University of Alberta

Hybrid Decision Support System for Risk Criticality Assessment and Risk Analysis

by

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This thesis is dedicated to my family

ABSTRACT

Risk management is essential for the construction industry to successfully fulfill project objectives. Several studies were conducted in the past decade to support quantitative risk analysis. These studies were based on using some of the commonly used techniques such as risk matrix, decision trees, Monte Carlo, and sensitivity analysis. However, some of these techniques are limited because they either do not support quantitative risk analysis, or are difficult to be utilized due to the required amount of data to support quantitative risk analysis.

To address such limitations, a comprehensive framework was developed, based on combining three well-known techniques in reliability engineering, i.e., failure mode and effect analysis, fault trees, and event trees with fuzzy logic. Fuzzy logic and failure mode and effect analysis were first combined to provide an answer to the problem of identifying of critical risk events through the development of a fuzzy expert system software package named Risk Criticality Analyzer.

To support quantitative risk analysis in the construction industry, fault tree and event tree were combined, and fuzzy logic is used to solve both of them. Fuzzy arithmetic operations on fuzzy numbers were used to represent logical gates in the fault tree structure, and to conduct event tree analysis. To automate solving both fault trees and event trees, Fuzzy Reliability Analyzer was designed and implemented using Visual Basic.net. Both tools were then validated through case studies. The

results indicate that by using the proposed methodology, the risk can be assessed effectively and efficiently.

The proposed framework presented in this research provides the contribution of combining fuzzy logic with failure mode and effect analysis, fault trees, and event trees in a comprehensive framework to support risk identification, risk assessment, and risk response. Since the proposed framework is based on using linguistic terms, risk analysts are offered a more convenient and practical framework to conduct risk analysis. The proposed framework was able to address several limitations attributed to the conventional application of failure mode and effect analysis and offered a generic framework that can be adapted to fit any industry or organization.

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1. Introduction

1.1 Background

The construction industry is distinguished by high level of risks and uncertainties due to the nature of construction business activities. In the UK, a 1975 report shows that one in six contracts overran by more than 40% of the original contract value, and a significant number overran by more than 80% of the original contact value (Thompson and Perry 1992). A 1983 report confirmed the same finding from 1975, where many projects experienced cost overruns and schedule delays (Thompson and Perry 1992).

Increasing projects' sizes and degrees of complexity are current trends in the construction industry, and these create more risk and uncertainties for the project team to cope with. Risks and uncertainties are inherent in all construction projects, starting from the conceptual phase of the project, passing by the planning phase, moving to the execution phase, and even remaining during the operational phase. Typically, the lack of information at the commencement of projects creates an outstanding environment for risks and uncertainties.

Several authors have discussed the advantage of quantifying risk and adding risk premium to the original estimate. Mak and Picken (2000) pointed out that an advantage of adding risk premium is that it ensures that the estimated project cost is realistic and sufficient enough to absorb any cost incurred by risk and uncertainty. Ford (2002) highlighted the advantage of adding risk premium in the original estimate to provide funds for unforeseen expenses. On the other hand, some authors questioned the additions of any allowance to cover risk. For instance, Thompson and Perry (1992) highlighted some weaknesses in the current practice of estimating the required risk premium. These weaknesses are attributed to the current trend of some estimators to rely on arbitrary approaches. In addition, some estimators tend to double count the effect of risk by adding extra allowances in the estimate, which leads to hiding the poor management of the project team. Mak and Picken (2000) described the work of Raftery (1994), who has identified personal bias and differences in personal risk attitude. Mak and Picken (2000) highlighted the effect of negative sanctions by imposing a penalty for an underestimate, where tender bids are above the pretender estimate but there is no reward or penalty for an overestimate.

Kangari and Riggs (1989) indicated that the construction industry is characterized as having a poor reputation when it comes to risk, and highlighted that risk analysis is either ignored, or done arbitrarily by simply adding a line item as a risk premium. Noor and Tichacek (2004) noted some problems in this practice. The most obvious problem is whether this line item is adequate to handle all project-specific risk events. The second problem lies in determining when the allocated money should be used. Shortfall to use the allocated money to address risk events will end up holding this premium until the end of the project, and then looking for ways to spend the money in non-efficient ways.

Based on a questionnaire survey of general contractors and project management practices, Akintoye and MacLeod (1997) concluded that formal risk analysis and management techniques are rarely used. Instead, the construction industry has approached risk management in terms of individual intuition, judgment, and experience gained from previous contracts. The reasons provided by contractors for not using techniques to perform risk analysis were: lack of familiarity and experience with the risk analysis techniques, the degree of sophistication involved in using some of these techniques, the doubts about the suitability of these techniques to the construction industry, the required amount of data to ensure confidence in the outcome, the fact that many risk events are fairly subjective and hence they are better dealt with based on experience from previous contracts undertaken by the firm, and the difficultly to see the benefits of going through these formal risk analysis processes.

Through a number of interviews, Smith and Bohn (1999) concluded that contractors had little knowledge of the formal risk modeling techniques that have been published, and tended to add risk premium as a percentage of the total cost based on their intuition and previous contract knowledge.

1.2 Problem Statement

Risk and uncertainty are associated with all projects undertaken by individuals and organizations, regardless of their size, nature, and place of execution. These risks could result in significant failures in the form of cost overruns, delays, environmental damage, and even injuries and loss of life. Datta and Mukherjee (2001) indicated that successful project completion within the targeted budgets of cost and time is highly dependent on the early identification of the immediate risk events, analyzing them, and making better decisions. Thus, any project team must aim at identifying key risk events so that they can be analyzed and assigned appropriate response actions (Andi 2006).

Companies need to estimate the bidding price of a construction project, and submit a bid even in scenarios when the probability of the occurrence of risk events and their associated consequences is uncertain. The problem will became large if the calculated expected monetary value resulting from risk events is not considered, or is underestimated. Thus, the expected monetary value of each risk event should be established based on thorough risk identification and risk analysis, and must be sufficient enough to cover the costs and/or time required to avoid, transfer, mitigate, or bear the consequences of risks.

In the literature, many researchers have proposed and utilized different risk analysis techniques, such as risk matrix, analytical hierarchy process (AHP), decision trees, Monte Carlo, neural network, regression analysis, fault trees, event trees, FMEA, and hybrid techniques between two or more of the previously mentioned techniques. These techniques can be classified under qualitative risk analysis techniques and quantitative risk analysis techniques. Although there are many techniques to perform risk analysis, most of these techniques are limited due to the non-availability of data. In the construction industry, data are either not available, or expensive to obtain, or not relevant, or sparse and require a lot of effort to be refined.

To ensure a correct reflection of this situation, it is necessary to develop a practical approach that considers uncertainty in inputs, and reflects that in a comprehensive framework. Since risk analysis is dealing with uncertain situations in which we do not have complete and accurate knowledge and data, risk events are often discussed using terms such as high or low. So far, fuzzy set theory has been used for cost range estimation, but has not been used as extensively to perform risk analysis, especially in the construction domain. This technique is characterized by the ability to assign membership values expressing a degree of belief that a certain value of a variable corresponds to a linguistic concept. Fuzzy set is intended to treat uncertainties that emerge as a result of linguistic approximation and measurement imprecision. Taking the approach of using linguistic terms could solve the uncertainty problem, especially when it comes to risk analysis. This thesis is intended to develop a comprehensive framework to screen critical risk evens and to support risk analysis as well as risk identification and risk response planning in the construction industry using linguistic terms. The proposed framework is intended to overcome the drawbacks of the commonly used risk analysis techniques by integrating fuzzy logic with three well-known techniques in reliability analysis.

1.3 Research Objectives

The overall aim of the research is to develop a framework for systematic modelling and analyzing of risk events affecting the construction industry, using combined fuzzy logic, event trees, fault trees, and failure mode and effect analysis. The overall objective of this research can be broken down to the following sub-objectives:

- To establish a framework for risk criticality analysis in the construction industry aiming at screening of critical risk events, and supporting the comparison of risk events at the project level as well as at the portfolio level.
- To investigate the concept of risk analysis, and introduce a new technique for analyzing and quantifying risk that is based on subjective assessment of risk events.
- To aid risk-based decision-making, especially for problems that involve multi-criteria decision-making.
- To extend the fuzzy set application(s) in the construction domain by incorporating the use of fuzzy logic with three commonly-used

techniques in risk analysis, known as failure mode and effect analysis, fault trees, and event trees.

- To aid in determining which risk events should be used for lessons learned, and which one must undergo detailed root cause analysis.
- To help in identifying the training needs for different risk individuals by identifying areas of weakness within each project.
- To support the decision-makers to identify the critical root causes by conducting fuzzy importance analysis on fault trees.
- To verify the validity of the proposed model by undertaking a case study and illustrating the advantage of using fuzzy logic to overcome the limitations of each technique.

1.4 Expected Contributions

The main contribution of the proposed research is the introduction of a comprehensive framework for risk management based on combining three well know techniques in reliability engineering in a novel way to support risk identification, risk analysis, and risk response while considering the subjective characteristics of the risk-related data. In this research, fuzzy logic is combined with both failure mode and effect analysis (FMEA) and analytical hierarchy process (AHP) to provide a practical and thorough approach for screening of critical risk events in the construction domain. Moreover, to support risk analysis, fuzzy logic is combined with both fault trees and event trees. The proposed integration of fuzzy logic to solve fault trees and event trees offers risk experts the ability to express the probability of the occurrence of basic events and the impact linguistically, and the ability to calibrate these linguistic terms to suit different organizations or contexts. The proposed framework can also help in understanding the logic that can lead to the occurrence of a risk event, and to identify critical root causes by analyzing the level of importance of each root cause. The proposed combination between fuzzy logic, event trees, and fault trees added more features and supports addressing more limitations of the currently available techniques for risk analysis. Moreover, the integrated system creates a more powerful modeling tool capable of quantifying the risk magnitude based on a subjective assessment of different risk events. The expected contribution of this research can be summarized as follows:

- The proposed approach explores different means of implementing fuzzy set theory concepts to risk analysis, and supports linguistic assessment of risk events in the construction domain.
- The proposed approach supports the screening of critical risk events and provides decision-makers with a practical tool to identify the level of importance of establishing corrective actions.
- The proposed approach explores the use of Fuzzy AHP to support risk-based multi-criteria decision-making using linguistic assessment.

- The utilization of the fuzzy expert system to calculate the risk criticality offers a transparent mean to understand the concept of risk criticality and to train new people.
- The proposed approach considers the calibration of the membership functions for both probability and impact assessment to support event trees and fault trees analyses.
- The utilization of fuzzy logic to solve fault trees and event trees offers a transparent and an easy to understand framework. Such transparency can help verifying the resultant expected monetary value as compared to other models such as Monte Carlo simulation based models.
- The proposed approach offers the contribution of combining fuzzy logic, event trees, and fault trees in a comprehensive framework not only to support risk analysis but also to support risk identification and risk response management.

1.5 Research Methodology

In order to achieve the research objectives, this research entails adapting three well-known techniques—failure mode and effect analysis (FMEA), fault trees (FTs), and event trees (ETs)—to the construction industry by using fuzzy logic. The use of fuzzy logic allows experts to provide an assessment of the probability of occurrence of risk events and their consequences linguistically, rather than using probabilistic distributions, which is more realistic in the construction domain. The research study is conducted in ten stages, as follows:

Stage one involves a literature review of the previous work conducted under the area of risk analysis and risk management. The purpose of this stage is to learn more about different risk analysis techniques, and to understand shortcomings and limitations of each study. A summary of these established techniques, areas of application, and limitations is explained in Chapter 2.

Stage two involves working with the participating organization to establish a risk register template, probability table, impact table, detection/control table, and a risk breakdown structure. Five linguistic terms are selected to define the probability of occurrence, impact, and detection/control. The risk register template is designed to collect data such as: risk ID, risk description, root causes, definition of risk (i.e., threat or opportunity), assessment of the probability of occurrence using the probability table, assessment of cost impact, time impact, scope/quality impact, safety impact, and environmental impact of each risk event using the impact table, definition of risk response, and assessment of the level of risk detection and control using the detection/control table. Risk acceptability level is a feature included in the risk register to screen risk events that have unacceptable risk level due to either safety or environmental impact. Such risk events are required to undergo detailed risk analysis using fuzzy fault tree and fuzzy event tree.

Stage three involves conducting a risk identification workshop to populate the risk register with the required data. During this stage, the selected case study project is broken down to its main components using the work breakdown structure (WBS), and each work package is analyzed to identify different risk events. Root cause analysis is conducted and the impact of each risk event is identified using three dimensions, i.e., cost impact, time impact, and scope/quality impact. Each risk event is then assigned a risk response strategy. An interview is then arranged with the risk analyst to analyze each risk response strategy and to asses the level of detection and control.

Stage four involves aggregating the multiple dimensions of impact into one variable named aggregated impact (AI). Fuzzy AHP is used during this stage to enable experts to express the multiple impact of risk on the project objectives using linguistic terms, which are translated into fuzzy scales.

Stage five involves establishing a fuzzy expert system, which calculates the risk criticality number (RCN) given the probability of occurrence, aggregated impact (AI), and the level of detection/control. Each of the input parameters is defined using five linguistic terms, while nine linguistic terms are used to define the output variable, i.e., the RCN. The direct method with one expert (Klir and Yuan 1995) is used to define the shape and the range of the membership functions for the inputs and output variables. One hundred and twenty-five rules were defined and used to represent the relationships between the input variables and the output and used to build the fuzzy rule base. The resultant RCN is assigned a corrective action. FuzzyTech® is used to build the fuzzy expert system and Visual Studio® is used to build a software package entitled Risk Criticality Analyzer (RCA). RCA is used to screen critical risk events that require detailed risk analysis as explained in the next stage.

Stage six involves identifying risk events that require conducting a detailed risk analysis. During this stage, an interview was conducted with a senior risk coordinator and a decision was made that any risk event that has a RCN that falls in categories 5–9 is defined as a critical risk event (CRE), and hence is required to undergo a detailed risk analysis in accordance with the steps defined in the next stages. All unacceptable risk events due to safety and environments, as defined in stage 2, are also required to undergo detailed risk analysis as defined in the next stages.

Stage seven involves establishing a fault tree structure for any identified CRE, and assessing the fuzzy probability of occurrence of basic events using the probability table defined in stage two. Two-step Delphi approach is used to reach consensus between two experts regarding the fault tree structure and to assess the probability of basic events. Minimal cut sets are then calculated using Hauptmann's (1988) algorithm. The direct method with one expert (Klir and Yuan 1995) is used to elicit the required information to build the membership functions. Each membership function is represented using alpha cuts, and fuzzy arithmetic operations on fuzzy numbers are then applied to calculate the probability of occurrence of the CRE. Finally, fuzzy importance analysis is applied, to rank different basic events according to their level of contribution to the top event's probability of occurrence.

Stage eight involves working in establishing risk response strategies. Each risk response strategy is thereafter studied to understand how this plan might fail. The failure of each risk response strategy is represented using a fault tree structure, and the same steps defined in stage seven are applied to calculate the probability of failure of each risk response plan.

Stage nine involves establishing an event tree structure, using the findings from stages seven and eight and assessing the impact of each path of the event tree. The direct method with one expert (Klir and Yuan 1995) is again applied to elicit the required information to build the membership functions. Each membership function is then represented using alpha cuts, and fuzzy arithmetic operations on fuzzy numbers are then applied to calculate the expected monetary value (EMV) of the CRE. Fuzzy Reliability Analyzer (FRA) is developed using Visual Studio® to automate fault trees and event trees analyses.

Stage ten involves validation of the findings obtained using RCA and FRA. During this stage, "Face Validation" was used to identify practical applications of the proposed framework. Further validation, of the risk criticality concept, was conducted by running several experiments using RCA and comparing the results against the traditional FMEA. The results obtained using fuzzy fault tree and fuzzy event tree were also validated by comparing the results against the results obtained using Monte Carlo simulation. The results indicate that performing risk analysis using fuzzy logic, faults trees, and event trees yields very comparable outputs when compared to the probabilistic approach. The expected contributions of this research were validated by running several experiments using RCA and FRA along the line with a questionnaire conducted with two risk experts. Results of the survey show validity of the proposed contributions and indicate the advantages of using fuzzy logic to solve the limitations of the traditional application of FMEA, fault trees, and event tree.

1.6 Thesis Organization

This thesis is organized as follows:

Chapter 1 provides background and the problem statement. This chapter also explains the expected contribution and the proposed methodology.

Chapter 2 contains a literature review of previous research conducted on the area of risk and risk analysis, and provides an overview of the limitations and drawbacks of previous studies.

Chapter 3 contains detailed background information about three commonly-used risk analysis techniques, known as failure mode and effect analysis, fault trees, and event trees, and highlights the advantages and limitations of each technique.

Chapter 4 introduces a framework for risk criticality analysis by integrating fuzzy logic and failure mode and effect analysis (FMEA).

Chapter 5 discusses a methodology proposed to integrate fuzzy logic, fault trees, and event trees to support risk analysis in the construction industry.

Chapter 6 presents data collection, a case study, and the validation of the risk criticality model and the risk analysis model.

Chapter 7 describes the conclusions of this research, the expected academic and industrial contributions, limitations, and recommendations for future research.

2. Literature Review

This chapter is intended to provide an in-depth literature review on the concept of risk and risk analysis. Presented in this chapter is a detailed overview of risk, uncertainty, risk management, and the risk analysis process. Previous studies are presented to clarify some of the concepts and techniques, and to illustrate the gaps. The first part of this chapter provides an overview of different risk and risk management definitions and terminologies, as introduced in different studies. The second part of this chapter presents an overview of previous research conducted in the area of risk analysis, and highlights the limitations and drawbacks of each study.

2.1 Risk Definition

Each industry shapes the definition of risk by viewing it through their own lens, yielding a wide range of perspectives of what “risk” means. For instance, Moskowitz and Bunn (1987) indicated that the term “risk” has many interpretations, and its meaning varies from one industry to another and from one context to another. Al-Bahar and Crandall defined risk as "the exposure to the chance of occurrences of events adversely or favorably affecting project objectives as a consequence of uncertainty" (1990, 535). Liu (1998) referred to “risk” as the volatility of outcomes, and argued that it can be measured as a deviation from the expected value.

Blair et al. defined risk as “the potential for loss as a result of a system failure” (2001, 70). Baloi and Price defined risk in the construction industry as” the likelihood of a detrimental event occurring to the project” (2003, 262). Jannadi and Almishar defined risk as “a measure of the probability, severity, and exposure of all the hazards of an activity” (2003, 492). Molenaar considered the negative side (threat) as a definition of a risk event, and defined risk events as “ potential adverse events that negatively affect the defined project resulting in negative impacts to cost, schedule, safety, performance, or other characteristic but do not include the minor variance inherent in Base Costs” (2005, 352). On the other hand, Molenaar defined opportunity events as “potential beneficial events that positively affect the project resulting in improvements to cost, schedule, safety, performance, or other characteristic but are greater than the minor variance inherent in Normal Costs ” (2005, 352). Cooper et al. defined risk in a project context as “the chance of something happening that will have an impact upon objectives” (2005, 3).

Some institutes also offer definitions for the term “risk.” For example, the Association for the Advancement of Cost Engineering (AACE) (2007) (International Recommended Practice No. 10S-90) established the following three definitions to define the term “risk”:

(1) “The degree of dispersion or variability around the expected or "best" value” (2007, 86).

(2) “An ambiguous term that can mean any of the following: a) All uncertainty (threats + opportunities); or b) Downside uncertainty (threats); or c) The net impact or effect of uncertainty (threats – opportunities)” (2007, 86).

(3) “Probability of an undesirable outcome” (2007, 86).

The PMBOK refers to project risk as an “uncertain event or condition that, if it occurs, has a positive or a negative effect on a project objective” (Project Management Institute (PMI) (2004, 238).

The classical definition of risk as represented by the risk matrix is shown in Equation 2-1 as follows:

Risk = probability of occurrence of a risk event x consequence (loss/gain) [2-1]

2.2 Risk versus Uncertainty

Some authors tend to use the terms “risk” and “uncertainty” interchangeably. For example, Kaplan & Garrick defined risk as “uncertainty + damage” (1981, 12). Chapman and Cooper defined risk as “an undesirable implication of uncertainty” (1983, 238). Motawa et al. defined risks as “uncertain outcomes or consequences of activities or decisions when they are manageable” (2006, 583).

On the other hand, some authors introduce some definitions to differentiate the meaning of “uncertainty” from the meaning of “risk.” For instance, Pilcher (1985) indicated that “uncertainty” referred to the situation in which data are unavailable, while the term “risk” is used to refer to situations in which historical data are available from previous projects (Öztaş and Ökmen 2005). Moskowitz and Bunn (1987) indicated that uncertainty is a term that refers to probabilities and to probability distributions associated with decision alternatives having uncertain outcomes. Al-Bahar and Crandall (1990) used the term "uncertainty" to represent the probability that an event occurs. Emblemsvag and Kjolstad (2005) provided another way to differentiate between risk and uncertainty. They noted that risk arises as a consequence of a choice that was made and a choice that was not made. On the other hand, uncertainty arises as a result of the lack of information or clarity, and has nothing to do with choices. Choi and Mahadevan (2008) indicated that uncertainties in expert judgment are due to: (1) the complexity of work; or (2) the level of education, confidence, and experience; while uncertainties in parameter estimation are due to (1) unreliable/insufficient data; or (2) approximation in statistical analysis methods.

As can be noticed from previous studies, the term “risk” is defined in many different ways. Any of the previous definitions can refer to the term “risk” since there is no way to judge if one definition is better than another. However, what is more important than just selecting a definition to be referred to by the term “risk” is to communicate the selected definition to the project team, and to make the selected definition consistently used to communicate “risk” within the organization. In this thesis, the Project Management Body of Knowledge (PMBOK) definition of risk, which is “an uncertain event or condition that, if it occurs, has a positive or a negative effect on at least one project objective, such as time, cost, scope or quality” (PMI 2004, 238) is adapted. This definition was selected because it offers a comprehensive definition in which the positive and negative effects of risk are considered on the project objectives.

