	0.667	0.667	0.660	0.425	0.660
DA4	0.425	0.749	0.810	0.325	0.222	0.425

A4.4 Transformation of the Attributes into Crisp Values (defuzzification)

Using the transformed attributes into Crisp values (Deffuzification), normalise the decision matrix.

Table A4.36 Fuzzy TOPSIS decision matrix

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	0.865	0.749	0.749	0.810	0.810	0.810
DA2	0.809	0.719	0.425	0.660	0.391	0.660
DA3	0.749	0.667	0.667	0.660	0.425	0.660
DA4	0.425	0.749	0.810	0.325	0.222	0.425

Normalisation of fuzzy decision matrix by applying,

$$\boxed{\frac{0.865}{[(0.865^2+0.809^2+0.749^2+0.425^2)]^{\frac{1}{2}}}=0.591}$$

This is an example of normalising EC1 with respect to DA1; the rest of the normalisation can be done using the same method. The results of can be presented in the format shown in the Table below.

Table A4.37 Normailsed decision matrix

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	0.591	0.519	0.552	0.634	0.795	0.620
DA2	0.552	0.498	0.313	0.516	0.384	0.505
DA3	0.512	0.443	0.491	0.516	0.417	0.505
DA4	0.290	0.519	0.597	0.254	0.218	0.325

Construction of weighted normalisation fuzzy decision matrix

By application of Equation 5.29, (see chapter 5):

$$\boxed{\tilde{V}=|\tilde{v}_{ij}|_{m\times n}}$$

where $\boxed{i=1,2,\cdots n}$ and $\boxed{\tilde{v}_{ij}=\tilde{r}\times\tilde{w}_j}$

$$\boxed{\tilde{v}_{ij}=normalised\ weight\times weight\ of\ the\ criteria}$$

$$\boxed{\tilde{v}_{1,1}=0.591\times0.167}$$

$= 0.098697$

weight of criteria, $\tilde{w}=\frac{100}{6}$ (where number of criteria is = 6)

$= 0.16666$

Table A4.38 Weighted normalised decision matrix

DA	EC1	EC2	EC3	EC4	EC5	EC6
DA1	0.098	0.086	0.092	0.106	0.132	0.103
DA2	0.092	0.083	0.052	0.086	0.064	0.084
DA3	0.085	0.074	0.082	0.086	0.069	0.084
DA4	0.048	0.086	0.099	0.042	0.036	0.054

A4.5 Obtain the distance of each alternative to the FPIS and FNIS

From the above weighted normalised decision matrix, insert largest values of 'Benefit category' of the attributes into columns of the PIS and smallest values into the NIS. In addition, insert the largest values of 'Cost category' of the attributes into the NIS and smallest values into the PIS.

Table A4.39 Representation of FPIS and FNIS values

Evaluation Criteria	Category	Key	PIS	NIS
Reliability	Benefit	EC1	0.098	0.048
Operability	Benefit	EC2	0.086	0.074
Maintainability	Benefit	EC3	0.099	0.052
Availability	Cost	EC4	0.042	0.106
Cost	Cost	EC5	0.036	0.132
Safety	Benefit	EC6	0.103	0.054

$$D^{+}=[(0.098-0.098)^{2}+(0.086-0.086)^{2}+(0.099-0.092)^{2}+(0.042-0.106)^{2}+(0.036-0.132)^{2}+(0.103-0.103)^{2}]^{\frac{1}{2}}$$

$$D^{-}=[(0.048-0.098)^{2}+(0.074-0.086)^{2}+(0.052-0.092)^{2}+(0.106-0.106)^{2}+(0.132-0.132)^{2}+(0.054-0.103)^{2}]^{\frac{1}{2}}$$

Table A4.40 Distance between each alternative to FPIS and FNIS

PIS/NIS	AT1	AT2	AT3	AT4
D^{+}	0.116	0.073	0.063	0.070
D^{-}	0.082	0.089	0.087	0.125

Obtain the closeness coefficient and ranking of alternatives

using, $d_1^{+}=0.116,\ d_1^{-}=0.082$

$$RCC_1=\frac{0.082}{0.116+0.082}=0.414$$

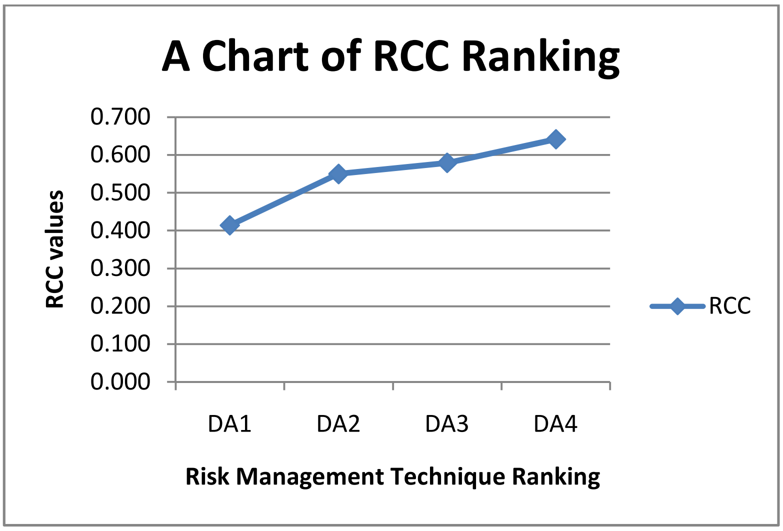
Table A4.41 Relative closeness coefficient for each alternative and ranking

	DA1	DA2	DA3	DA4
RCC	0.414	0.550	0.579	0.641
Ranking	4	3	2	1

Table A4.42 Ranking of the risk management technique

Alternative	RCC	Ranking
DA1	0.414	4
DA2	0.550	3

DA3	0.579	2
DA4	0.641	1



FigureA4.1 Ranking order of risk management technique

Table A4.43 FTOPSIS analysis final results

Key	Decision alternatives	d^+	d^-	RCC	Ranking
AT1	Structured brainstorming and evaluation	0.178	0.101	0.414	4
AT2	Probability-Impact calculations	0.095	0.134	0.550	3
AT3	Informal direct assessment of risks	0.087	0.128	0.579	2
AT4	Checklists method	0.088	0.187	0.641	1