2.3 Risk Breakdown Structure (RBS)

The PMI defined the RBS as “A hierarchically organized depiction of the identified project risks arranged by risk category” (2004, 117). According to the PMBOK (PMI 2004), RBS can provide a structure that ensures a comprehensive framework to identify the risk event in a project. Hillson (2002) noted that the RBS is similar to the WBS and can provide a number of benefits, by decomposing potential sources of risk into layers of increasing detail.

Dorofee et al. (1996) proposed an RBS to categorize the risk for software developers. The first level includes the following groups: project engineering, development, environment, and program constraints. The second level includes: requirements, design, code and unit test, integration test, engineering specialties, development process, development system, management process, management methods, work environment, resources, contract, and program interfaces (Hillson 2002).

Chapman (2001) proposed an RBS for construction design that includes the following groups: environment, industry, client, and project. The second level contains: statutory, market, client team, PM team, targets, funding, tactics, team, and task.

Dikmen and Birgonul (2006) established an RBS for international construction projects. The first level of the hierarchy is composed of two components, i.e., project and country. The project is further subdivided into four sub-elements, including: complexity, unavailability, vagueness, and constraints/restrictions. The country is divided into seven sub-elements: poor international relationship, instability of political conditions, poor attitude towards foreign companies, unfavourability of economic environment, immaturity of legal system, societal conflict, and differences.

Hillson (2002) indicated that the RBS can aid risk identification by considering the upper level of the RBS as a prompt list with any risk identification method. For example, a risk identification workshop or brainstorm might work through the various elements of the RBS. Hillson (2002) noted that the RBS can help in establishing a common language and terminology that supports capturing lessons learned and provides consistent reporting.

2.4 Risk Management

Risk Management is a process that aims at identifying risk events as early as possible, quantifying their effects, and working on managing them for preventing the harmful effects (threats) and maximizing the positive effects (opportunity) of the risks on the project objectives. Al-Bahar and Crandall defined risk management as "A formal orderly process for systematically identifying, analyzing, and responding to risk events throughout the life of a project to obtain the optimum or acceptable degree of risk elimination or control" (1990, 534). Gray defines risk management as the area of project management that "identifies as many risk events as possible (what can go wrong), minimizes their impact (what can be done about the event before the project begins), manages responses to those events that do materialize (contingency plan), and provides contingency funds to cover risk events that actually materialize" (2003, 207).

Like every project management knowledge area, risk management entails several processes, which can be summarized as follows:

- Risk management planning: This is defined as the process of describing methods for identifying, analyzing, prioritizing, and tracking risk. This process entails assigning specific responsibilities for the management of risk, and prescribes the timing, monitoring, and reporting processes to be followed. Typically, this activity is performed at the early stage of the project.
- Risk identification: This is defined as the process of investigating which risk events might affect the project, classifying them, and identifying their root causes. Typically, a risk identification workshop is facilitated to capture different risk events and

potential causes of risk. Other techniques for risk identification include: checklist, interviews, and Delphi. During this process, initial response strategies could be assigned to risk events. Readers can refer to PMI (2004) and Chapman (1998) for further details about risk identification techniques.

- Risk analysis (qualitative and quantitative): This can be defined as the process of quantifying the effect of risk events on the project objectives. A complete risk analysis entails providing an answer to the following two questions:
    - What is the likelihood of the risk?
    - What are the impacts of the risk over different project objectives?
- Risk response: This is defined as the process in which risk response strategies are assigned to different risk events, and commitments are obtained from different stakeholders. Strategies for threats include: mitigation, transfer, avoidance, or acceptance. Strategies for opportunities include: exploiting, sharing, enhancing, or accepting. Readers can refer to Al-Bahar (1988), Al-Bahar and Crandall (1990), and PMI (2004) to understand more about different risk response strategies.
- Risk monitoring and control: This process entails monitoring the implementation of risk response strategies, identifying new risk events, conducting root cause investigation for realized risk

events, and tracking the contingency expenditure. It is worth noting that communication of the risk-related data during all of the previously mentioned processes is crucial for the successful implementation of risk management.

Smith and Merritt (2002) noted that companies fail at risk management because they fail at cross functionality and proactiveness. Instead of firefighting the risk after its occurrence, which is not an effective approach to deal with risk, companies should consider starting risk management at the earliest stage of the project life cycle. They introduced risk management implementation guidelines, which can be summarized as follows:

- Enforce consistent terms for risk within the company.
- Train the management team to understand and prioritize risk events and understand the existing company thresholds.
- Consider risk an opportunity for gain and a chance for loss.
- Collect information and use it to make better decisions.

Since the focus of this thesis is on the quantitative aspect of risk throughout risk analysis, the rest of this section is dedicated to provide more details about previous studies conducted on the area of risk analysis. In addition to a critical review of the proposed technique, the weakness and limitations of each study are also provided.

2.5 Risk Analysis

There are various techniques to perform risk analysis of construction projects. Kangari and Riggs (1989) classified these techniques under two categories: (1) classical models (probabilistic methods), and (2) subjective models (i.e., fuzzy set methods). In analyzing risk, we are trying to predict how the future will be if we undertake a certain course of action (Kaplan and Garrick 1981). For a complete risk analysis, the following questions have to be answered:

(1) What is the probability that it will happen?

(2) What is the impact if it happens?

Kaplan and Garrick (1981) indicated that risk analysis must be established to provide input(s) to the decision problem, which involves not only risks but also other forms of costs and benefits. Based on a survey, McGregor (1983) concluded that the major problems in building risk analysis models are: lack of sufficient data, the inability to establish probability distributions, the difficulty of understanding the probability concepts, the correlation assumptions between variables and across time, and management refusing to accept that there were risks involved in the project and understanding the output.

Simister (1994) conducted a questionnaire to rank the benefits of using risk analysis. Benefits indentified are ranked as follows:

(1) Allows the formulation of more realistic plans

(2) Gives an increased understanding of the risks in a project

(3) Allows the assessment of contingencies

(4) Facilitates realistic risk-taking

(5) Identifies the party best able to handle a risk

(6) Leads to the use of the most suitable form of procurement

(7) Builds up statistical information about historical risks

(8) Assists in distinguishing between good luck/good management and bad luck/bad management

The rest of this section is intended to provide details about different techniques that can be used to quantify risk. Some of these techniques are qualitative in nature and are flexible enough to be utilized under numerous situations. Qualitative techniques can be applied as a preliminary stage to screen significant risk events, which can be further studied by exploring one of the quantitative techniques. This section is also intended to highlight advantages and disadvantages of each technique. It is important to note that risk events should first be identified, by means of risk identification, before conducting risk analysis. Readers can refer to Thompson and Perry (1992), Chapman (1998), and PMI (2004) for further details about risk identification techniques, and the strengths and weaknesses of each technique. Chapter 6 provides a detailed overview of the risk register template and the risk breakdown structure, which are developed to support collecting the risk-related data.

2.5.1 Risk Matrix (Qualitative Risk Analysis)

Risk matrix is a tool that can be used to conduct qualitative risk assessment by evaluating probability of occurrence and impact to calculate the risk magnitude. Typically in the risk matrix analysis, each risk event is allocated to a grid with probability (P) along one axis and impact on the other axis. After risk events have been identified, they are analyzed for the probability of occurrence and impact by selecting from a pre-identified linguistic scale for probability and impact. Table 2-1 illustrates sample linguistic terms and numerical limits for both probability of occurrence (P) and impact in terms of schedule (IS) and cost (IC). The matrix shown in Figure 2-1 can be used to calculate risk magnitude. A threshold is typically constructed according to the organizational policy, and is used to show the risk tolerance zone. For example, the risk matrix in Figure 2-1 shows three risk levels represented by white, light grey, and dark grey. The white area represents an acceptable level of risk, in which risk events allocated in this area are monitored during project execution. The light grey area in the “threats” section represents an undesirable level of risk in which avoidance or transfer are to be considered. The dark grey area in the “threats” section represents an unacceptable level of risk. Risk events assigned to this area must be eliminated or transferred. Haifang et al. (2009) utilized the risk matrix to identify the key risk events for private companies participating in government projects in China, and to provide a basis for risk prevention. Examples of using the risk matrix to perform risk analysis can be found in Abdelgawad and Fayek (2008) and PMI (2004).

The risk matrix approach has a number of advantages. The concept presented in the risk matrix is simple to understand, and the tool is easy to use. Risk matrix can be adjusted and calibrated to fit any type of project. Most importantly, the matrix can be used as a screening tool by identifying risk events that require further quantitative assessment. However, this method is primarily qualitative, which can be a disadvantage, limiting its use in assessing the risk impact on capital projects. For example, this technique cannot be used alone to determine the required amount of risk premium. This technique also cannot support risk-based multi-criteria decision-making. For example, the technique can not be used if multiple criteria, i.e., cost, time, scope, safety, and environment, are required to be included to assess the level of impact of different risk events (Abdelgawad and Fayek 2008). Moreover, the risk tolerance zone for the risk matrix is subjective and is based on using sharp boundaries (Markowski and Mannan 2008).

Table 2-1. Sample probability of occurrence and impact table (adapted from PMI 2004)

Term	Probability (P)	Schedule impact (IS)	Cost impact (IC)
Very Low	< 1% chance	Critical path unaffected	Cost increase< 1%
Low	1≤ P<20% chance	<2% Critical path	Cost increase 1≤ IC<2%
Medium	20≤ P<50% chance	2%≤ IS <5% increase in duration	Cost increase 2≤ IC <5%
High	50≤ P <85 % chance	5% ≤ IS ≤8% increase in duration	Cost increase 5≤ IC ≤10%
Very High	Over 85% chance	>8% increase in duration	Cost increase >10%

		Threats					Opportunities				
Impact	VH (8)	8	16	24	32	40	40	32	24	16	8
	H (6)	6	12	18	24	30	30	24	18	12	6
	M (4)	4	8	12	16	20	20	16	12	8	4
	L (2)	2	4	6	8	10	10	8	6	4	2
	VL (1)	1	2	3	4	5	5	4	3	2	1
Risk Magnitude		VL	L	M	H	VH	VH	H	M	L	VL
		1	2	3	4	5	5	4	3	2	1
		Probability of Occurrence									

Figure 2-1. Risk matrix (adapted from PMI 2004)

2.5.2 Risk Analysis Using AHP (Qualitative Risk Analysis)

Mustafa and Al-Bahar (1991) utilized the Analytical Hierarchy Process (AHP) to perform a risk assessment of a bridge construction. Significant risk events are identified and incorporated in this assessment. The AHP analysis starts by representing the decision problem as a hierarchical structure, where the top level of the hierarchy reflects the overall objective. The elements affecting the decision are represented in the intermediate levels and called decision criteria, while the lowest level comprises the decision alternatives (Dey 2003). Experts are required to prioritize elements in each level of the hierarchy using the pairwise comparison scale shown in Table 2-2. Elements at each level are compared in pairs with respect to their importance in making the decision. The relative weights of the elements at each level compared to an element in the upper level are computed as the components of the normalized eigenvector associated with the largest eigenvalue of their comparison matrix (Mustafa and Al-Bahar 1991).

After constructing of the AHP hierarchy, the relative weights of the various elements are determined from expert opinions. The methodology integrated during this study includes the determination of the importance of the risk factor and the sub-factors and the likelihood of the risk. Readers can refer to Abdelgawad and Fayek (2008) for a detailed explanation of the steps that can be used to conduct AHP analysis.

Table 2-2. AHP pairwise comparison scale and definition (adapted from Saaty 1982)

Scale	Definition
1	Equal importance
3	Slightly favors one over another
5	Strong importance of one over another
7	Demonstrated importance of one over another
9	Extreme importance of one over another
2, 4, 6, 8	Intermediate values

Dey (2003) presented an AHP model for predicting the risk of pipeline failures during the operation phase of a 1,500 km length of crude oil pipeline, three intermediate booster stations, and an offshore terminal. The throughput of the project is 9 million metric tons per annum. The objective of the model can be summarized in predicting the greatest risk factors, analyzing the effect of them in pipeline failure, responding to risk, analyzing the costs and benefits, and rationalizing insurance premium. The methodology adopted during this study involves conducting brainstorming workshops to split the pipeline project into sections, and analyzing the effect of risk factors that lead to failure of each section. The next step involves presenting risk factors in the form of an AHP hierarchy, and conducting a pairwise comparison between risk factors and sub-factors to determine the likelihood of pipeline failure due to each factor and sub-factor. An analysis of the result is conducted, and effective mitigation actions are determined. The last step is to establish a cost-benefit analysis to justify the proposed investment and to formulate a cost-effective insurance plan for pipeline.

The AHP is characterized as a multi-criteria decision-making problem that allows subjective and objective assessment of factors while offering a systematic thinking environment. A measure of consistency used by the AHP can be computed and is known as the Consistency Ratio (CR). This ratio is designed so that values of the ratio exceeding 0.1 are indicative of inconsistent judgments. This ratio can support the decision-maker so he or she can judge the level of consistency in the expert's judgment and reach a more reliable analysis. However, one shortcoming of using the AHP method is attributed to the level of uncertainty and subjectivity of selecting a single number from the pairwise comparison scale. Zeng et al. (2007) noted that experts sometimes found difficulties in selecting a single number for comparison, and argued the advantage of allowing for a range values for comparison. In addition, the output obtained from this tool is a scale number, which can support the decision-maker only to judge the level of riskiness of the project but cannot be used to provide an estimate of the required risk premium. Moreover, this model cannot be calibrated if a new risk event is required to be added to the model and calculations are required to be conducted all over again.

2.5.3 Risk Analysis Using AHP and Decision Tree (Quantitative Risk Analysis)

A decision tree is an excellent tool that allows a choice between several courses of action. It is constructed as a graphical representation of possible outcomes of known choices and their probability of occurrence. Decision trees are widely employed to explore varies mitigation alternatives in a tree arrangement and to select the best mitigation alternative given the probability and consequence of every alternative (Akintoye and Macleod 1997).

Dey (2002) established a decision support system to perform risk analysis for a pipeline project in India. The proposed approach is based on combining the analytical hierarchy process (AHP) and a decision tree. The AHP is used to analyze risk in the project and the decision tree is used for selecting the risk response strategy. The methodology adopted by Dey (2002) involves decomposing the project using the work breakdown structure, identifying critical work packages, conducting risk identification using brainstorming sessions, conducting AHP analysis, calculating the impact of each risk event in terms of cost and time, brainstorming for various risk response strategies for each risk factor, estimating the cost associated with each risk response strategy, establishing a decision tree structure for the problem, calculating the expected monetary value, and selecting the best option.

Although decision trees offer several advantages—including conducting quantitative risk analysis in this study—this technique nevertheless has some limitations. For instance, Thompson and Perry (1992) indicated that there is rarely historical data available to calculate accurate probability values for decision points, which makes it difficult to conduct decision tree analysis especially if the numerical value for one or more consequent(s) is/are not available. The proposed model also did not explain how critical work packages can be identified, since they did not establish an approach for risk criticality assessment. Additionally, the proposed model did not investigate the root causes of different risk events to select the most appropriate mitigation strategy and limit the selected mitigation strategy to five pre-identified options.

2.5.4 Risk Analysis Using Neural Networks (Qualitative/Quantitative Risk Analysis)

Maria-Sanchez (2005) introduced a risk analysis model to quantify risks in terms of dollar value. During this study, several discussions were held with the contractor, and the final decision was to concentrate on 17 risk events, defined as: risks caused by the change in law and regulations, risks by problems on permissions, inflation risks, management risks caused by the subcontractor, contract risks caused by the subcontractor, risks from security and health protection, force majeure risks, weather risks, transport risks, design and construction risks, quality risks, technical and execution risks, risks from water and air pollution, contract risks, guarantee risks, business and market risks, and risks caused by the client. A scale ranging from 0–100 was established to assess the 17 risk factors over sixteen projects. Twelve projects were used to train the neural network (NN) model, while the remaining four projects were used for testing. The total risk (TR) value (output) was obtained using Equation 2-2 as follows:

$$TR = \frac{Business\ Costs - Total\ Profit}{Total\ Production\ Cost} * 100 \qquad [2\text{-}2]$$

The results obtained from using NN indicated that the NN was able to recognize a pattern between inputs and the output even with a very small set of data. Results also show that the obtained NN model is capable to produce the total risk (TR) value for new projects. Authors noted that the main constraint in using the NN model is related to the data for training and testing. Having a small set of data increases the chances of the NN to fail at recognizing a pattern between the inputs and output(s).

Al-Sobiei et al. (2005) introduced a hybrid neural network and genetic algorithm technique to predict the likelihood of contractor default in Saudi Arabia. The model is designed to support the construction owners to assess the likelihood of contractors' failure and to aid in assigning the bid to the most reliable contractor. Twenty-three risk factors were identified and classified depending upon the overall health of the contractor, the contract characteristics, and the nature of the project. Likelihood of the twenty-three risk factors represents the input pairs, while the output is defined in binary format as default/not default. The genetic training strategy is added to make the NN work better, especially when the training data are sparse. The performance of the network was assessed by measuring the R-square. The maximum R-square was reached when 14 hidden neurons were used in one hidden layer. The model was then tested using data from five projects. NN and GA were found not able to predict the outcome of two of the five projects. Authors indicated that a minimum contingency should be allocated to cover for the inaccuracies in the predictions of the model and classify the amount according to the contractor strategy to deal with risk. For instance, for a 'risk seeking' strategy, it is recommended to budget 9–15% of the contract value. For a 'risk averse' strategy, the contingency should be 15–24% of the contract value, whereas for a 'risk neutral' strategy, the contingency may be around 15%.

Eventually, NN is characterized as an excellent technique, which can offer a number of advantages. For example, there is no need to define statistical distributions for either inputs or output(s). Neural networks can be trained by defining the inputs and the output(s) subjectively, which makes NN a best candidate technique to be utilized in the area of risk analysis.

However, NN is also characterized by some disadvantages that limit the usability of this technique. For example, NN models are considered to be black boxes since it is difficult to explain the logic behind how these models do reasoning to calculate the output(s). NN can also be limited by over-fitting, a case in which the error in the training set is reduced to a very small value, but when new data are presented to the network, the error is large. Another limitation, attributed to the ability of the NN to train, is constrained when small sets of data are used for the training. In this particular application of NN to risk analysis, the authors ended their study recommending adding some ranges for contingency to cover the inaccuracy of the prediction of their model without explaining the logic behind these numbers, which make the practice of estimation more dependent on guessing, rather than relying on evidence and facts. Moreover, the output obtained from this model is binary, i.e., either default or not default, but does not provide a value of the likelihood of defaulting or not defaulting. In addition, both studies didn’t consider risk mitigation during the analysis, and focus on connecting the likelihood of the risk with the risk magnitude.

2.5.5 Risk Analysis Using Regression Analysis (Qualitative/ Quantitative Risk Analysis)

Fang et al. (2004) established a model for risk analysis of the Chinese construction market based on questionnaire investigation and the use of regression analysis. The methodology adopted during this study involves the following steps:

(1) Design questionnaires to collect different risk events in the construction market.
(2) Collect data using the questionnaire established in step 1.
(3) Review the outcomes obtained in step 2 and conduct an initial selection of the risk events, which will be included in the risk assessment model. Bivariate cross table analysis and univariate logistic regression analysis were used to determine which variables can enter the last regression analysis. Based on conducting the analysis, sixteen independent variables were identified.
(4) Establish the final risk assessment model by using multivariate regression analysis. Equation 2-3 and Equation 2-4 show the findings from this study.

$$\text{Risk Value} = \frac{e^{x}}{1+e^{x}} \quad [2\text{-}3]$$

$$x = 14.33 - 12.73 * x_1 - 13.50 * x_2 - 13.90 * x_3 - 12.84 * x_4 - 0.674 * x_5 + 11.31 * x_6 \quad [2\text{-}4]$$

where $x_1 = 1$ if owners' project capital mainly comes from their own funds and 0 otherwise; $x_2 = 1$ if contractors and owners have cooperated previously and 0 otherwise; $x_3 = 1$ if bidding competition is relatively fierce or moderate and 0 otherwise; x_4 = 1 if the bid price is reasonable and 0 otherwise; x_5= 1 if the company fully supports its project team and 0 otherwise; x_6= 1 if the owner is a civilian-run enterprise and 0 otherwise.

The model obtained from regression analysis is robust and can help in establishing a confidence interval of the results (Ng 2006). However, this technique requires sufficient data to establish the regression model, which is difficult to obtain in the construction domain. In addition, the analysis must start from scratch if a new risk event is required to be added to the regression equation, which makes this technique static and time-consuming (Abdelgawad et al. 2010). Moreover, Equation 2-3 is a qualitative equation and can be only used to perform comparisons between projects to identify if one project is more favourable than another. However, this model cannot be used to assign a dollar value to each risk event, which limits its applicability. Finally, this model did not consider the risk mitigation within the analysis of risk events.

2.5.6 Risk Analysis Using Monte Carlo Simulation (Quantitative Risk Analysis)

Monte Carlo simulation has been widely used in a lot of applications related to risk analysis. The simulation process is built on iterations that make use of internally generated random numbers to generate results. Monte Carlo simulation can be used to calculate the required amount of risk premium. In this regard, the identified risk events are assigned probability distributions to represent the probability of occurrence (P) and the impact (I). During each iteration, a randomly generated number (R), that follows a pre-identified probability distribution, is created to represent the value of (P) and (I), and to calculate the total risk magnitude (TRM). The simulation is repeated several times and the calculated TRM is saved. The mean and the standard deviation of the resulting TRM are used to construct a normal distribution function of the expected monetary value (EMV). Finally, the risk premium can be established by selecting a probability percentile of under run.

Kraemer (1976) applied Monte Carlo simulation to evaluate the cost, schedule, and technical risk of an aircraft development program. The proposed program is divided into seven major phases, named: air vehicle design, major subcontractors, A/C manufacturing, subsystem test, ground and wind tunnel test, and project management. Lower risk elements are evaluated using subjective assessment, while higher risk elements are evaluated using Monte Carlo simulation. Upon the identification of higher risk elements, risk identification is conducted and experts' judgment is used to define the probability of occurrence and to capture a three point estimate (i.e., minimum, most likely, and maximum) of the risk impact, represented in terms of time and cost. Experts are then required to estimate the most likely number of risk events that are expected to occur during the schedule of each element. Poisson distribution, defined using the most likely number, is used to represent the monthly occurrence of different risk events. Monte Carlo simulation is then conducted starting with the first month and proceeding to the end of the program span. The results of conducting Monte Carlo simulation are represented in probability density functions that represent the cost and time of the program.

Javid and Seneviratne (2000) proposed using Monte Carlo simulation to estimate and understand the impacts of cash flow uncertainties on project feasibility. The risk issues addressed pertain to investment decisions made by developers in airport parking infrastructure facilities. The authors defined total investment risk as a function in three sources of risk, i.e., project risk, competitive risk, and market risk. Competitive risk arises from the practices of other competitors seeking to increase their market share, while market risk is triggered by inflation, interest rate, and legislative restrictions. The authors noted that changes in income and expenditure due to inflation, interest rate, and legislative restrictions are the most difficult to describe in terms of probability density functions (PDFs). The investment risk is then represented as the probability of the net present value (NPV) being less than the target value (V). The NPV over a period of time (i) is represented as a function in three parameters, named: total revenue, total operating and maintenance cost, and discount rate. Equations used to define the three parameters contain random quantities defined using PDFs. Monte Carlo summation is then conducted to calculate the NPV and to estimate the investment risk.

During this study, the authors assumed that there is sufficient expertise to establish PDFs for all the parameters and variables used in this study.

Molenaar (2005) presents a methodology for cost and schedule risk analysis of highway megaprojects. Monte Carlo simulation was utilized to generate probability distributions for total cost and schedule to completion that considers the base cost estimate and the probable cost/duration of risk and opportunity events.

Molenaar (2005) noted that the process can be used to help determine where the cost risks and opportunities are located. Thus, management can focus its resources to effectively manage and mitigate these uncertainties. A sensitivity analysis, which was conducted to rank different risk events, supports management to identify high risk items and establish immediate mitigation measures that can be taken to reduce the uncertainty.

Moses and Hooker (2005) developed a Monte Carlo based model for probabilistic cost and schedule risk assessment for a satellite launcher. A schedule was developed from past launchers of similar types, and was composed of 136 major tasks. Risk identification was conducted and each identified risk event was mapped to the developed schedule. Binomial distributions were used to define the likelihood of each identified risk event and triangular probability density distributions were selected to represent the consequences (impact).

Öztaş and Ökmen (2005) proposed a schedule risk analysis method, called the judgmental risk analysis process (JRAP). JRAP is classified as a pessimistic risk analysis methodology based on Monte Carlo simulation. This pessimism is imposed through equations that use the maximum operator to calculate the overall effect of different risk events. The author attributed their selection of a pessimistic approach to the various judgmental decisions that are normally conducted based on experience and intuition, which would add more uncertainty to the analysis. Steps identified under the proposed methodology include the following:

- Identify critical risks that may affect activity durations.
- Assign probability distributions to the identified risk event, and define the maximum and minimum duration of each activity using a set of predefined equations.
- Define the percentage effect of each risk over each activity.
- Conduct Monte Carlo simulation to calculate the variation in activity duration.

Although Monte Carlo simulation based models have been utilized by many researchers to conduct risk analysis, these models entail some difficulties attributed to the required amount of data; otherwise, uncertainties in the input parameters may result in large uncertainties in the resulting estimate. As can be noticed from the previously highlighted studies, researchers tend to rely on assumptions to define the PDFs to overcome the limited availability of data. Moreover, in some cases, the output obtained from the simulation is very wide in range, and therefore cannot help to establish an accurate estimate of risk. Thevendran and Mawdesley (2004) pointed out that although Monte Carlo simulation and sensitivity analysis are commonly used for quantitative risk analysis, these risk analysis techniques cannot accurately forecast the effects of human factors because of its complex, unpredictable, and qualitative nature. Establishing correlation between risk events is another challenge in conducting Monte Carlo simulation. Öztaş and Ökmen (2005) indicated that assessment of the correlation between risk factors is as important as the identification of risks, and any risk model should consider defining these correlation coefficients, if correlation exists. Otherwise, the simulation results would not be realistic.

Guyonnet et al. (1999) conducted a study to compare the fuzzy approach to the Monte Carlo approach to evaluate environmental risks related to contaminated sites. They concluded, based on reviewing the results, that the result obtained using the fuzzy approach had considered all possible combinations of inputs, while in the Monte Carlo analysis, scenarios that combine low probability inputs have very little chance of being randomly selected. Failure to consider low probability inputs may result in wrong decisions—especially for environmental context, where human health is often at risk.

2.5.7 Risk Analysis Using Fuzzy Logic (Qualitative/Quantitative Risk Analysis)

The concept of fuzzy sets was first suggested by Zadeh (1965), and since then, has been used for many applications. Fuzzy sets provide an adequate model for modes of reasoning that are approximate rather than exact. This technique is characterized by the ability to assign membership values expressing a degree of belief that a certain value of a factor corresponds to a linguistic concept. Thus, instead of representing risk events using probability density functions, the concept of fuzzy logic uses possibility distributions. Possibility distributions can be used to describe the relationship between a variable and its membership value. The use of fuzzy logic is helpful to solve complex problems in which there is no simple mathematical solution to accommodate the problem. The imprecise and uncertain nature of construction projects lends itself to the use of fuzzy sets, and many applications have been developed to perform risk analysis.

Dikmen et al. (2007) introduced a fuzzy risk analysis tool to quantify risk ratings in the construction domain at an early phase of a project. The proposed approach is based on using influence diagrams as a risk identification tool, and utilizing fuzzy logic for risk assessment. The influence diagramming method is used to establish relationships between project and country level risk sources and influencing factors, i.e., root causes. Factors that may affect the magnitude of country risk include: experience of the company in the host country, immaturity of the legal system, instability of political conditions, societal conflict, poor attitude towards foreign companies, poor macroeconomic conditions, cultural/religious conflicts, and contract clauses about country risk. Factors that may affect the magnitude of project risk include: construction risk, technical risk, managerial risk, resource risk, productivity risk, design risk, payment risk, client risk, and subcontractor risk. Experts are required to rate the risk factors and the influencing factors using five linguistic terms, defined as low, low to medium, medium, medium to high, and high. During the risk assessment phase, aggregation rules between the rating of the country risk factors and the favorability of the contract clauses, and between the project risk factors and the experience of the company in similar projects, are used to calculate the final risk rating. The minimum operator is used for implication between different rules, and the maximum operator is used for aggregation. The final risk rating is then defuzzified. The output of the fuzzy risk assessment procedure is a final cost overrun risk rating, calculated by using a scale of 1 to 10.

The proposed model offers guidance for the company about the amount of risk premium that should be included in the mark-up. This tool can be also used as an organizational learning tool, since knowledge is captured in the form of (if, then) rules. However, the proposed model entails some limitations and drawbacks. For instance, the output obtained from this tool is a scale number between 1 and 10, which limits the usability of this tool to provide qualitative assessment of risk rather than providing quantitative assessment of the risk premium. In addition, and as noted by the authors, the influence diagram given in this paper covers only the major sources of risk rather than providing a complete list, which make this risk model a specific model rather than being a generic model. As a result, considering the addition of any new risk event will imply electing all the rules to include the new risk event. Thus, the calibration of these models to serve in another context was not taken into consideration. Finally, and similar to the previously illustrated NN models, this model did not consider risk mitigation during risk assessment.

Markowski and Mannan (2008) established a fuzzy risk matrix to support risk analysis. The fuzzy risk matrix is based on establishing a fuzzy inference system between probability of occurrence, severity, and the risk magnitude. The probability of occurrence is categorized into seven categories (A: remote, B: unlikely, C: very low, L: low, M: medium, H: high, and G: very high). The severity of the risk is categorized into five categories (I: negligible, II: low, III: moderate, IV: high, and V: catastrophic). Four risk tolerance zones were identified (A: acceptable, TA: tolerable acceptable, TNA: tolerable unacceptable, NA: unacceptable). The relation between probability, severity, and the risk magnitude is described in the form of if-then rules. Thirty-five rules were identified to establish the relationship between probabilities of occurrence, severity as inputs to the fuzzy inference system, and the expected risk magnitude over the identified four tolerance zones. The Mamdani fuzzy inference system was utilized to perform aggregation and implications. The center of area (COA) method was used to defuzzify the outcomes and provide a crisp value of the risk magnitude.

The proposed fuzzy matrix offers the advantages of reducing sharp transitions between different risk zones by incorporating the membership function, which allows gradual transition between concepts. The proposed fuzzy matrix offers the advantage of supporting qualitative assessment of risk events. However, this approach suffers from the limitation of its inability to support quantitative assessment of risk events and calculate the required risk premium.

Nasirzadeh et al. (2008) presented a new model for risk analysis that considers the interrelationships and interactions between risk events. Authors argued that the cumulative impact of a group of risk events may be greater than the sum of their individual impacts. Five risk events were considered during this study and are defined as: (1) pressure to crash project duration, (2) contribution of local community, (3) deficit in financial sources, (4) inefficiency of owner supervisors, and (5) inflation risk. The proposed methodology is a hybrid system dynamics (SD) and fuzzy logic approach in which both direct and indirect effects of risk events are modeled through feedback loops. Forrester (1961) introduced SD in the early 1960s as a simulation methodology for analysis of industrial systems, and since then, it has been used for many applications. SD is used to present the interaction between the five risk events, and also to model the relationship between each risk event and its root causes. Input data of the five risk events are represented using fuzzy numbers and are represented using α-cut. To quantify the cumulative impacts of risk events, the crisp values of each risk event at each α-cut are determined from their membership functions. Accordingly, dynamic simulation is performed with these crisp values. The output of the simulation yields the overall risk magnitude of the project and is represented as a fuzzy number. The center of area method was used to defuzzify the output. The results of using the hybrid fuzzy system dynamic model were then compared to using fuzzy arithmetic operation alone, to quantify the magnitude of each risk event without considering interactions. The results obtained from using the hybrid model indicated that the project is expected to have more project delays and cost overrun, as compared to the fuzzy model. The authors argued that modeling interrelationships between different risks using SD provided an appropriate measure to quantify the full impact of different risks. However, the authors did not validate their argument and provide proof that the results obtained from using the hybrid model better representing reality than the fuzzy model. In addition, the construction industry is subject to many complex interrelationships that are difficult to be modeled, and for this reason, this study is limited to only five risk events. Moreover, this study did not show how the authors had established the mathematical model within the SD to define each risk event.

Gürcanli and Müngen (2009) propose a method for assessing risk events that workers are exposed to at construction sites, using the fuzzy expert system. Three input parameters were considered during the development of the fuzzy expert system, i.e., risk likelihood, current safety rating, and risk severity. Accidents considered during this study include: fall from height, contact with electricity, falling object, heavy equipment accidents, traffic accident on site, building or structure collapse, cave-ins, other causes of accidents, fire or explosion, and material bouncing to face or other parts of the body.

The accident likelihood was obtained from past data. Accident severity for each accident was derived from interviews. To assess the safety rating, a set of safety measures (SM) were determined and a checklist comprised of 120 questions was prepared. AHP was utilized to calculate the weighting for each safety measure (SM) in the checklist. By answering all questions in the checklist, the overall safety rating was calculated. A fuzzy expert system was designed to establish the relationship between the input parameters and the risk level in the form of if-then rules. To utilize the expert system, the likelihood and severity are assessed linguistically using a scale ranging from 1 to 10. To assess the safety level, experts have to provide a rating from 1 to 10 for each safety measure (SM) in the checklist. The safety rating is then calculated by applying AHP and exporting the rating to the fuzzy expert system. Aggregation and implications are performing using the Mamdani inference system, and the result is defuzzified to assess the hazard level of the job site.

The proposed model offers the advantage of using linguistic terms to assess the level of risk in the construction industry; however, this model only supports a qualitative assessment of risk in a scale from 1 to 10, rather than providing a quantitative assessment. Moreover, this model requires assessing 120 safety measures (SM) to assess one of the input variables, i.e., safety rating. Finally, this model does not take into consideration calibration of the model, which would be necessary if a new safety measure was required to be added to the model.

Sachs and Tiong (2009) proposed a knowledge-based fuzzy expert system for quantifying risk in a generic, systematically structured, and coherent process. The proposed model utilizes fuzzy sets to capture expert opinion and to translate uncertain information on risk and mitigating strategies into dollar values. The proposed method combines fuzzy set, possibility, and probability theory to provide a quantitative assessment of risk. As compared to the previous studies, this study provides a comprehensive framework for risk analysis, and thus, a detailed summary of the work conducted under this study is summarized as follows:

(1) Seven trapezoidal linguistic terms were chosen to assess the expert's opinion on impact and likelihood of the risk factors. These seven alternatives are defined as: extremely low (EL),

very low (VL), low (L), medium (M), high (H), very high (VH), and extremely high (EH).

(2) The project is broken down into several cash flows, and each cash flow that is perceived to be at risk is investigated to identify different risk events.

(3) Each identified risk event is structured using an influence diagram to show its root causes. For each risk event, the likelihood (L) and the impact (I) of its root causes are collected using expert opinions or judgments. Multiple opinions on the same root cause are aggregated, as shown in Equation 2-5:

Agg (x) = $\sum_{i=1}^{n} w_i * A_i(x)$ where $\sum_{i=1}^{n} w_i = 1$ [2-5]

where A_i (x) denotes the selected linguistic term by expert i; w_i = weight attributed to each expert; and n = number of expert opinions collected.

(4) The opinions collected from experts on the likelihood and impact are aggregated by the fuzzy weighted mean method to calculate the risk magnitude for each risk event and is defined as follows:

$$I_i = \frac{\sum_{r=1}^{k} L_r * I_r}{\sum_{r=1}^{k} L_r} \quad [2\text{-}6]$$

where L_r is the aggregated likelihood for each root cause following the rule presented in Equation 2-5, and I_r is the aggregated impact following the rule presented in Equation 2-5. The multiplication, division, and summation in Equation 2-6 are based on applying fuzzy arithmetic operations on fuzzy numbers.

(5) The aggregated impact in the previous step is converted into a probability density function (PDF), as shown in Equation 2-7:

$$\text{Height (h)} = \frac{2}{[(c-b)+(d-a)]} \qquad [2\text{-}7]$$

(6) If the risks affecting a cash flow are perceived as high, then a mitigating measure can be applied to minimize the effect. The ability of the proposed mitigation (M) in controlling the impact of each risk event is represented as a trapezoidal fuzzy number (a_2,b_2,c_2,d_2), and the remaining impact of the risk is calculated, applying the subtraction operator on fuzzy numbers.

Step 3 involves the use of influence diagrams, which can be used in risk analysis to help describe the behaviour of systems that are too complex. Influence diagrams can be easily understood and used without the aid of an expert. These diagrams can help with testing alternative strategies or policy decisions by propagating the influences of the decision throughout the diagram (Diekmann 1992). Although this study has offered a generic model to assess risk event, it does have some limitations. For instance, the influence diagram, as compared to fault trees, does not offer the ability to use logical gates (i.e., AND or OR) to represent the logic between root causes and the risk event. Diekmann (1992) noted one serious weakness of using influence diagrams attributed to the way how those diagrams are solved. The most commonly used method of solving influence diagrams is throughout the uses of conditional-probability, which make the problem more complex especially when a risk event is attributed to more than one root cause. Moreover, the authors did not establish a framework to identify critical cash flow and to judge the level of risk criticality.

Shaheen et al. (2007) explores an alternate approach to range estimating based on fuzzy set theory. The intent of using fuzzy logic is to address some of the limitations of Monte Carlo simulation associated with computational burden, sensitivity to the input distribution shapes, and the need to assume correlations among all inputs. The following steps summarize the proposed model:

(1) Consult the experts to identify work packages that have major effects on the total cost of the project.

(2) Ensure each expert gives his/her estimate based on his/her experience, using one of the following distributions:

- triangular,
- trapezoidal, or
- uniform.

(3) Aggregate the experts' inputs using the Fuzzy Delphi approach.

(4) Calculate the total cost estimate by adding up the costs of the work packages.

(5) Calculate the expected mean value, standard deviation, fuzziness measure, ambiguity measure, and fuzzy number

quality index, and use this information to assess the precision and quality of the output compared to outputs obtained from different estimating techniques.

The authors compared the results obtained from range estimating using fuzzy arithmetic against outputs obtained using the probabilistic approach. The results from both approaches show comparable results. The use of fuzzy logic offers the ability to reduce the number of iterations required to generate the output. This study also proposed the use of some quality measures that can be used to compare the results to outputs obtained from other estimating techniques.

Sadeghi et al. (2010) proposed a fuzzy Monte Carlo simulation (FMCS) framework for modeling risk in construction projects. This framework is capable of considering both fuzzy and probabilistic uncertainty of the input variable. Authors introduced the fuzzy cumulative density function (CDF) as a generalized form of CDF. Fuzzy CDF has the ability to represent both fuzzy and probabilistic uncertainty in a single figure. FMCS was used to develop a cost range estimating template for construction projects. The examples used to verify the proposed framework indicated that the FMCS framework is very effective for providing decision support for construction projects.

The models proposed by Shaheen et al. (2007) and Sadeghi et al. (2010) have some limitations. For instance, none of these models is capable of explaining the logic that might lead to the occurrence of a risk event. In addition, both models represent the aggregated impact of different risk events as a range estimate, rather than estimating the expected monetary value of each risk event. Thus, both models lack the ability of defining how much money can be allocated to address each specific risk event. Moreover, none of the above models consider the effect of establishing mitigation strategies and how this might affect the expected monetary value of a risk event.

2.6 Summary

This chapter presented a different perspective on risk and risk analysis. This chapter also presented some studies that were conducted in the past to address risk analysis. An overview of the proposed approach was presented, followed by a discussion of the advantages and disadvantages of each proposed approach. Some of the proposed approaches are qualitative, which implies that they can be used only for the ranking of risk events or to judge the level of riskiness of the project. However, these techniques cannot offer risk analysts the ability to conduct quantitative risk analysis by calculating the expected monetary value of each risk event. Some of the proposed techniques require identifying critical work packages or critical cash flows without establishing a framework to indentify them. It is also quite obvious that the shortfalls of the studies that are based on a probabilistic approach. For example, decision trees and Monte Carlo are due to the lack of sufficient data to establish the required distributions and the level of transparency of using these models. Many of the highlighted studies are not generic, which implies that any further modification to the risk analysis model—for example, adding new risk event—will require rebuilding the model from scratch.

Thus, in order to develop a comprehensive risk analysis model, further research is required. This research should be conducted to address the limitations of previous studies, by offering a generic risk model that can do reasoning even if data do not exist to quantify the required risk premium, offering experts the ability to express themselves linguistically, and also considering the ability to mitigate risk during the analysis process. Such a model is required to be transparent enough by offering the ability to trace the results and understand how a certain conclusion is obtained. Such a model is also required to be more comprehensive to support other risk management processes such as risk identification, risk response, and risk monitoring and control. The next section will provide an introduction to three well-known techniques to perform risk analysis. These are known as failure mode and effect analysis (FMEA), fault trees, and event trees. These three techniques are combined together to construct the proposed framework. Fuzzy logic is used to address the limitations of each technique, as will be highlighted in chapter 4 and chapter 5.

3. Risk Analysis Techniques (FMEA, Fault Trees, and Event Trees)

The purpose of this chapter is to review some common techniques for risk analysis, such as failure mode and effect analysis, fault trees, and event trees, and to highlight issues and challenges associated with using these techniques to develop a robust risk analysis framework.

3.1 Introduction

One can anticipate that risks always exist and can lead to unsuccessful outcomes, especially in the construction domain, in which high levels of risk and uncertainty are expected due to a lack of information. Each project is considered to be unique, which adds more uncertainty for the project team since accumulated data about risk events could be irrelevant for new projects.

To help manage risk events in a construction project, many techniques have been developed. This chapter describes three techniques that can be used effectively to analyze risk events at the early stages of the project, as well as during the execution phase.

The first technique to be covered is failure mode and effect analysis (FMEA). This technique can help project teams anticipate project failure modes and assess the level of priority of establishing corrective actions.

By establishing a priority rating of different risk events, the management team can establish its priority for responding to different risk events, which will aid in establishing cost effective response strategies.

The second technique described in this chapter is fault tree analysis (FTA), which can be viewed as complementary to FMEA, as it considers more levels of details. Unlike FMEA, which stops the level of analysis at the top level (risk level), FTA drills deeply into the root causes by establishing a logical diagram between a risk event and its associated root causes. Fault trees can be solved qualitatively, by determining minimal cut sets, and quantitatively, by calculating the probability of occurrence of the risk event.

The third technique described in this chapter is event tree analysis (ETA). The outcomes of an event tree are determined by considering all possible permutations of the success and failure of mitigation strategies. Event trees are used to estimate the severity of the adverse consequence that a project may be eventually subjected to as a result of the occurrence of a specific risk event.

3.2 Failure Mode and Effect Analysis (FMEA) - Concepts and Framework

The first work in establishing a procedure for performing FMEA and criticality analysis was created by the U.S. military in 1949. In the early 1960s, the U.S. military established a military standard (MIL-STD-1629a) for systematically evaluating the potential impact of functional or hardware failures on mission success, system performance, maintainability, and maintenance requirements. The aerospace industry adopted this technique in the 1960s because of the potential risk to life when their products fail. In the early 1980s, the automotive industry began to incorporate FMEA into the product development process (McDonald et al. 2008).

The military standard (MIL-STD-1629a) defined FMEA as “A procedure by which each potential failure mode in a system is analyzed to determine the results or effects thereof on the system and to classify each potential failure mode according to its severity” (1980, 4). Goel and Graves defined FMEA as “an inductive bottom-up approach that identifies potential failure modes in a system caused by either design or manufacturing or assembly process deficiencies” (2007, 128). Within any traditional FMEA framework, risk analysts start from the component level of the system, work on compiling a list of potential failure modes, and try to analyze the effects of those failure modes on the system by calculating an index score, named the risk priority number (RPN).

FMEA is an effective method used to analyze the risk associated within any system, and to support evaluating the level of risk criticality. Similar to other risk analysis tools, FMEA can provide an answer to the following questions:

- What can go wrong?

- What is the probability that it will happen?
- What is the consequence if it happens?

One of the aspects of the FMEA that makes it widely accepted is the group dynamic in which personnel from different functional groups are gathered to evaluate the risk associated with a system from various standpoints and concerns. One of the main concerns is the omission of some critical failure modes because the brainstorming session is not sufficiently comprehensive. Thus, it is crucial to bring the right team to the session. Goel and Graves (2007) indicated that the optimal size of the team to perform FMEA is 4 to 6, and the maximum is 10. The team is responsible of determining the level of risk severity (S), occurrence (O), and detection (D), and to establish the acceptable level of risk for the system being evaluated. The level of training and practical experience of the user of this technique is essential to the analysis since it provides the user with a better understanding of how the tool is working and enhances the way in which he/she perceives risk within a specified situation.

FMEA can be applied following three phases. The first phase is concerned with identifying a potential failure mode within a system. The failure mode can be internal or external to the system. Root cause analysis is conducted to understand the relationship between different causes and their effects. The second phase is concerned with using feedback from subject matter experts to assess the occurrence (O), severity (S), and the level of detection (D) of each identified failure mode.

The assessment of O, S, and D is used to calculate the RPN. According to the calculated value of the RPN, team members can work on establishing improvements to the system to mitigate the identified failures.

FMEA entails several advantages, which can be summarized as follows (Dhillon 1992):

- FMEA can help provide data for developing fault tree analysis.
- FMEA can support establishing corrective actions.
- FMEA can aid in selecting design alternatives with high reliability at the initial design stages.
- FMEA can support the identification of possible failure modes.
- FMEA can be regarded as the basis for developing test methods.

Chapter 6 provides more applications and advantages attributed to the utilization of FMEA as perceived by experts in the construction domain.

3.2.1 Failure Modes and Failure Causes

Identifying different failure modes is an important step of any FMEA process. According to the military standard (MIL-STD-1629a), a failure mode is defined as “the manner by which a failure is observed. Generally describes the way the failure occurs and its impact on equipment operation” (1980, 4). Each failure can be attributed to several root causes, entitled failure causes. A failure cause is defined by the military standard (MIL-STD-1629a) as “the physical or chemical processes, design defects, quality defects, part misapplication, or other processes which are the basic reason for failure or which initiate the physical process by which deterioration proceeds to failure" (1980, 4). Each failure mode can result in an effect known as "failure effect." Failure effect is defined by the military standard (MIL-STD-1629a) as "the consequence(s) a failure mode has on the operation, function, or status of an item" (1980, 4).

Bluvband and Grabov (2009) proposed a checklist that can be used by the FMEA team to identify potential failure modes. This list is based on asking the key question "What can go wrong?" The checklist can be summarized as follows:

- The intended function is not performed.
- The intended function is performed with some safety problems.
- The intended function is performed at a wrong time.
- The intended function is performed at a wrong place.
- The intended function is performed in a wrong way.
- The intended function is performed with lower performance level.
- The intended function is performed with cost overrun.
- The life time of the intended function is lower than planned.
- Providing support for the system to perform its intended function is impossible or problematic (maintenance problems, repairability problems).

The same checklist can be adapted to identify failure modes (risk events) in the construction domain. For instance, the first question can be reformatted as follows:

- What can go wrong in the project that can make the project unable to perform its intended function?

If the intended function of the project is to transfer 50,000 bpd of crude oil from point A to point B, then any problems that can lead to a reduction in that quantity has to be questioned and analyzed to identify potential failure modes. After identifying all potential failure modes (risk events), the second phase is applied to assess O, S, and D.

3.2.2 Risk Priority Number (RPN)

Within the context of the traditional FMEA, the degree of criticality is determined by calculating the risk priority number (RPN). The RPN ranges from 1 to 1000 and is an index score calculated as the product of three measurement scales: severity (S), occurrence (O), and detection (D) (i.e., S * O * D). The RPN is a unitless measure normally used to prioritize a list of failure events. The higher the RPN, the more critical the failure event is. The severity (S) reflects the seriousness of the effects of the failure. The severity rating is evaluated over a range from 1 to 10 to reflect the potential consequence of a failure mode. The occurrence rating (O) is the frequency of the occurrence of the failure over the life cycle of the system, evaluated over a range from 1 to 10. Occurrence (O) and severity (S) represent the two dimensions known as probability and impact for any risk matrix. The extra dimension that FMEA had brought is the evaluation of the level of detection (D). Ayyub defined the detection rating (D) as "a measure of the capability of the current controls" (2003, 61). Within traditional FMEA, a numerical scale ranging between 1 and 10 is used to asses the level of detection (D). Risk events with a low probability of occurrence cannot be assumed to have high detection ratings unless there is an effective measure established in place to control these risk events. Thus, detection rating adds more meaning to the analysis compared to the traditional approach of using O*S in the risk matrix. Industry and companies usually establish their own versions of the severity, occurrence, and detection rating that fits their needs and requirements. Tables 3-1, 3-2, and 3-3 list sample criteria to rate severity (S), occurrence (O), and detection (D).

According to the value assigned to the previously mentioned terms, the value of the PRN is calculated. Figure 3-1 shows an example of an FMEA worksheet to collect data. Chapter 6 presents the risk register designed to collect data.

The outcome of conducting FMEA is compiled in the FMEA report. The FMEA report contains a summary of the results, sources of the data, a system definition narrative, analysis assumptions, and recommendations based upon the analysis (MIL-STD-1629a). Results obtained out of the FMEA provide a lot of valuable information that can be used to reduce the impact of risk events and increase the chances of meeting the project objectives.

Table 3-1. Severity (S) rating evaluation criteria (adapted from Ayyub 2003)

Linguistic Terms	Rating	Description
Minor	1	No effect.
Low	2–3	Slightly noticeable.
Moderate	4–6	Noticeable effect on subsystem.
High	7–8	Effects on major system, but not on safety or government regulated compliance items.
Extreme	9–10	Effects on safety or involving noncompliance with government regulation.

Table 3-2. Occurrence (O) rating evaluation criteria (adapted from Ayyub 2003)

Linguistic Terms	Rating	Description
Minor	1	Failure is unlikely.
Low	2–3	Only isolated failures associated with almost identical processes.
Moderate	4–6	Failure of similar processes that have experienced occasional failures, but not in minor operations.
High	7–8	Failure associated with similar processes that have often failed.
Extreme	9–10	Failure is almost inevitable.

Table 3-3. Detection rating evaluation criteria (adapted from Ayyub 2003)

Linguistic terms	Rating	Description
Certainty of non-detection	10	Controls will not detect a defect.
Very low	9	Controls probably will not detect a defect.
Low	7–8	Controls have a poor chance of detecting a defect.
Moderate	5–6	Controls may detect a defect.
High	3–4	Controls have a good chance of detecting a defect.
Very high	1–2	Controls certainly will detect a defect.

Failure Mode and Effect Analysis Worksheet

System
Reference

Date
Compiled By
Approved By

Identification Number	Item	Function	Failure Mode	Failure Causes	Failure Effect	Failure Detection Method	Severity Rating (1-10)	Occurrence Rating (1-10)	Detection Rating (1-10)

Figure 3-1. Sample failure mode and effect analysis worksheet

3.2.3 Previous FMEA Studies

Paparella (2007) utilized FMEA to support redesigning the health care systems and to prevent the future occurrence of error. During FMEA investigations, the following questions were asked:

- What could go wrong?
- How could a failure happen?
- What would be the worst outcome if something did go wrong?
- What needs to be done to prevent these failures in our systems?

The steps taken during this study are as follows:

(1) Select a process for study and define the process.

(2) Identify potential failure modes and why they might happen, and determine their effects.

(3) Rank the impact and likelihood of each failure.

(4) Determine root causes of critical failure modes.

(5) Redesign the process where the effects of errors are unacceptable.

(6) Analyze and monitor the new process.

The author concluded that being a conscious practitioner includes thinking and working proactively, by using techniques such as FMEA to reduce the chances of adverse events occurring, to achieve a safe environment free from preventable harms.

Cassanelli et al. (2006) applied FMEA during the design phase of an electric motor control system for vehicle HVAC (heating/ventilation/air conditioning). FMEA analysis has started with lowest level and has proceeded in a bottom-up approach until the end effect on the system has been identified. After two years of production, the occurrence factor for a failure event was increased up to 5, leading the RPN to exceed the threshold. After several reviews, the problem was attributed to the failure of the diode (D1). A group of single chip Schottky rectifier was analyzed. The result of the analysis indicated that they were subject to short circuits and excess leakage. This first generic analysis suggests that some mechanical stress is the root cause of the observed failures. A detection strategy was suggested to introduce a stress screening test, which forced the RPN to decrease by decreasing the detection (D) (a decrease from 3 to 2). This correction was mainly to prevent the problem from reaching the customer, but did not fix the problem itself. However, a persistent, excessively high return rate remained, which forced the team to look further for the failure mechanism in order to find the right corrective actions to reduce the occurrence (O). Several studies that were conducted resulted in the conclusion that the diode must be replaced with a more robust device against reverse voltage overstress to reduce the occurrence (O) of this failure. The author concluded the importance of educating different teams in the application of FMEA, and considering the results obtained from the analysis in implementing corrective actions.

Rhee and Ishii (2003) introduced life cost based FMEA, which measures risk in terms of cost by comparing and selecting design alternatives that can reduce the overall life cycle cost of a particular system. The authors noted that failures may occur at any stage of the product life cycle, and the cost of failure becomes greater as the origin of the failure and the detection become further apart in time.

Failure cost is defined over three major components—labor cost, material cost, and opportunity cost—and is defined as shown in Equation 3-1, 3-2, and 3-3:

Labor cost = occurrence * (detection time * labor rate * No. of operators) + (fixing time* labor rate * No. of operators) + (delay time * labor rate * No. of operators) [3-1]

Material cost = occurrence * cost of part [3-2]

Opportunity cost = (detection time + fixing time + delay time)* hourly opportunity cost [3-3]

Equation 3-4 defines the availability of a reparable component, as follows:

$$\text{Availability (AV)} = \frac{\text{Mean Time to Failure}}{\text{Mean Time Between Failure}} \qquad [3\text{-}4]$$

Equation 3-5 defines the total availability of a system, as follows:

$$TA = (AV_{1\text{component}})^{\text{no. of components}} \qquad [3\text{-}5]$$

Equation 3-6 defines the failure frequency, as follows:

$$FF = \frac{\text{Detection time+Fixing Time+Delay Time}}{\text{Mean Time to Repair}} \qquad [3\text{-}6]$$

A Monte Carlo simulation is applied to the life cost based FMEA assuming triangular distribution of variables associated to failure cost, including failure frequency, detection time, fixing time, delay time, and parts cost.

Dhillon (1992) presents a brief introduction and an extensive list of references on failure modes and the effects analysis concept. Readers can refer to this list to understand more about the concept and the variety of applications prepared using FMEA.

3.2.4 FMEA Limitations

Despite the apparent simplicity of the method and the advantages of applying this technique, many shortcomings were identified by several authors. For instance, Bowles and Peláez (1995) and Puente et al. (2002) noted several shortcomings in both the ways in which calculations are made, by using the multiplication operator, and the ways in which the results are interpreted. For example, a failure mode with the following assessment of severity (S), occurrence (O), and detection (D) (say 9, 5, and 5, respectively) may have a lower RPN (225) than one with high severity (S), high occurrence (O), and a moderate level of detection (D) (say 6, 7, and 6, yielding a RPN of 252). Yet from the management perspective, the first failure must induce higher priority for corrective action compared to the second one, since the severity of the first one is high. Gilchrist (1993) indicated that there is no rationale as to why S, O, and D should be multiplied to produce the RPN. Bowles and Peláez (1995) indicated that the traditional application of FMEA may fail to estimate the RPN when the impact of failure is calculated over multi-dimensions, since only the most severe effect is used in the calculation. Puenta et al. (2002) and Pillay and Wang (2003) noted that the RPN does not differentiate between the importance of the input variables—i.e., severity (S), occurrence (O), and detection (D)—during the calculation of the RPN, since they are all coming with one weight. Herrera (1997) noted the advantage of using linguistic terms to capture the preference of experts especially in situation in which experts can not provide exact numerical number. Xu et al. (2002) noted the shortcomings of using numerical values to evaluate the occurrence of the failure event, and argued the advantage of using other techniques that can support linguistic assessment of failure modes. Xu et al. (2002) also noted the difficulty for experts to provide precise assessment of the probability of failure events to conducted FMEA. Bowles and Peláez (1995) noted the advantage of using fuzzy logic to conduct FMEA especially in situations in which the information on which they are based is vague, ambiguous, qualitative, or imprecise. Chin et al. (2007) Indicated that most of the information required to conduct FMEA are better expressed using linguistic terms, such as 'likely', 'important' or 'very high'. Braglia et al. (2003) noted the difficulty for experts to give a numerical evaluation of these (intangible) quantities. Braglia et al. (2003) noted that "Even if the technique is thought as "quantitative" approach, it is really based on qualitative assessments, predicted failure rates, and other factors that are only guesses at the best."

Abdelgawad and Fayek (2010a) reviewed the rule of thumb proposed by Ayyub (2003), in which he noted that any failure mode with a RPN greater than 125 should be considered seriously. Abdelgawad and Fayek (2010a) noted that such a rule of thumb is very subjective, since there is no proof to verify this argument. Abdelgawad and Fayek (2010a) also indicated that without linking the value of the RPN to linguistic terms describing the priority to take corrective action, the project team will not be able to recognize the difference, for example, between a risk event with an RPN equal to 140 versus one with an RPN equal to 160. In order to address many of the above mentioned limitations, fuzzy logic was combined with the traditional FMEA and used to develop a fuzzy expert system, as will be explained in detail in the next chapter. Fuzzy logic and fuzzy expert systems are described next.

3.2.5 Fuzzy Logic

The concept of fuzzy set was first suggested in the mid-sixties by Zadeh (1965) to achieve a simplified modelling of complex systems that require approximate solutions rather than exact. Yager and Zadeh (1992) indicated that the conventional approaches do not provide an adequate model for modes of reasoning that looks for approximate solutions rather than exact. Since 1975 there were attempts to develop applications for laboratories as well as for large scale technical utilization. Mamdani was the first large scale application that was realized successfully for controlling a cement kiln (Kruse et al. 1994). Starting at the beginning of the 80s, Japan was the leader in using fuzzy expert systems for practical applications, including video cameras, washing machines, rice cookers, etc. (Zimmermann 1999).

Zimmermann (1999) noted several advantages of using fuzzy logic in real world applications. These advantages can be summarized as follows:

(1) Fuzzy logic based models are conceptually easy to understand, since fuzzy logic imitates human-like reasoning.
(2) Fuzzy logic based models are tolerant of imprecise data.
(3) Fuzzy logic based models can model most nonlinear complex functions.
(4) Fuzzy logic based models can be built on top of the experience of experts.
(5) Fuzzy logic based models are based on natural language, and hence can provide better communication between experts and managers.

Due to the imprecise nature of many factors that affect construction projects, fuzzy logic lends itself well to many construction applications. Many construction-related factors are subjective and uncertain, and thus fuzzy logic is being used more and more to model construction issues where the information is only available in the mind of an experienced construction practitioner (Knight and Fayek 2002).

Since fuzzy logic is based on a natural way of human communication, the subjective assessment of the problem can be utilized to derive an acceptable approximation. Fuzzy logic is combined with FMEA to overcome the deficiencies associated with the traditional approach of computing the RPN number. Instead of depending on the multiplication of S, O, and D to calculate the RPN, the proposed approach uses a fuzzy expert system, based on information elicited from experts, to analyse and prioritise different risk events.

3.2.6 Fuzzy Expert Systems

The fuzzy expert system is a popular computing framework based on the concepts of fuzzy set theory, fuzzy IF-Then rules, and fuzzy reasoning. It has found successful applications in a wide variety of fields. Because of its multidisciplinary nature, the fuzzy expert system is known by numerous other names, such as fuzzy-rule-based system, fuzzy inference system, fuzzy model, fuzzy associative memory, and fuzzy logic controller (Jang et al. 1997).

Jang et al. (1997) noted the ability of fuzzy expert system to take advantage of domain knowledge that might not be directly employed in other modeling approaches. The basic structure of a fuzzy expert system consists of three conceptual components referred to as fuzzification, fuzzy inference, and defuzzification. In fuzzy FMEA, the fuzzification process is the process in which occurrence (O), severity (S), and detection (D) are converted into their fuzzy representations. During this process, the user provides assessments of severity (S), occurrence (O), and detection (D), and according to the assessment of S, O, and D, the fuzzy expert system identifies the corresponding membership value for each variable.

The second component of the fuzzy expert system is the knowledge base, which is a database of IF-Then rules that define the relationships between the premise, represented by the input variables S, O, and D; and the consequent, represented by the RPN in the proposed framework. During the fuzzy reasoning process, each rule is fired according to the degree of matching between the input value and the premise of each rule. Implications and aggregations are used during this process to calculate the contribution of each rule to the overall value of the RPN. The final step is the defuzzification process, in which a crisp output value of the RPN is calculated from the aggregated fuzzy set. Figure 3-2 shows different components of the fuzzy expert system. The steps conducted to develop the fuzzy FMEA expert system are described in the next chapter.

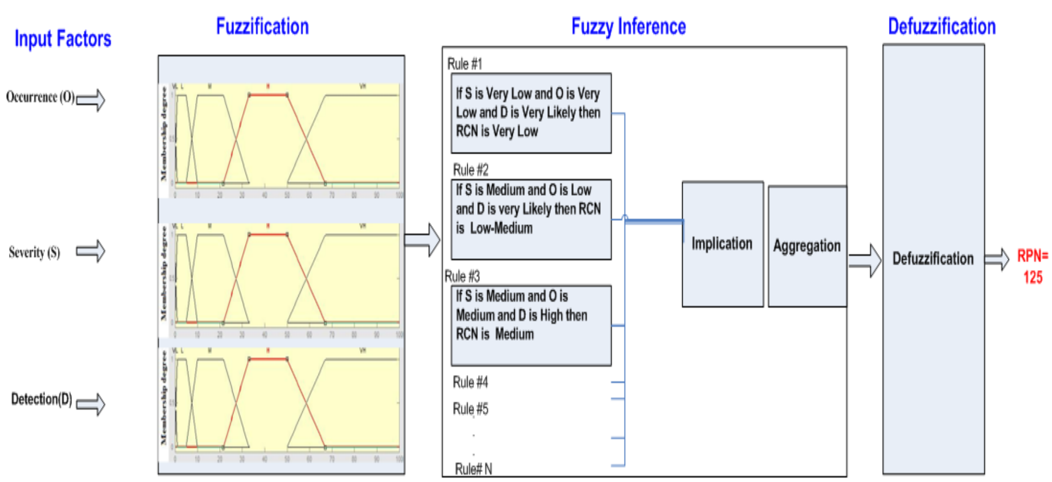

Figure 3-2. Fuzzy inference system

In order to demonstrate how fuzzy expert system works, let us assume that we are required to design a fuzzy expert system in which we have two input variables named: X1, and X2, and one output variable named Y. Let us assume that the two input variables were defined over the range of 1 to 10 using three linguistic terms named: low, medium, and high. Let us also assume that the output variable is defined over the range of 1 to 100 using five linguistic terms named: very low, low, medium, high, and very high. Figure 3-3 shows a simple structure of the fuzzy expert system developed using the Fuzzy Logic Toolbox running under MatlabR2008b ® environment.

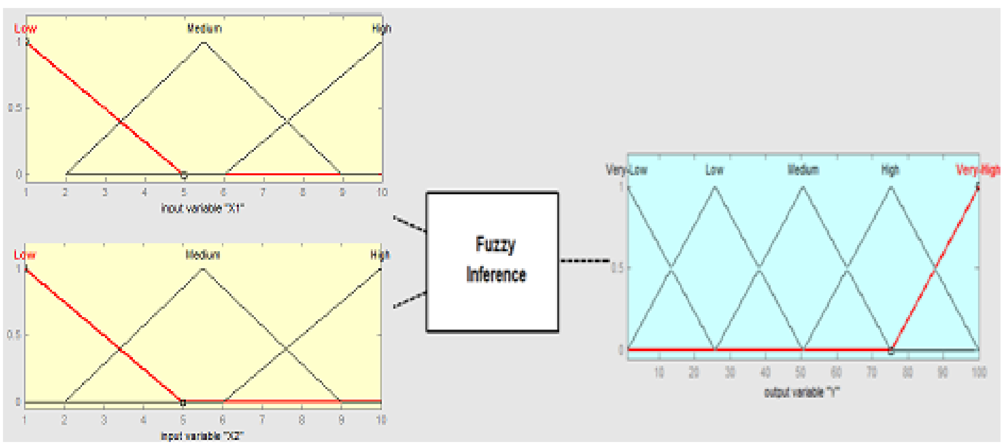

Figure 3-3. Example fuzzy expert system

After defining the membership functions for the inputs and the output variable, expert's opinion can be used to define the relationship between the inputs and the output variable in the form of (if-then) rules. Figure 3-4 shows nine rules to represent the relationship between X1, X2, and Y. For example, rule 1 indicates that: if (X1 is low) and (X2 is low) then (Y is very Low). Figure 3-5 shows the membership functions representation of the nine rules. For example, the first rule shows the membership of (X1 is low) and (X2 is low) and (Y is very low). The second rule shows the membership of (X1 is low) and (X2 is medium) and (Y is very low). The same concept can be applied to understand the remaining rules in Figure 3-5. Please note that the if-part of the rule “X1 is low” and “X2 is low” is called the premise, while the then-part of the rule “Y is very low” is called the consequent or conclusion.

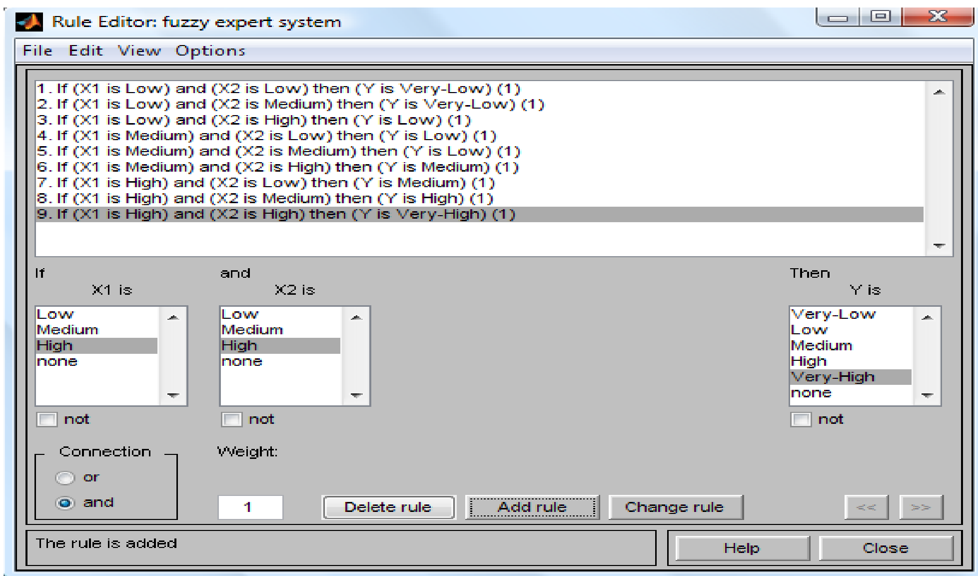

Figure 3-4. Sample (if-then) rules

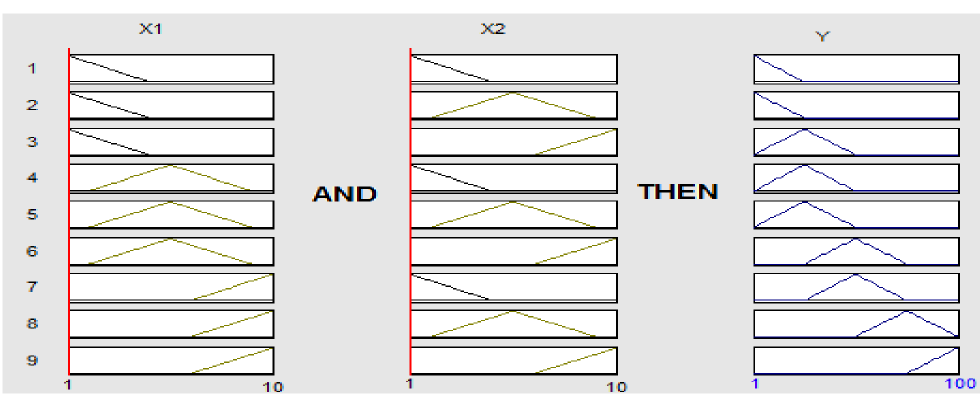

Figure 3-5. Membership representation of the nine rules

The next step is defining a t-norm to represent the logical operator (AND). Any t-norm is a binary operation that satisfies the following rules (Pedrycz and Gomide 2007):

1- Commutatively: a t b= b t a [3-7]

2- Associatively: a t (b t c)= (a t b) t c [3-8]

3- Monotonicity: if b ≤ c, then a t b ≤ a t c [3-9]

4- Boundary conditions: $\begin{cases} a\ t\ 1 = a \\ a\ t\ 0 = 0 \end{cases}$ [3-10]

Where a, b, c ∈ [0, 1]

Some of the commonly t-norms are defined as follows (Pedrycz and Gomide 2007):

1- Minimum= min (a, b) [3-11]

2- Product= a*b [3-12]

3- Lukasiewicz= max (a+b-1, 0) [3-13]

If the relationship between the inputs is defined using an (OR) operator, an s- norm is required to be defined. Any s-norm is a binary operation that satisfies the following rules (Pedrycz and Gomide 2007):

5- Commutatively: a s b= b s a [3-14]

6- Associatively: a s (b s c)= (a s b) s c [3-15]

7- Monotonicity: if b ≤ c, then a s b ≤ a s c [3-16]

8- Boundary conditions: $\begin{cases} a\ s\ 1 = 1 \\ a\ s\ 0 = a \end{cases}$ [3-17]

Where a, b, c ∈ [0, 1]

Some of the commonly s-norms are defined as follows (Pedrycz and Gomide 2007):

4- Maximum= max(a, b) [3-18]

5- Probabilistic Sum= a+b- a*b [3-19]

6- Lukasiewicz = min (a+b, 1) [3-20]

By defining values for the input variables, the membership value (μ) of each input variable is calculated applying the following equation for triangular distributions (Pedrycz and Gomide 2007).

$$\mu(x) = \begin{cases} 0 \quad if\ x \leq a\ or\ x \geq b \\ \frac{x-a}{m-a}\ \ if\ x\ \in [a, m) \\ \frac{b-x}{b-m}\ if\ x\ \in [m, b] \end{cases} \qquad [3\text{-}21]$$

where a is the minimum, m is the most likely, b is the maximum, and x is the value at which the membership function is required to be calculated.

To demonstrate how Equation 3-21 is used, let us assume that the value of X1 is defined as X1=7 and the value of X2 as X2=5. Firstly, the membership value of the X1 and X2 is calculated for each rule using Equation 3-21 as shown in Figure 3-6. As can be noticed in Figure 3-6, only rule 5 and rule 8 were fired since the input values for X1 and X2 satisfy the premise of both rules. To demonstrate how the membership value of X1 is calculated in rule 5, Equation 3-21 can be used as follows:

$$\mu(X1 = 7) = \frac{9-7}{9-5.5} = 0.57 \qquad [3\text{-}22]$$

The membership value of X2 is calculated using Equation 3-21 as follows:

$$\mu(X2 = 5) = \frac{5-2}{5.5-2} = 0.86 \qquad [3\text{-}23]$$

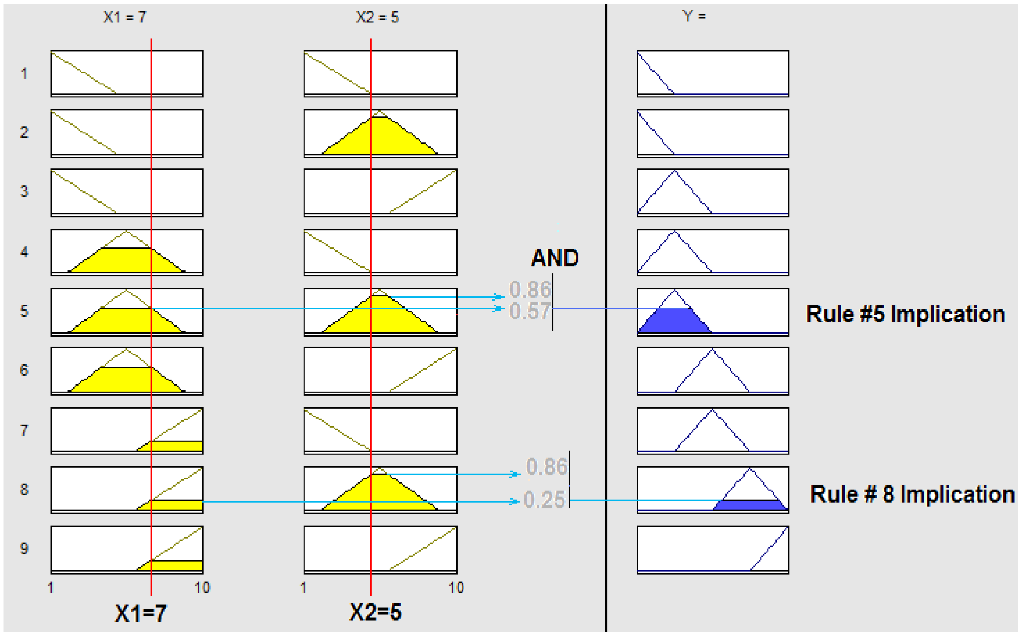

Figure 3-6. Membership values of the input variables

After calculating the membership value for each input variable at different rules, the logical operator is represented using one of the t-norms or s-norms. Since X1 and X2 is connected using an (And) operator, refer to Figure 3-4, then one of the t-norms as defined in Equations 3-11 to 3-13 can be used. For the sake of this example, let us assume that the minimum operator defined in Equation 3-11 is to be used as follows:

X1 And X2 = min (0.57, 0.86) = 0.57 [3-24]

The implication operation is then performed based on the calculated value in Equation 3-24. For the sake of the example, we are going to use one of the commonly used operators to do the implication, i.e., the minimum operator. Thus, the implication of rule 5 can be represented as the min (0.57, Y is low). Figure 3-6 shows the results of the implications for different rules. The same concept can be applied to calculate the value of the membership function for X1 and X2 in rule 8 and to perform the implication. The implicated membership function from each rule is then aggregated using the max operator. Figure 3-7 shows the resultant membership function after aggregating the implicated membership functions from all rules.

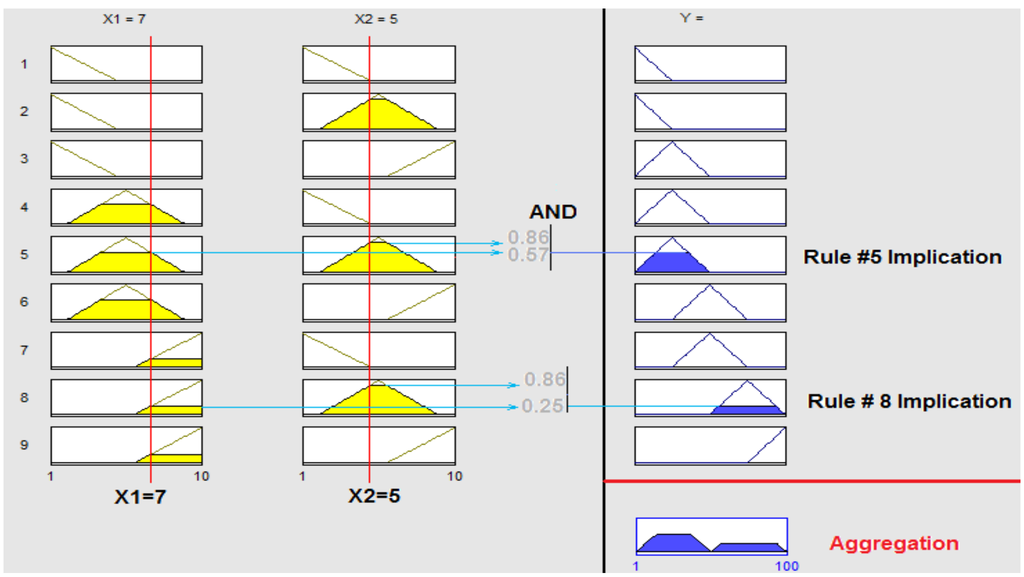

Figure 3-7. Aggregation of membership function

The final aggregated membership function is then defuzzified using one of the defuzzification methods. Some of the common defuzzification methods are (Yager and Zadeh 1992):

1. Center of area method: the center of area method calculates the center of the distribution. Figure 3-8 shows the defuzzified value of Y, the output, after applying this method.
2. Mean of Maximum: The Mean of Maximum Method (MOM) is based on averaging the support values which their membership values reach the maximum.

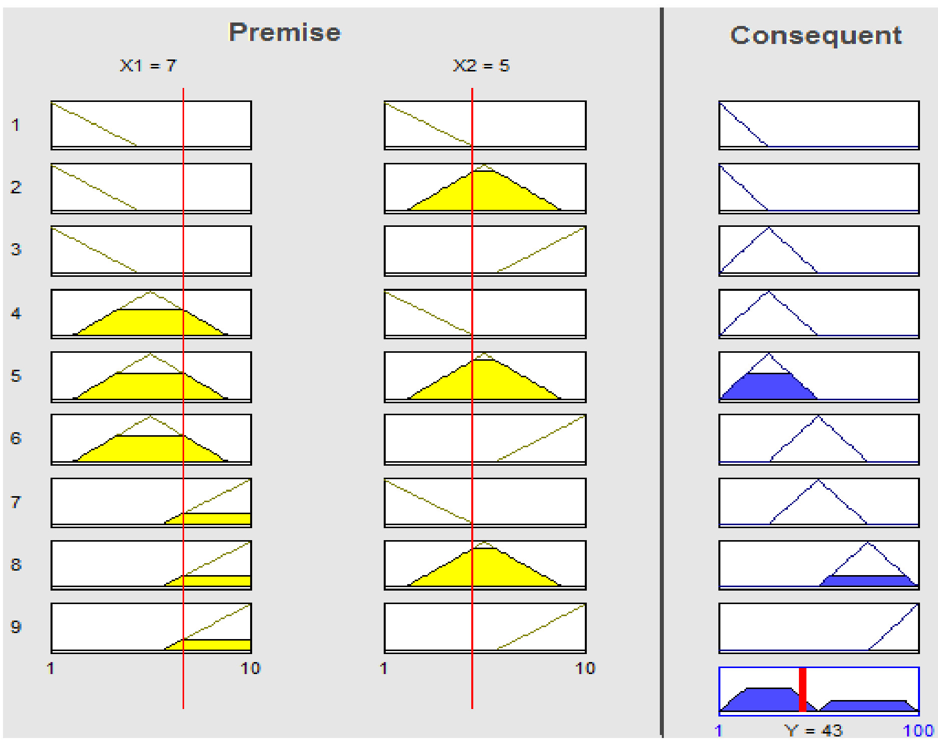

Figure 3-8. Defuzzification of the output function

3.3 Fault Tree Analysis (FTA)

The concept of FTA was first introduced in 1961 by H. A. Watson of Bell Laboratories, by an order of the U.S. Air Force (Ericson 1999). In 1963, Boeing was the first commercial company to recognize the advantages of FTA and to establish FTA applications (Ericson 1999). Following the advancement of using FTA in the aerospace industry, the technique began to gain widespread acceptance amongst practitioners in the nuclear industry. Since then, significant contributions have been made in advancing FTA by developing algorithms and software to solve fault trees (Ericson 1999).

NASA defined fault tree as “a graphic model of the various parallel and sequential combinations of faults that will result in the occurrence of the predefined undesired event. The faults can be events that are associated with component hardware failures, human errors, software errors, or any other pertinent events which can lead to the undesired event” (2002, 2). The undesired event of any system is represented by the top event in a fault tree structure. The analyst next determines the immediate and sufficient causes for the occurrence of this top event, which represents the intermediate events (gate events). The intermediate events (gate events) are then treated as sub-top events, and the analyst proceeds to determine their immediate and sufficient causes. The analysis continues until reaching the primary events (basic events and undeveloped events). The primary events are the events that are not further developed. The logical gates integrate the primary events to the top event. The most commonly used logical gates to connect root causes with upper events are AND (intersection) or OR (union) gates. The AND gate indicates that the upper event can not occur unless all the lower events occur. The Boolean symbol “*” is equivalent to the AND-gate. The OR gate indicates that the occurrence of any of the events in the lower level is sufficient for the upper event to occur. The Boolean symbol “+” is equivalent to the OR gate. Figure 3-9 shows a simple structure of a fault tree using OR and AND gates.

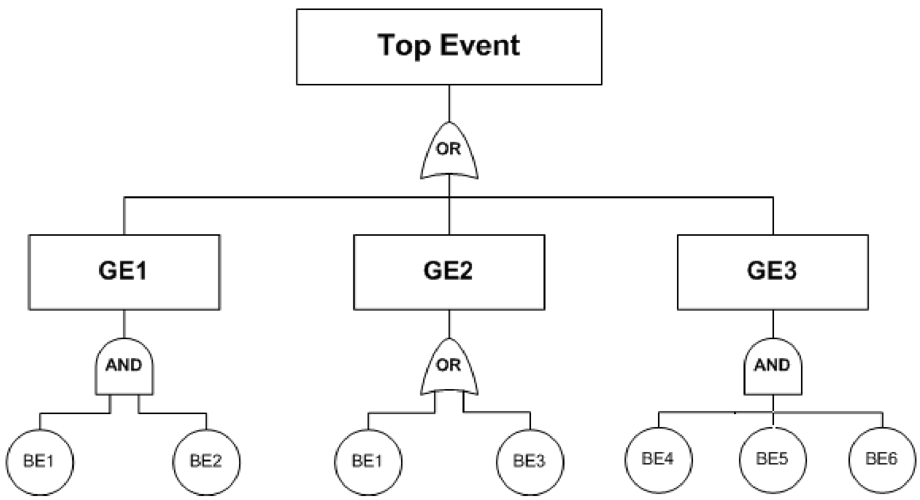

Figure 3-9. Sample fault tree structure

Fault tree (FT) is mathematically represented by a set of Boolean equations. The qualitative fault tree analysis identifies the minimal cut sets. Ayyub defined a minimal cut set (MCS) as “a cut set with the condition that the non-occurrence of any one basic event from this set results in the non-occurrence of the top event” (2003, 76). Thus, MCSs can be looked at as the smallest number of combinations between basic events, which, if occurring simultaneously, can lead to the occurrence of the top event.

The quantitative fault tree analysis represents the calculation of the top event probability of occurrence. Probability of occurrence is a numerical measure of the degree of certainty of the occurrence of an event, and is calculated as the ratio of a possible outcome of an event to all possible outcomes. Within FTA, the probability of occurrence of the top event (TE) is calculated by assigning values to the probability of basic events and propagating the calculations of the probabilities, using Boolean algebra, until the top event is reached.

3.3.1 Advantages of FTs in Decision Making

Fault trees can provide valuable information to decision-makers. Some of its advantages are summarized as follows (NASA 2002):

(1) Fault trees provide visual representation to communicate the logic behind the occurrence of top events, i.e., risk events. This information can be used more effectively by the project team as a way to communicate risk.

(2) Fault trees can be utilized as a proactive tool to help create proactive response strategies. By understanding the logic behind each risk event, proactive response strategies can be designed to control those root causes at early stages before risk events are realized. For instance, any MCS with one basic event indicates a critical combination in which a single event alone can cause the top event to occur. These single failures

combinations are often weak links, and should be the focus of prevention actions.

(3) Fault tree analysis and importance analysis provide valuable information to risk analysts by allowing the prioritization of the contribution of events to the occurrence of the top event. Using such an approach, the project team can work on establishing proactive risk response strategies to minimize critical root causes.

(4) Fault trees can be used to conduct root cause investigation after the realization of any risk event. By analyzing the logic between different root causes, decision-makers can understand why a risk event is realized. Thus, lessons learned can be captured, and more effective risk response strategies can be planned in the future.

(5) Fault trees are flexible to model any system and to help analyze the effect of change of one or more basic events on the probability of failure of the top event.

3.3.2 Fault Tree Analysis Steps

A successful FTA requires the following steps be carried out (NASA 2002, Ferdous 2006):

(1) Acquire knowledge about the system that will be analyzed.

(2) Define the top event (risk event) and the level of detail to which the failure causes for the top event will be developed.
(3) Define the ground rules, including the procedure by which basic events and gate events are named in the FT.
(4) Define the scope of the analysis, and proceed with fault tree construction.
(5) Conduct a qualitative FTA by calculating the MCSs.
(6) Conduct a quantitative FTA by calculating the top event probability.
(7) Conduct a sensitivity analysis by evaluating the level of contribution of root causes to the top event probability.
(8) Analyze and interpret the results.

3.3.3 Qualitative Fault Tree Analysis

After constructing fault trees, risk analysts can perform qualitative fault tree analysis to obtain MCSs. MCSs can be obtained by performing a Boolean algebra analysis on the constructed fault tree. The analysis can be conducted following either a top-down approach or a bottom-up approach. The difference between both is the starting point of the analysis. For instance, in the top-down approach, the analysis starts from the top event (TE) and moves down until reaching the basic events. The bottom-up approach starts from basic events and moves up until reaching the top event. Applying either the top-down approach or the bottom-up approach will lead to the same minimal cut sets (MCS) and it is left to the analyst's preference to select whatever techniques are more suitable for him/her to work with.

To demonstrate the calculations of MCSs, the structure shown in Figure 3-9 is used to apply the top-down approach for obtaining MCSs, as shown in Equations 3-25 to 3-30:

$$TE = GE1 \cup GE2 \cup GE3 \quad [3\text{-}25]$$

$$GE1 = BE1 \cap BE2 \quad [3\text{-}26]$$

$$GE2 = BE1 \cup BE3 \quad [3\text{-}27]$$

$$GE3 = BE4 \cap BE5 \cap BE6 \quad [3\text{-}28]$$

$$TE = (BE1 \cap BE2) \cup BE1 \cup BE3 \cup (BE4 \cap BE5 \cap BE6) \quad [3\text{-}29]$$

$$M1 = (BE1, BE2);\ M2 = (BE1);\ M3 = (BE3);\ M4 = (BE4, BE5, BE6) \quad [3\text{-}30]$$

where M1, M2, M3, M4, and M5 are the minimal cut sets.

Equation 3-30 shows that there are four minimal cut sets. M1 indicates that BE1 and BE2 must occur together to cause the top event (TE) to occur. M2 and M3 indicate that BE1 and BE3 are critical basic events, because each one is sufficient by itself to cause the top event to occur. M4 indicates that BE4, BE5, and BE6 must occur together to cause the top event to occur. Following the creation of the MCSs, Boolean simplifications are conducted according to the standard Boolean rules shown in Table 3-4.

Table 3-4. Boolean algebra rules (adapted from NASA 2002)

Law	Rule 1	Rule 2
Commutative	$x \cap y = y \cap x$	$x \cup y = y \cup x$
Associative	$x \cap (y \cap z) = (x \cap y) \cap z$	$x \cup (y \cup z) = (x \cup y) \cup z$
Distributive	$x \cap (y \cup z) = (x \cap y) \cup (x \cap z)$	$x \cup (y \cap z) = (x \cup y) \cap (x \cup z)$
Idempotent	$x \cap x = x$	$x \cup x = x$
Absorption	$x \cap (x \cup y) = x$	$x \cup (x \cap y) = x$
Transitivity	If $x \subset y$ and $y \subset z$, then $x \subset z$	
Involution	$\bar{x}^{-} = x$	
Boundary Conditions	$x \cap \emptyset = \emptyset$	$x \cap X = x$
	$x \cup \emptyset = x$	$x \cup X = X$
DeMorgan's	$(x \cup y)^{-} = \bar{x} \cap y^{-}$	$(x \cap y)^{-} = \bar{x} \cup y^{-}$
Complementation	$x \cap \bar{x} = \emptyset$	$x \cup \bar{x} = X$

In this example, BE1 is a repeated basic event (RBE), since it appears in both M1 and M2, and is simplified by applying the absorption law as shown in Equation 3-31:

$$(BE1 \cap BE2) \cup BE1 = BE1 \qquad [3\text{-}31]$$

Thus, Equation 3-29 can be further simplified, as shown in Equation 3-32:

$$T = BE1 \cup BE3 \cup (BE4 \cap BE5 \cap BE6) \qquad [3\text{-}32]$$

3.3.3.1 Minimal Cut Set Automation

Qualitative fault tree analysis is conducted to obtain MCSs, which can be performed manually, as shown in Equations 3-25 to 3-30. However, manual calculation of MCSs is a tedious and time-consuming job, particularly for large fault trees. Several attempts have been made to automate the calculation of minimal cut sets, and the main challenge is to find an effective algorithm for minimal cut set identification. In 1974, Fussell developed an algorithm named MOCUS (method for obtaining cut sets) to automate the generation of minimal cut sets (Ferdous 2006). However, the MOCUS algorithm contains some problems, which limits the usability of this algorithm. For instance, Vatin (1992) noted that users of this algorithm may run out of memory, since it is required to define the number of columns to be large enough to hold the cut set with the highest number of basic events, and the number of rows to be large enough to hold all (non-minimal) cut sets. Vatin (1992) also noted that the algorithm entails many unnecessary and duplicated steps, and the final cut set matrix is hard to be reduced to obtain the minimal cut sets.

Hauptmanns (1988) introduced an algorithm to automate the calculation of minimal cut sets. Compared to MOCUS, Hauptmanns' (1988) algorithm is intuitive, can create MCSs for any fault tree structure, and can be easily automated. In order to automate the algorithm, the following steps are applied (Hauptmanns 1988):

(1) Transform the fault tree logic into a Boolean matrix (BM) composed of 0's and 1's. "0" is used to indicate that no

connection exists, while “1” is used to indicate a connection between events. The rows of the BM are divided into two sections: the OR gate events (GE) in the upper part, and the AND gate events (GE) in the lower parts. The columns of the BM are divided into three blocks starting with basic events, followed by OR gate events (GE), and finally followed by AND gate events (GE). Table 3-5 shows the Boolean matrix (BM) for the example fault tree shown in Figure 3-9.

Table 3-5. Boolean matrix representation of example fault tree

Gate event ID	Gate type	Basic events						OR (GE)		AND (GE)	
		BE 1	BE 2	BE 3	BE 4	BE 5	BE 6	TE	GE 2	GE 1	GE 3
TE	OR	0	0	0	0	0	0	0	1	1	1
GE2	OR	1	0	1	0	0	0	0	0	0	0
GE1	AND	1	1	0	0	0	0	0	0	0	0
GE3	AND	0	0	0	1	1	1	0	0	0	0

(2) Create another empty matrix, referred to as the working Boolean matrix (WBM), and start the analysis from the top event.

(3) Replace the top event in the WBM with it is equivalent (basic events/gate events) from the Boolean matrix, referred to as the connection list (CL), by taking the following two rules into consideration:

3a) If the top event is connected by an OR gate with its CL, then insert each event from the CL into a separate row in the WBM.

3b) If the top event is connected by an AND gate with its CL, then insert all the events from the CL into a single row in the WBM. Table 3-6 shows the WBM after applying step 3. As shown in Table 3-6, since the top event in the BM, shown in Table 3-5, is connected by "1" with three gate events (GE1, GE2, GE3) using an OR gate, the WBM is created by inserting three separate rows, applying rule 3a, and adding a connection "1" under each gate event.

Table 3-6. Initial working Boolean matrix representation of the example fault tree

Basic events						OR (GE)		AND (GE)	
BE1	BE2	BE3	BE4	BE5	BE6	TE	GE2	GE1	GE3
0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	1

(4) Scan all the rows of the WBM to check if there is any connection "1" under any of the two blocks named "OR (GE)" and "AND (GE)." If so, then replace each gate event in the WBM with its equivalent (basic events/gate events) from the

Boolean matrix, referred to as the connection list (CL), by taking the following two rules into consideration:

4a) If a gate event is connected by an OR gate with its CL, then insert each event from the CL into a separate row in the WBM.

4b) If a gate event is connected by an AND gate with its CL, then insert all the events from the CL into a single row in the WBM.

(5) Repeat step 4 until the WBM contains 0 connections in the last two blocks, "OR (GE)" and "AND (GE)." Table 3-7 shows the final WBM for the example fault tree.

Table 3-7. Final working Boolean matrix representation of the example fault tree

Basic events						OR (GE)		AND (GE)	
BE1	BE2	BE3	BE4	BE5	BE6	TE	GE2	GE1	GE3
1	1	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	0	0	1	1	1	0	0	0	0

(6) Use each row in the final WBM to develop the MCS equations by converting each connection "1" in a row with its related basic event, and connect basic event(s) within each row using intersection "∩". For example, the first row in Table 3-7 can be

read as “BE1 $\cap$ BE2”. Basic event(s) in a row is/are connected with basic event(s) in another row using the union “$\cup$” operator. For example, the first and the second rows in Table 3-7, can be read as “BE1 $\cap$ BE2” $\cup$ “BE1”. By applying step 6 to all the rows in Table 3-7, a similar result to Equation 3-29 is obtained.

(7) Perform Boolean simplifications on the MCS equations. The simplification of the Boolean equation will lead to Equation 3-33, which is exactly similar to Equation 3-32.

$$T = BE1 \cup BE3 \cup (BE4 \cap BE5 \cap BE6) \qquad [3\text{-}33]$$

3.3.4 Quantitative Fault Tree Analysis

Equation 3-33 shows the result after conducting a qualitative fault tree analysis, and can be used to understand and explain how different root causes are connected logically to cause the top event (TE) to occur. To conduct quantitative fault tree analysis, the union and the intersection operators in Equation 3-33 must be converted as follows:

The Boolean symbol “+” is equivalent to the OR gate ($\cup$). For example, if the top event is connected with an OR gate with two basic events (A, B), this will be equivalent to the Boolean expression, TE = A + B. Either A or B or both must occur in order for TE to occur. In terms of probability, the probability of the top event can be written as shown in Equation 3-34 (NASA 2002):

$$P(TE) = P(A) + P(B) - P(A \cap B) \text{ Or } = P(A) + P(B) - P(A)P(B|A) \qquad [3\text{-}34]$$

- If A and B are mutually exclusive events, then P(A∩B) = 0. Event A and event B are mutually exclusive if they cannot both occur simultaneously (i.e., if $A \cap B = \emptyset$).
- If A and B are independent events, then P(B|A) = P(B) and

  P(TE) = P(A) + P(B) - P(A) P(B).

Finally, the probability of the top event (TE) or gate events connected by an OR gate is defined as shown in Equation 3-35 for mutually exclusive events after applying the De-Morgan law (Singer 1990).

$$\mathrm{Pr(Top\ Event)} = 1 - \prod_{i=1}^{N}(1 - \mathrm{MCS_i}) \qquad [3\text{-}35]$$

where N represents the total number of MCSs, and Pr represents the probability of occurrence.

On the other hand, the Boolean symbol “*” is equivalent to the AND-gate (∩). For example, if the top event is connected with an AND-gate with two basic events (A, B), this will be equivalent to the Boolean expression, TE = A * B. In terms of probability, the probability of the top event can be written as shown in Equation 3-36 (Singer 1990).

$$\mathrm{Pr(Top\ Event)} = \prod_{i=1}^{N}(\mathrm{MCS_i}) \qquad [3\text{-}36]$$

To illustrate Equation 3-35 and 3-36, assume that all the basic events connected by an OR gate in Figure 3-9 are mutually exclusive, and that there are sufficient data to estimate the probability of basic events as follows:

Pr(BE1) = 0.20; Pr(BE2) = 0.25; Pr(BE3) = 0.35; Pr(BE4) = 0.45; Pr(BE5) = 0.35; Pr(BE6) = 0.60

Hence, the probability of occurrence of the top event is calculated as follows in Equation 3-37:

$$Pr\ (Top\ Event) = 1-[(1-0.20)*(1-0.35)*(1-0.45*0.35*0.60)] = 0.53 \qquad [3\text{-}37]$$

3.3.5 Fault Tree Applications

Sianipar and Adams (1997) proposed FTA to evaluate element interaction phenomena in which the deterioration of one element can influence the deterioration of other elements. The implementation of the FTA involves several steps, including: knowledge elicitation, construction of the FT model, and qualitative and quantitative analyses of the FT. Seventeen basic events were considered in this study and modeled using AND and OR gates. Due to the non-availability of data, a bridge engineer was invited to provide an assessment of the probability of basic events assuming that the bridge is located at interstate highways and constructed in compliance with standard procedures. Basic events are also assumed to be mutually exclusive from each other. The qualitative FTA indicated 60 MCSs. The top seven important interactions are identified as follows:

(1) Transverse flexure cracks and damage to joint seals.

(2) Flexure cracks and damage to joint seals.

(3) Transverse flexure cracks and loose or missing fasteners.

(4) Transverse flexure cracks and heavy traffic volume causing deficiency in joint anchoring.

(5) Flexure cracks and heavy traffic volume causing deficiency in joint anchorage.

(6) Flexure cracks and loose or missing fasteners.

(7) Damage to area exposed to traffic, and damage to joint seals.

The authors noted the advantage of using FTA to alert departments of transportation of potential deterioration problems, which will aid in establishing prompt mitigation scenarios. The authors also highlighted the problem of non-availability of data to establish probability distribution for basic events.

Johnson (1999) established a fault tree model to examine the interactions and sequences of events that could lead to a bridge failure due to scour or channel instabilities at the piers or abutments. The author noted that although there are mathematical models to quantify scouring, the field is more complex and cannot be modeled entirely in the laboratory. During this study, the top event is defined as failure of the bridge. A bridge can fail due to failure at the abutment, or failure at the piers, or both. Abutment or pier failure can occur due to: channel widening, lateral migration of the channel, local scour, contraction scour, or channel degradation. The author indicated the difficulty of determining probability information for basic events to calculate the top event probability. Engineering judgement and physical limitations were used to establish three estimates of the lower, most likely, and upper limit of the probabilities of basic events. The author concluded by noting the advantage of using a fault tree to asses the probability of failure or a range of probabilities of failure for the current problem.

Hadipriono (2001) utilized FTA to investigate a real situation in which a woman fell on a ramp in front of a pub and broke her ankle. In this case, the investigations are performed by forensic engineers who are knowledgeable in the area of construction safety. Steps conducted can be summarized as follows:

(1) Identify details about all possible causes that contributed to the accident, and classify them as follows:
   I. Enabling events (internal events).
   II. Trigger events (active external events).
   III. Supporting events (passive external events).

(2) Model the findings in step 1 using FTA.

(3) Assess the probability of occurrence of different causes.

(4) Conduct qualitative and quantitative FTA.

(5) Identify the probable and most probable causes of the accident.

The possible causes of failure were identified as follows: drunk, sudden illness, friend impact, storm impact, defective shoes, damaged shoes, defective slope, slippery ramp, no guardrail, no warning sign, and inadequate light. Qualitative and quantitative fault tree analyses were conducted, and the results of the analyses reveal that the most probable causes are defective slope and slippery ramp. Results show the suitability of using fault tree analysis to perform forensic studies.

Ortmeier and Schellhorn (2007) presented the formalization of fault tree analysis (FTA) to verify whether a certain combination of component failures in a radiobased railroad crossing is critical for system failure or not. The main difference between this technology and the traditional railroad crossings is that hardware on the route are replaced by radio communication and software computations in the train and railroad crossing. Using the radiobased communication tools, the train identifies the position where it has to send a signal to close the barriers. The risk associated with this operation can happen when a train passes the crossing and the crossing is not secured. A fault tree analysis was conducted to represent the failure of communication between the radiobased communication and software. In this regard, the top event of the fault tree is defined as collision, and connected to two intermediate gate events using an OR gate. The first primary event is that the train passes the crossing, while the bars are not closed and the closing signal has not been released. The other is a situation where the train passes the crossing, while the bars are not closed, but a signal has been sent. The authors concluded that FTA is the only one which has a logic background structure that can be read and understood, and can be more easily accepted.

Ralph (1983) noted a drawback of using fault trees, which could be attributed to the difficulty of analysis due to the limited availability of data. Chapter 5 presents the proposed framework to address this limitation by incorporating fuzzy arithmetic operations to solve fault trees. Ferson (2002) indicated that fuzzy arithmetic operations are computationally simple, can be easily explained, does not require detailed empirical information, and does not require knowledge of correlations among variables, which makes fuzzy arithmetic operation to be more favourable scenario in case of non availability of data.

Ralph (1983) also noted that the top event of the fault tree is described in two states, i.e., failure or success; however, fault trees fail to represent the partial success state of a system. Ralph (1983) suggested combining fault trees with event trees to address this limitation. The next section introduces event trees and previous research in combining fault trees and event trees. Chapter 5 presents in detail our proposed framework to combine fault trees, event trees, and fuzzy logic.

3.4 Event Tree

The concept of an event tree was first used in 1960 by the U.S. Nuclear Regulatory for the assessment of risk in nuclear power plants. Afterward, the concept was used to study risk in various contexts (Srivastava 2008). Pate-Cornell (1984) suggests that if the purpose of the risk analysis is to compute the probability of system failure, then it is preferable to use fault trees. However, if the problem involves other variables that affect consequences, then it is better to use event trees.

The event tree can be defined as a horizontal graphical tool that starts on the left with an initiating event—a “risk event”—and proceeds chronologically by adding risk response strategies represented by branches to mitigate the initiating event. The branching point at which a new risk response strategy is introduced in the tree is called a node. The event trees are usually developed in a binary format, e.g., a success or a failure defined for each node variable. At a branching point, the upper branch of an event usually shows the success of the event, and the lower branch shows the failure. The probability of success or failure is calculated for each branch. Moreover, the outcome of each sequence of events, or path, is illustrated at the end of each sequence (Ahmadi and Soderhölm 2008).

According to Koren et al. (1984), the application of the event tree requires the following tasks to be done by the risk analyst:

(1) Understanding of the systems that are modeled using the event tree.

(2) Defining the set of possible failures and successes.

(3) Constructing the event tree.

(4) Defining the probability and its complement for each branch pair in the tree.

(5) Determining the overall probability (OP) of each path.

(6) Documenting the finished tree and determining the possible cost overrun and/or delay.

In conducting event tree analysis (ETA), the probability of occurrence of dependent events is conditional on the occurrence of events that precede it in the tree (Pate-Cornell 1984). For independent events, the overall probability (OP) of a chain of events (path) is calculated by multiplying the probability of occurrence associated with all events on the chain that connects the initiating event point to the corresponding end node. The same concept is applied to dependent events, but by viewing the probability of each event as conditional probability on the events that precede the event in the chain, and using the product operator to calculate the combined probability of each chain (path). The expected monetary value is calculated as the sum of the probability-weighted consequences over all the paths in the event tree (Sherali et al. 2008). To explain the above concept, let us consider the event tree structure given in Figure 3-10. Figure 3-10 represents an event tree structure composed of two mitigation strategies, referred to as mitigation1 and mitigation2. The probability of occurrence of the risk event is defined as (X), the probability of failure of mitigation 1 is defined as F_{m1}, and the probability of failure of mitigation 2 is defined as F_{m2}. For the sake of the example, let us assume that X = 0.50; F_{m1} = 0.30, and F_{m2} = 0.45. The probability of success of mitigation 1 and mitigation 2 can be calculated as follows in Equations 3-38 and 3-39:

$$S_{m1} = 1 - F_{m1} = 1 - 0.3 = 0.70 \quad [3\text{-}38]$$

$$S_{m2} = 1 - F_{m2} = 1 - 0.45 = 0.55 \quad [3\text{-}39]$$

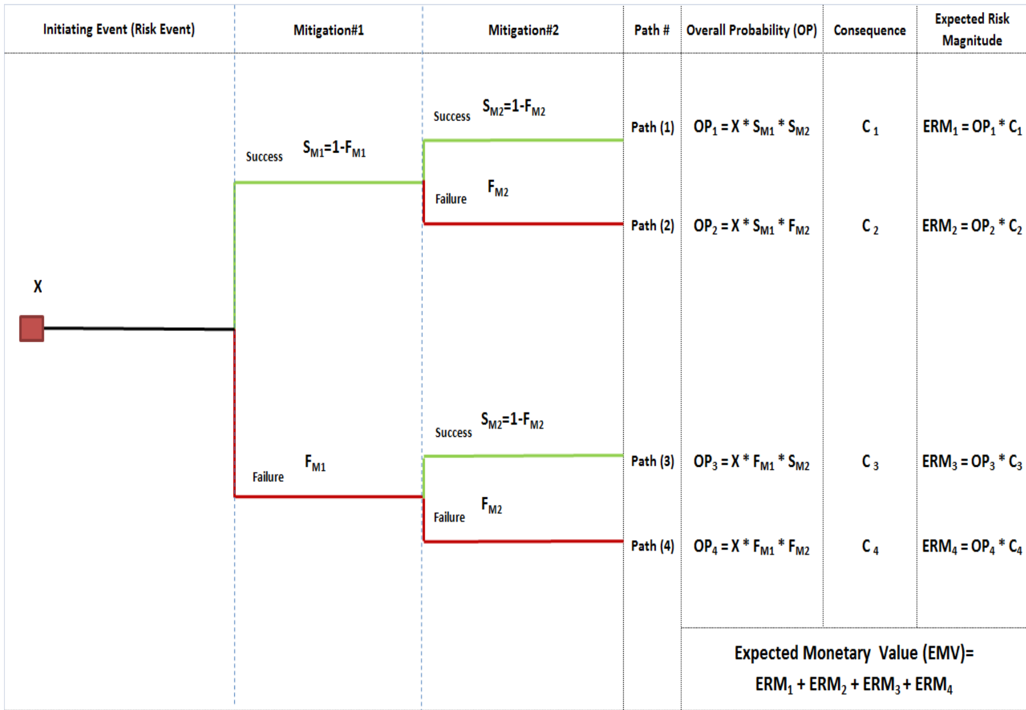

Figure 3-10. Simple event tree structure and ETA using two mitigations (Abdelgawad and Fayek 2010c)

The overall probability (OP) of each path is then calculated by multiplying the probability of events located on the selected path. For example, path 1 indicates that the risk has occurred, and mitigation 1 and mitigation 2 were both successful in mitigating the risk. Accordingly, the OP of this path is calculated as shown in Equation 3-40:

$$OP_1 = X * S_{m1} * S_{m2} = 0.5*0.70*0.55 = 0.19 \qquad [3\text{-}40]$$

The same concept can be applied to calculate OP_2 to OP_4. To calculate the expected risk magnitude (ERM_1) of path 1, let us assume that the estimated consequence (C_1) of path 1 is \$100,000. Thus, the ERM_1 is calculated as shown in Equation 3-41:

$$ERM_1 = OP_1 * C_1 = 0.19 * 100,000 = \$19,000 \qquad [3\text{-}41]$$

The same concept can be applied to calculate ERM_2 to ERM_4. For the sake of the example, let us assume that ERM_2, ERM_3, and ERM_4 were estimated following the previous steps, as shown in Equations 3-42, 3-43, and 3-44:

$$ERM_2 = \$30,000 \qquad [3\text{-}42]$$

$$ERM_3 = \$35,000 \qquad [3\text{-}43]$$

$$ERM_4 = \$78,000 \qquad [3\text{-}44]$$

Accordingly, the expected monetary value (EMV) can be estimated as in Equation 3-45:

$$EMV = ERM_1 + ERM_2 + ERM_3 + ERM_4 = \$162,000 \qquad [3\text{-}45]$$

Event trees are characterized to have many advantages. Fjellheim and Fiksel (1990) summarized these advantages according to the life cycle of the project as follows:

- During design of the plant, event trees can be used to identify hazardous accident or failure scenarios.
- During operation of the plant, event trees may be used for dynamic assessment of the possible outcomes of an accident, and to help identify appropriate actions.

- During modification of the plant, an event tree can provide insights into the required safety features.

3.4.1 Event Tree Applications

Since 1960, many studies have been done using event trees related to the fields of nuclear industry, chemical processing, offshore oil and gas production, and transportation. For instance, Bott (1999) developed an event tree methodology for national security analysis by estimating the relative likelihood of espionage scenarios that involve employees or visitors to a secure facility who are recruited as agents by an outside interest. The analyst identifies target information and users who might attempt to gain that information, and uses an event tree to develop a set of espionage scenarios called “compromise paths.” A compromise path begins when an ultimate user identifies target information in a secure facility. The ultimate user recruits an agent (employee) who gains entrance to the secure facility. Once inside the facility, the agent uses an access mode to access the target information and then transmit the compromised information to the ultimate user. Probability models were developed for each compromise path in the event tree, based on historical data and expert judgments.

The author assumed that security breaches occur at a constant rate per person, and the time to first occurrence of the security breaches is represented as exponential distribution. The author draws some conclusion based on ETA. For example, one way to reduce the threat of recruiting an internal agent (employee) is to restrict the number of people with authorization. Another strategy would be to require two-man authentication to access any valuable information. Also, reducing the threat can be obtained by limiting the time that an employee has access to valuable information.

The other option of espionage is through the recruitment of visitors. In this regard, the occurrence of an agent in a group of visitors was modeled with a binomial distribution. According to ETA, the author indicated that one way to reduce the espionage risk from visitors is to host only one well-escorted group rather than a large number of smaller groups. The author concluded that this model provides many useful insights into espionage prevention, even in the absence of quantitative data.

Novack et al. (2005) investigated the use of event trees to analyze accident scenarios attributed to oil spill. The research conducted includes two steps. The first step is concerned with a literature review of different studies that are related to oil spill incidents. To ensure consistency in reviewing information, the following facility types were considered during the review: production facilities, vessels, terminals, refineries, and storage tanks. Case studies were selected based on the fulfilment of the following criteria: (1) must be a comprehensive study covering most of the identified facilities; (2) must cover different types of spills, including different types of human interactions; and (3) must have an availability of enough details to establish event trees. The findings from this step indicate that ten case studies can be selected.

The second step is the construction of event trees for the case studies, based on the findings from the first step. In order to limit the number of generated event trees, nine safety measures (risk response strategies) were identified: (1) planning and resources; (2) execution of the plan developed during the planning phase; (3) monitoring the ongoing process to detect failure and perform avoidance, depending on the findings from monitoring; (4) establish primary containment; (5) establish early detection; (6) establish early recovery; (7) establish hazard containment; (8) establish secondary containment; and (9) late recovery. The analysis of the ten case studies leads to a number of conclusions about risk response strategies, which can be summarized as follows:

(1) A missing oil spill detection alarm was identified as the reason of failure for four case studies.

(2) Violation of the operation procedure was identified as the potential reason of failure for five case studies.

The authors noted the advantage of using an event tree to perform the analysis of different case studies, and highlight the suitability of this technique to analyze the case studies by supporting graphical representations of different alternatives.

Sherali et al. (2008) proposed an approach for the strategic allocation of certain available prevention and protection resources, based on ET, to reduce the failure probabilities of a safety system and the total expected loss from a sequence of events. Resources such as investments in improved technologies or equipment could be used to reduce the failure likelihood of different safety features, given that a particular sequence of preceding events has occurred. To reduce the consequence of an event, resources such as clean-up devices and trained emergency response personnel could be utilized. This research contributes to the development of an optimization algorithm for manipulating event probabilities and end effect consequences, through technological and emergency response investments. The objective was to minimize the overall expected loss (risk) of the project. The proposed algorithm was tested, and the results show that it can converge to a global optimal solution.

Hong et al. (2009) analyzed the risk of an underwater tunnel excavation using an earth pressure balance (EPB) type tunnel boring machine (TBM). The event tree analysis (ETA) is used to perform risk analysis at the design stage to identify problems which can happen during tunnel construction. Components that are considered to be under high risk have been analyzed, and their probabilities of occurring were evaluated based on expert judgements. Several risk response measures have been investigated to mitigate or eliminate the major problems that were predicted during the evaluation process.

The initiating events in the ETA have been selected based on a checklist constructed based on the analysis of design reports and case studies of underwater tunnel problems. Three initiating events that have been identified are defined as: poor ground condition, high water pressure, and heavy rainfall. Various general countermeasures were analyzed, and it has been found that survey/design, process planning, type of construction machine during the design stage, and construction management and reinforcement during construction stage can be applied as the safety functions against poor ground condition, high water pressure, and heavy rainfall. The quantitative assessment of risk was conducted based on ETA. The quantification of results per each accident path are obtained from averaging assessment results estimated by four experts. Assessment of each path on the ET is performed by multiplying the probabilities of all events located on the selected path. The summary of the findings indicated that the probability of occurrence of an accident due to poor ground condition is 0.59, the probability for an accident due to high water pressure is 0.56, and the probability of an accident due to heavy rainfall is 0.46. The results indicated that the site has a relatively high probability for accidents if only the general countermeasures are considered. The consequence of each path is analyzed using five categories, named: catastrophic, critical, serious, manageable, and negligible. A risk rating was established based on the probability of occurrence and consequence of each path, and classified into three levels. The first level is the case that needs significant countermeasure applications to reduce the risk level or to remove it. The second level also requires adding countermeasures to reduce the risk level or to remove it. The third level requires active construction management and management of disaster. The authors noted that safety measures should be established to satisfy both safety and economical criteria, because an excessive application of countermeasures may result in financial burden. A series of mitigation actions were identified based on ETA, and applied for the tunnel construction.

The authors concluded that ETA is useful for improving system performance and for identifying useful methods to protect a system from failure. The authors also noted that the suggested framework and a process utilizing ETA can be applied for the estimation and analysis of risks in the construction industry. However, conducting ETA is subject to the same limitations of FTA attributed to the required data to complete the analysis of the event tree, which makes fuzzy arithmetic operations on fuzzy numbers to be a more favourable option to solve event trees, especially in the construction industry. Chapter 5 presents the proposed framework to address this limitation by incorporating fuzzy arithmetic operations to solve events trees.

3.5 Fault Trees, Event Trees, and FMEA

Fjellheim and Fiksel (1999) indicated that fault trees and event trees constitute an important part of the risk analyst's tool kit for assessing failure causes and consequences for different systems. Christian (1997) applied fault trees and event trees to predict process safety. The process is applied to a heat treating chamber, and analyzes the probability of expansion due to the existence of oxygen. Fault trees were established to trace various failures in the system. Event trees were established to trace the list of actions based on an initiating event. The author noted the advantage of combining fault trees and event trees in quantifying potential hazards, since all root causes can be traced through the trees.

Khodabandehloo (1996) developed a combined FMEA, a fault event tree model to assess human-robot interaction to identify the risks associated with the use of robots in everyday application. This study considered a number of cases by focusing on the safety and reliability issues of robotic systems.

The robot system considered in this study is composed of five joints, while each joint is controlled by a hydraulic servo mechanism. The author noted that the safe operation of a robotic system relies heavily on establishing safety procedures, and the availability of appropriate safety features to support the practice of such procedures by people operating the robot. The reason behind any accident can be attributed to equipment malfunction and bad operation practice. Khodabandehloo (1996) applied FMEA to examine all possible component failure modes and to identify their effects on the system. Each component of the system is considered during the analysis, and each component is also studied with regard to its effects on other components as well as on the whole system. FTA and ETA were then applied to examine the errors and failures in the system. Major risk events identified from performing FMEA are identified as follows:

(1) Undesirable robot movement in playback mode.

(2) Undesirable robot movement in teach mode.

(3) Arm runaway when switching on.

(4) No emergency stop action when demanded.

(5) Arm 'creep' or degradation of repeatability.

Each of the identified major risk events were considered as a top event for FTA. The author indicated that the branching of the FT is terminated by an event for which the required failure rate data is available. A set of safeguards were added into the equipment, and the system was further analyzed using ETA. Specific consideration has been given to welding cells for a detailed ETA. A number of observations were obtained out of ETA which help improve safety integrity and minimize the hazards.

Khodabandehloo (1996) concluded that the inclusion of safety features in both hardware and software can reduce the likelihood of failure. The author also noted the need for incorporating FMEA, ETA, and FTA at the early design phase to produce long-term cost savings. The proposed framework can help establish appropriate safety measures, and aids in the development of an awareness of the hazards present in a robot system. Hence, it provides a basis for the selection of the necessary contents of safety training. However, even with these advantages, the author noted that it was not an easy task to assign probabilities to a number of events in the trees.

3.6 Summary

This chapter provides an overview of three well-known techniques in reliability engineering, known as failure mode and effect analysis, fault trees, and event trees. This chapter provided a detailed explanation of the steps that can be followed to solve each technique, illustrated some applications, and noted the advantages of each technique. The limitations of each technique were also highlighted. Chapter 4 and chapter 5 are intended to present the proposed framework to address some of these limitations.

4. Risk Criticality Analysis (Fuzzy FMEA)

The purpose of this chapter is to present the framework to address the limitations of the traditional application of FMEA. The framework is based on combining fuzzy logic and FMEA. To support multi-criteria decision-making, fuzzy logic is combined with AHP to aggregate cost impact, time impact, and scope/quality impact into one variable, known as aggregated impact. The framework is intended to help management in screening of critical risk events such that detailed risk analysis, using fuzzy fault tree and fuzzy event tree, can be conducted for critically identified risk events.

4.1 Introduction

The traditional FMEA approach of calculating the RPN is easy to understand and straightforward. However, several authors noted concerns related to using the traditional FMEA approach to calculate the RPN as previously highlighted under section 3.2.4. The following is a summary of these concerns:

(1) The use of the multiplication operator to calculate the risk priority number (RPN) may result in an incorrect interpretation of the final outcomes.

(2) The traditional application of FMEA relies on using numerical values to evaluate the input parameters, i.e., “occurrence,” “severity,” and “detection,” which are difficult to evaluate in the construction domain.

(3) The traditional application of FMEA may fail to estimate the RPN when the impact of failure is calculated over multi-dimensions.

(4) There is a lack of established formal guidelines that associate the calculated RPN with the required corrective actions.

In order to address these limitations, a comprehensive framework was established based on combining fuzzy logic with the traditional FMEA. The use of fuzzy logic offered the advantage of addressing the first two concerns. In order to address the third concern, a fuzzy analytical hierarchy process (AHP) was utilized to address the multi-criteria decision-making process. The resultant RPN was associated with the required corrective action to provide meaningful results. The project manager can rely on the recommended corrective actions to aid in successful completion of a project by identifying critical risk events that require immediate corrective actions. In addition, the results obtained from using this technique can aid in identifying risk events that require comprehensive root cause analysis and detailed lessons learned. Thus, more successful projects can be achieved in the future using this technique.

4.2 Fuzzy Failure Mode and Effect Analysis (FMEA) Proposed Terminologies

The first step in establishing the framework is to establish definitions and ranges for different FMEA terminologies, i.e., "failure mode," "occurrence," "severity," "detection," and the "RPN," and to ensure that different team members use them consistently. In this regard, we used the "risk" definition as defined in the PMBOK to refer to "failure mode," which is "an uncertain event or condition that, if it occurs, has a positive or a negative effect on at least one project objective, such as time, cost, scope or quality" (PMI 2004). Occurrence, severity, detection, and RPN are defined as follows:

- Occurrence (O) is the frequency of the occurrence of the failure, and is referred to as probability of occurrence (P). This variable is defined over the range of 1 to 10.
- Severity (S) is used to represent the potential effects associated with the occurrence of a risk event. Severity (S) is referred to as impact (I) and has three dimensions: cost impact (CI), time impact (TI), and scope/quality impact (SI). They are all defined over the range of 1 to 10.
- Detection (D) is referred to as detection/control and is defined as "the ability of the risk response strategy to detect and control the root causes before they lead to the occurrence of the risk event,

and to control the effect given the occurrence of the risk event“ (Abdelgawad and Fayek 2010a). Detection/control (D) is defined over the range of 1 to 10.

- PRN is referred to as risk criticality number (RCN) and is defined over the range of 1 to 1000.

To overcome many of the previously noted limitations of the tradition application of FMEA, fuzzy logic was combined with the traditional FMEA and used to develop a fuzzy expert system. The fuzzy AHP was utilized to address the multi-criteria decision-making process. The following sections describe the approach taken to develop the framework.

4.2.1 Linguistic Definition of Input Variables

The first step in integrating fuzzy logic and FMEA is to define the probability of occurrence (P), impact (I), and detection/control (D) using linguistic terms. Each variable is defined using membership functions (MFs) over the universe of discourse of 1 to 10. To define the linguistic terms for each variable, several meetings were arranged with a senior risk coordinator working at one of the largest pipeline companies in North America. The objective of the first meeting was to introduce FMEA to the expert and to understand the company’s current practice to assess risk. The feedback received on the first meeting showed great acceptability of the expert to explore the idea, noting that the current risk matrix of the company is based on linguistic definition for both probability of occurrence

(P) and impact (I). Table 4-1 and Table 4-2 present five linguistic terms and their definition for both probability of occurrence (P) and impact (I), as defined in the company risk management standard. The meaning of each linguistic term can be calibrated to suit a different organization or context. For example, the meaning of the very high probability of occurrence can be changed to represent "> 50% chance." The same concept can be applied to other terms.

Table 4-1. Probability of occurrence (Abdelgawad and Fayek 2010a)

Linguistic term	**Probability of occurrence (P)**
Very High (VH)	> 67% (2/3) chance.
High (H)	Between 33%–67% (2/3) chance.
Medium (M)	Between 10%–33% (1/3) chance. Event may occur.
Low (L)	Between 1%–10% chance. Event is unlikely to occur.
Very Low (VL)	Less than 1% chance. Event is highly unlikely to occur.

Table 4-2. Impact (I) (Abdelgawad and Fayek 2010a)

Terms	**Impact categories**		
	Cost	**Time**	**Scope/quality**
Very High (VH)	Cost increase is ≥ 10% of project cost.	In service date delayed ≥ 10% of project duration.	Project scope or quality does not meet business expectations.
High (H)	Cost increase is ≥ 7% and < 10% of project cost.	In service date delayed ≥ 7% and < 10% of project duration.	Scope changes or quality are unacceptable to project sponsor.
Medium (M)	Cost increase is ≥ 4% and < 7% of project cost.	In service date delayed ≥ 4% and < 7% of project duration.	Major areas of scope or quality are affected.
Low (L)	Cost increase is ≥ 1% and < 4% of project cost.	In service date delayed ≥ 1% and < 4% of project duration.	Few areas of scope or quality are affected.
Very Low (VL)	< 1% of project cost.	Insignificant schedule slippage.	Scope change is not noticeable/quality degradation is not noticeable.

To define the detection/control linguistic terms, some deviations from the traditional FMEA definition were considered during this study. The meaning of control of root causes and controlling the effect of the risk event have been incorporated into the definition of detection/control. Several interviews were arranged with two risk experts and the senior risk coordinator. Table 4-3 provides a summary of the findings from these interviews. The meaning of each of these linguistic terms can be calibrated to suit a different organization or context.

Table 4-3. Linguistic definition of detection/control (D) (Abdelgawad and Fayek 2010a)

Terms	Detection/control
Very Low (VL)	The project team was unable to identify a risk response strategy capable of detecting the risk event, controlling root causes, and controlling the consequence of the risk event.
Low (L)	The project team has identified a risk response strategy with a low chance of detecting the risk event, controlling the root causes, and controlling the consequence of the risk event.
Moderate (M)	The project team has identified a risk response strategy with a moderate chance of detecting the risk event, controlling the root causes, and controlling the consequence of the risk event.
High (H)	The project team has identified a risk response strategy with a high chance of detecting the risk event, controlling the root causes, and controlling the consequence of the risk event.
Very High (VH)	The project team has identified a risk response strategy that has been proven in the past to have high effectiveness in detecting the risk event, controlling the root causes, and controlling the consequence of the risk event.

4.2.2 Membership Functions for Input Factors

The development of membership functions of different input factors represents the second stage. During this stage, the senior risk coordinator was asked to define five membership functions for probability of occurrence (P), impact (I), and detection/control (D), in accordance with the information shown in Table 4-1, Table 4-2, and Table 4-3, while considering that the universe of discourse ranged between 1 and 10. Trapezoidal and triangular representation were selected to represent the membership functions of different variables. The direct method with one expert (Klir and Yuan 1995) was used during this stage to define the membership functions. Figures 4-1, 4-2, and 4-3 show the findings from this stage.

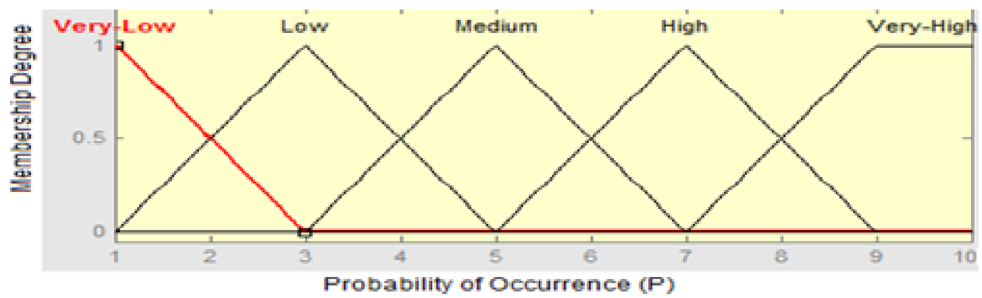

Figure 4-1. Membership functions for probability of occurrence (P)

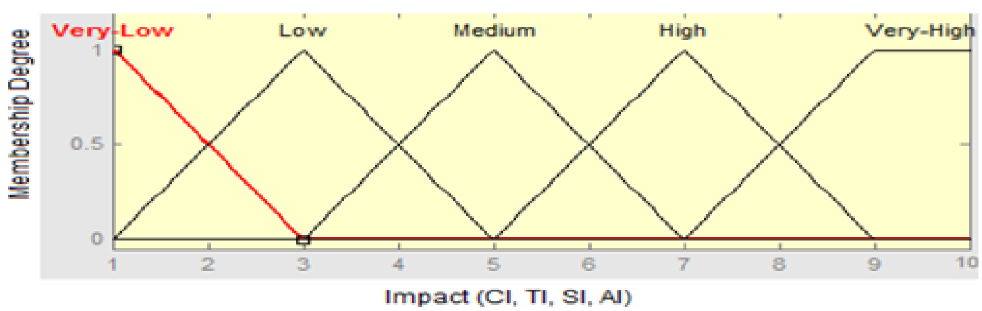

Figure 4-2. Membership functions for impact (CI, TI, SI, AI)

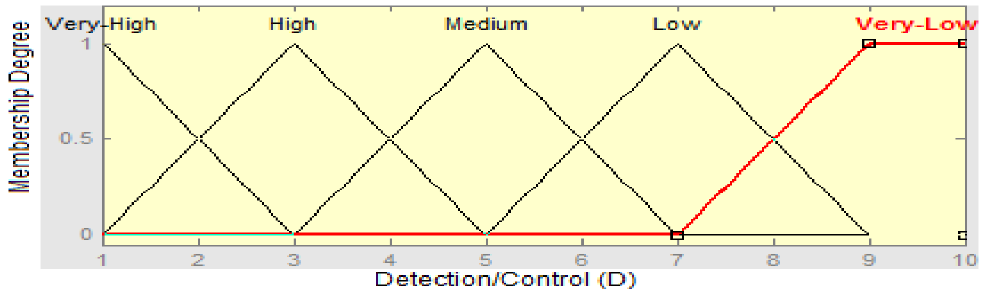

Figure 4-3. Membership functions for detection/control (D)

4.2.3 Membership Definition for the Output Variable (RCN)

In order to select the membership functions for the RCN, more discussions have been conducted with the senior risk coordinator. During these discussions, it was agreed that nine linguistic variables—very low (VL), very low-low (VL-L), low (L), low-medium (L-M), medium (M), medium-high (M-H), high (H), high-very high (H-VH), and very high (VH)—would be sufficient to cover the universe of discourse for the RCN. As per the expert's request, eight options had been proposed for further discussions with the expert, as shown in Figure 4-4. The expert's vote was give to option 2 since it starts with a small interval at the beginning and increases rapidly near the end. Figure 4-5 presents the membership functions for the RCN, as agreed with the expert. Table 4-4 presents the relationship between the value of the RCN and the requirement of establishing corrective actions, as agreed with the expert. It is important to note that any risk event that is assessed to have an RCN that falls within the range defined by categories 5 to 9, as shown in Figure 4-5, must undergo detailed risk analysis, as will be presented in chapter 5.

Option 1

Ser	Criticality Range	Interval	Cumulative	Mid point Score	Category
1	0-50	50	50	25	VL
2	50-100	50	100	75	VL-L
3	100-150	50	150	125	L
4	150-250	100	250	200	L-M
5	250-350	100	350	300	M
6	350-450	100	450	400	M-H
7	450-600	150	600	525	H
8	600-800	200	800	700	H-VH
9	800-1000	200	1000	900	VH

Option 2

Ser	Criticality Range	Interval	Cumulative	Mid Point score	Category
1	0-50	50	50	25	VL
2	50-125	75	125	87.5	VL-L
3	125-200	75	200	162.5	L
4	200-300	100	300	250	L-M
5	300-400	100	400	350	M
6	400-525	125	525	462.5	M-H
7	525-650	125	650	587.5	H
8	650-800	150	800	725	H-VH
9	800-1000	200	1000	900	VH

Option 3

Ser	Criticality Range	Interval	Cumulative	Mid point Score	Category
1	0-25	25	25	12.5	VL
2	25-75	50	75	50	VL-L
3	75-150	75	150	112.5	L
4	150-250	100	250	200	L-M
5	250-375	125	375	312.5	M
6	375-525	150	525	450	M-H
7	525-700	175	700	612.5	H
8	700-900	200	900	800	H-VH
9	900-1000	100	1000	950	VH

Option 4

Ser	Criticality Range	Interval	Cumulative	Mid Point score	Category
1	0-25	25	25	12.5	VL
2	25-75	50	75	50	VL-L
3	75-150	75	150	112.5	L
4	150-250	100	250	200	L-M
5	250-375	125	375	312.5	M
6	375-525	150	525	450	M-H
7	525-700	175	700	612.5	H
8	700-850	150	850	775	H-VH
9	850-1000	150	1000	925	VH

Option 5

Ser	Criticality Range	Interval	Cumulative	Mid point Score	Category
1	0-50	50	50	25	VL
2	50-100	50	100	75	VL-L
3	100-200	100	200	150	L
4	200-300	100	300	250	L-M
5	300-400	100	400	350	M
6	400-600	200	600	500	M-H
7	600-800	200	800	700	H
8	800-900	100	900	850	H-VH
9	900-1000	100	1000	950	VH

Option 6

Ser	Criticality Range	Interval	Cumulative	Mid Point score	Category
1	0-50	50	50	25	VL
2	50-150	100	150	100	VL-L
3	150-250	100	250	200	L
4	250-400	150	400	325	L-M
5	400-600	200	600	500	M
6	600-750	150	750	675	M-H
7	750-850	100	850	800	H
8	850-950	100	950	900	H-VH
9	950-1000	50	1000	975	VH

Option 7

Ser	Criticality Range	Interval	Cumulative	Mid point Score	Category
1	0-50	50	50	25	VL
2	50-100	50	100	75	VL-L
3	100-150	50	150	125	L
4	150-250	100	250	200	L-M
5	250-350	100	350	300	M
6	350-500	150	500	425	M-H
7	500-650	150	650	575	H
8	650-800	150	800	725	H-VH
9	800-1000	200	1000	900	VH

Option 8

Ser	Criticality Range	Interval	Cumulative	Mid Point score	Category
1	0-50	50	50	25	VL
2	50-100	50	100	75	VL-L
3	100-200	100	200	150	L
4	200-300	100	300	250	L-M
5	300-400	100	400	350	M
6	400-500	100	500	450	M-H
7	500-600	100	600	550	H
8	600-800	200	800	700	H-VH
9	800-1000	200	1000	900	VH

Figure 4-4. Eight proposals for the membership functions of the RCN

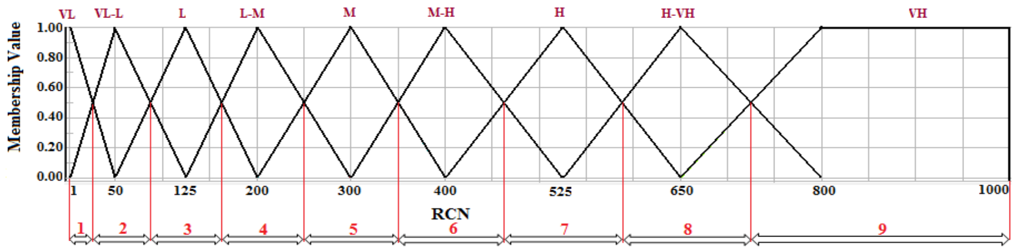

Figure 4-5. Membership functions of the RCN (Adapted from Abdelgawad and Fayek 2010a)

Table 4-4. RCN and priority for corrective action (Adapted from Abdelgawad and Fayek 2010a)

Label	Corrective Action Categories	RCN value
1	No corrective action is required	x < 25.5
2	Unnecessary to take any corrective action(s)/accept	25.5 ≤ x < 87.5
3	Low priority to take any corrective action(s)/accept	87.5 ≤ x < 162.5
4	Somewhat moderate priority to take corrective action(s)/ consider mitigation	162.5 ≤ x < 250
5	Moderate priority to take corrective action(s)/consider mitigation or transfer	250 ≤ x < 350
6	Somewhat high priority to take corrective action(s)/ consider mitigation or transfer	350 ≤ x < 462.5
7	High priority to take corrective action(s)/consider avoidance or transfer	462.5 ≤ x < 587.5
8	Necessary to take corrective action(s)/consider avoidance or transfer	587.5 ≤ x < 725
9	Absolutely necessary to take corrective action(s)/consider avoidance options	x≥ 725

4.2.4 Aggregate Cost Impact, Time Impact, and Scope/Quality Impact

In order to address the concern that the RPN may be underestimated when a failure mode has multiple dimensions of effect (Bowles and Peláez 1995), the fuzzy AHP concept has been adopted in this study. The analytical hierarchy process (AHP) was first established by

Saaty (1982) to aid in decision-making for problems that involve multiple criteria. To overcome the uncertainty and subjectivity of selecting a single number from the pairwise comparison scale, presented in Table 2-2, fuzzy AHP was utilized. Zeng et al. (2007) noted that experts sometimes found difficulties in selecting a single number from the pairwise comparison scale, and argued the advantage of allowing for a range values for comparison.

To address this deficiency, the fuzzy AHP approach, as proposed by Zeng et al. (2007), is adopted in this study. The steps conducted in this study can be summarized as follows:

(1) Establish the AHP hierarchy for the problem under analysis. Figure 4-6 shows the finding of this step.

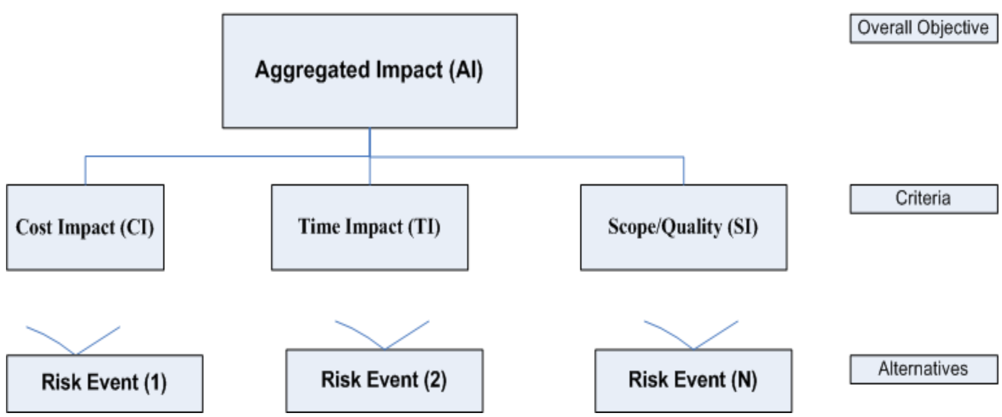

Figure 4-6. AHP hierarchy

(2) Conduct pairwise comparison between elements on the criteria level, i.e., between cost impact (CI), time impact (TI), and scope/quality (SI), to establish the preference of these factors in

affecting the project objectives. During this step, three preferences, i.e., time (T) vs. cost (C), named (a_{tc}); cost (C) vs. scope/quality (S), named (a_{cs}); and time (T) vs. scope/quality (S), named (a_{ts}); were required to be collected from the same senior risk coordinator. The preference of the expert was captured using a standard trapezoidal fuzzy number (STFN), i.e., each preference was captured using four parameters (a, b, c, d). The preference of the expert was then used to establish the MF in accordance with Equation 4-1 (Pedrycz and Gomide 2007).

$$\mu_{(x)} = \begin{cases} \frac{x-a}{b-a} \; if \; x \in [a,b) \\ \frac{c-x}{d-c} \; if \; x \in [c,d] \\ 1 \; if \; x \in [b,c) \\ 0 \; otherwise \end{cases} \qquad [4\text{-}1]$$

where a represents the minimum, b and c represents the most likely, and d represents the maximum.

Figure 4-7 shows a summary of the finding. For instance, when comparing time (T) vs. scope/quality (S) to calculate (a_{ts}), the expert believed that the minimum is that time (T) is equally to moderately more important than scope/quality (S) (i.e., a = 2), the most likely is that time (T) is moderately more important than scope/quality (Q) (i.e., b = c = 3), and the maximum is that time (T) is moderately to strongly more important than scope/quality (S) (i.e., d = 4).

The defuzzified value for each preference was calculated according to Equation 4-2:

$$a_{ij} = \frac{a+2*(b+c)+d}{6} \qquad [4\text{-}2]$$

where a_{ij} is the relative importance of factor i over j. For example, the defuzzified value of time (T) vs. scope/quality (S) is calculated as follows:

$$a_{ts} = \frac{2+2*(3+3)+4}{6} = 3.0 \qquad [4\text{-}3]$$

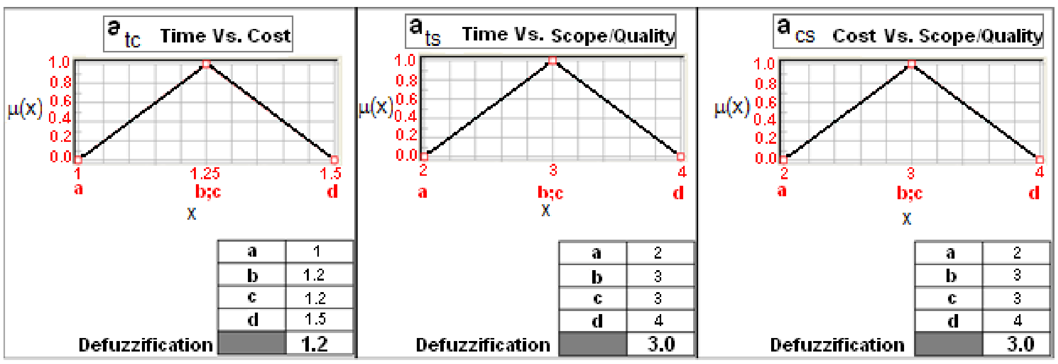

Figure 4-7. Pairwise comparison using trapezoidal fuzzy number (Abdelgawad and Fayek 2010a)

(3) Use the reciprocal value to define the inverse comparison, i.e., scope/quality (S) vs. time (T). Apply the same concept to calculate the defuzzified value of time (T) vs. cost (C), and cost (C) vs. scope/quality (S) and their reciprocal terms.

(4) Construct the pairwise comparison matrix and use AHP standard calculations to calculate the weighting of each factor and the consistency index. After construction of the pairwise

comparison matrix, a summation of each column is calculated and used thereafter to normalize each column. The overall priority (OP) for each criterion is calculated by taking the average of the summation of each row result. Table 4-5 summarizes the calculations. Table 4-6 shows the calculation conducted to calculate λ_{max} (the maximum eigenvalue).

Table 4-5. Standard AHP calculation of OP (Adapted from Abdelgawad and Fayek 2010a)

	C	**T**	**S**	Normalized	**C**	**T**	**S**	**OP**
C	1.00	0.80	3.00	C	0.40	0.38	0.43	**0.40**
T	1.20	1.00	3.00	T	0.47	0.47	0.43	**0.46**
S	0.33	0.33	1.00	S	0.13	0.15	0.14	**0.14**
∑	**2.5**	**2.1**	**7.0**	∑ column	**1.0**	**1.0**	**1.0**	**1.0**

Table 4-6. λ_{max} calculations (Adapted from Abdelgawad and Fayek 2010a)

	C	**T**	**S**	∑	**λmax**	**Overall λmax**
C	0.40	0.37	0.42	1.19	3.0	**3.0**
T	0.48	0.46	0.42	1.36	3.0	
S	0.13	0.15	0.14	0.42	3.0	

Equation 4-4 shows the calculation for the consistency index.

$$\text{Consistency Index} = \frac{\lambda_{\max} - n}{n-1} = \frac{3-3}{3-1} = 0 \qquad [4\text{-}4]$$

where n is the dimension of the pairwise matrix.

The result of the analysis is consistent since the consistency index is less than 0.1 (Pedrycz and Gomide 2007).

According to the AHP results in Table 4-5, the aggregated impact (AI) is calculated as shown in Equation 4-5, and is extended over the universe of discourse of 1 to 10 with membership functions similar to CI, TI, and SI in Figure 4-2.

AI = 0.40 * Cost Impact + 0.46 * Time Impact + 0.14 * Scope/Quality Impact [4-5]

Please note all that risk events that have an impact on either safety and/or environment are treated using the risk acceptability level concept as will be explained in chapter 6. All risk events that have a risk level, i.e., probability * impact, greater than 5 due to either safety and/or environment are considered unacceptable risk events; and hence detailed risk analysis using fuzzy fault tree and fuzzy event tree is required to be conducted.

Steps 1 to 4 represent a general framework that can be further investigated to represent different contexts or organizations. An equation similar to Equation 4-5 will be obtained with some modifications to the weights, i.e., 0.40, 0.46, and 0.14. The use of AHP supports conducting multi-criteria decision-making, and supports conducting consistency analysis. One of the shortcomings of using AHP is attributed to the difficultly of selecting a single number from the pairwise comparison scale. In this regard, the concept of fuzzy AHP was introduced in which the user can provide a range represented by trapezoidal distribution to represent his/her preference. The use of fuzzy AHP offered a more practical approach to collect experts' preference. Moreover, the proposed integration between fuzzy logic and AHP supports addressing one of the shortcomings of the traditional application of FMEA, attributed to the failure to estimate the RCN when the impact of failure is calculated over multi-dimensions. In this regard, Equation 4-5 was established to aggregate the multi-dimensions of the impact into one variable, named the aggregated impact (AI).

4.2.5 Fuzzy Rule Base

The next step in the construction of the fuzzy expert system is to build the rule base between inputs and the output. Since we have three inputs (P, I, and D) and each input is represented using five linguistic variables, $5^3 = 125$ rules can be generated from this scenario. An interview has been arranged with the same senior risk coordinator to elicit different rules. A sample example of the Fuzzy If-Then rules is:

IF Impact is “very low” and probability of occurrence is “very low” and detection/control is “high” THEN RCN is “very low.”

Appendix I contains the identified rules between input(s) and the output as elicited from the expert. The Max-Min was selected to do the implication and aggregation because of their wide applicability and easy graphical interpretation (Jang et al. 1997). The center of the area was selected for defuzzification. Membership functions presented in Figure 4-1, Figure 4-2, Figure 4-3, and Figure 4-5, together with the fuzzy rules, were utilized to build a fuzzy expert system. This system was implemented using Fuzzy Tech 5.72©, as shown in Figure 4-8.

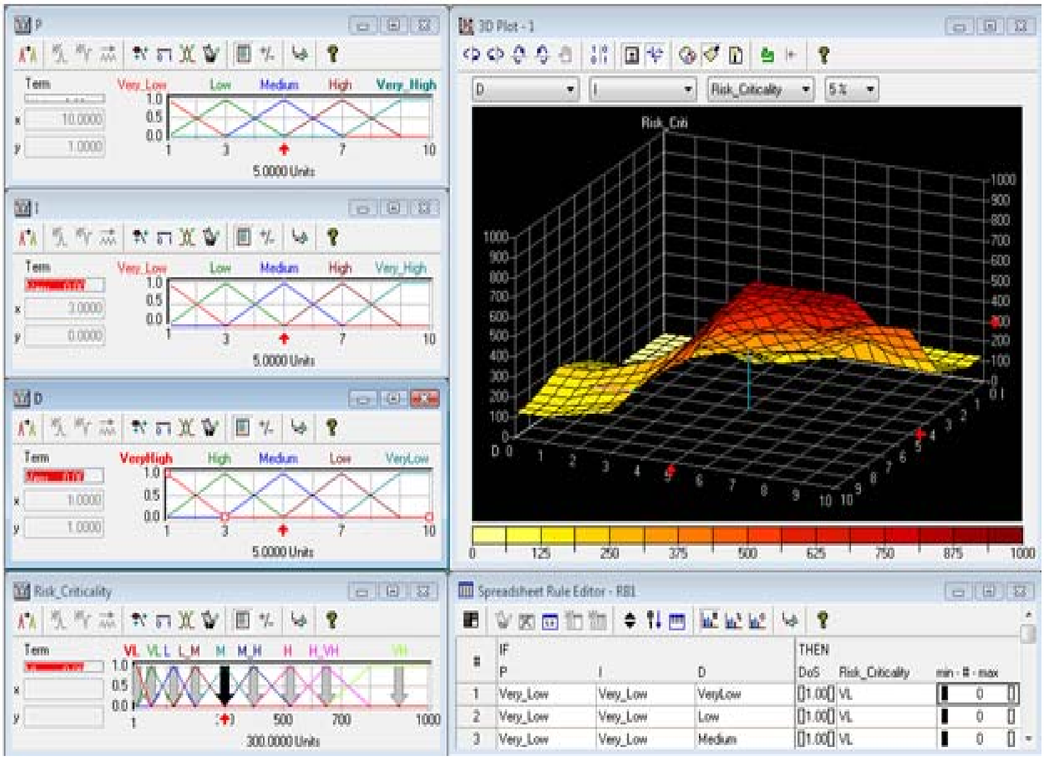

Figure 4-8. Fuzzy expert system for risk criticality analysis

The use of the fuzzy expert system has offered the ability to solve many of the limitations of the traditional application of FMEA. Using the fuzzy expert system, the multiplication operator was replaced by a fuzzy rule base. The fuzzy rule base is composed of 125 rules, which were built to represent the preference between the probability of occurrence, impact, and detection/control in contributing to the calculated RCN. Thus, the calculated risk priority number (RCN), as obtained from the fuzzy expert system, represents the right interpretation of the final outcomes, since the weighing of each input variable is considered during the building of the rule base.

Moreover, instead of asking for exact numerical values to evaluate the input parameters, i.e., “occurrence,” “severity,” and “detection,” the fuzzy expert system offers the ability to connect between these numerical values and the linguistic terms to evaluate the input variables. A formal guideline was established to associate the calculated RCN and the required corrective actions, as presented in Table 4-4. Thus, the use of the fuzzy expert system has offered the ability to establish a comprehensive framework that provides a practical and transparent approach for assessing the level of criticality of risk events in the construction domain.

4.3 Risk Criticality Analyzer (RCA)

The proposed approach has been used to design a software package entitled “Risk Criticality Analyzer” (RCA), implemented using Visual Studio 2008©. The purpose of using RCA is to support the decision-makers in assessing the level of risk criticality. Figure 4-9 shows the main screen of the software.

The software is composed of two modules to support beginners and advanced users. The “Beginner Module” is based on manual manipulation of data, in which the user has to input linguistic assessment for probability of occurrence (P), cost impact (CI), time impact (TI), scope/quality impact (SI), and detection/ control (D). The system is automated to calculate the aggregated impact (AI) according to the weighting defined in Equation 4-5. The software also supports the user to conduct fuzzy AHP analysis and to update the weighting of cost impact, time impact, and scope/quality impact in Equation 4-5. This analysis can be carried out for each individual risk event by clicking on the “Update” button. This action will direct the user to a built-in Excel sheet for conducting fuzzy AHP calculation. The calculated weighting for cost, time, scope/quality, will be exported to the upper right corner of RCA. Further discussions around the suitability of using one consistent weighting to evaluate all the risk events in a project are provided in section 6.5

The last step is to calculate the RCN by clicking on the “Calculate” button—which communicates with the fuzzy expert system presented in Figure 4-8—export values of the input variables, fire the associated fuzzy rules, and calculate the defuzzified value of the risk criticality number (RCN). The defuzzified value of the RCN is then presented to the user together with the recommended action, as shown in Figure 4-9. RCA is used to screen critical risk events such that detailed risk analysis can be applied using the concept presented in chapter 5.

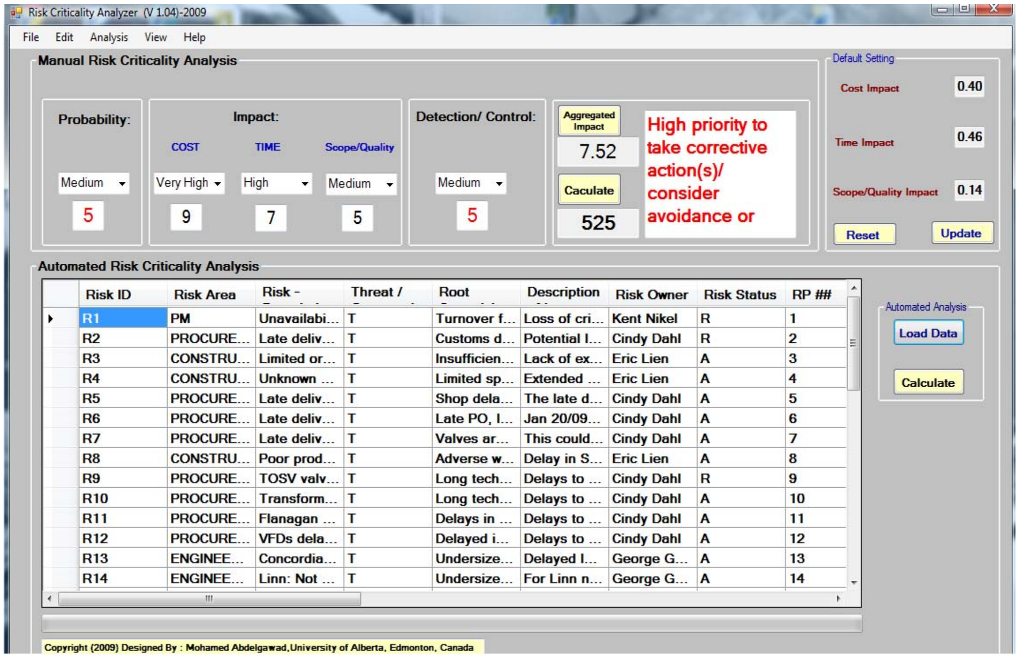

Figure 4-9. Risk Criticality Analyzer (Beginner Module)

Please note that RCA can use any value that falls within the range 1 to10 to define the probability of occurrence, cost impact, time impact, and scope quality impact. For instance, using the previous example, if the risk analyst believes that the probability of occurrence is located somewhere between low to medium, then he/she can use number 4 to define the probability of occurrence. In this case, the fuzzy rule base is fired to a different degree resulting in a different RCN as shown in Figure 4-10. As can noticed in this example, although Table 4-1 does not have a term named “low to medium”, the use of the membership function concept has facilitated gradual transition between the two concepts. For instance, in this case, all the rules that have low or medium probability of occurrence and satisfy the aggregated impact and detection control conditions, will be fired resulting in a lower RCN compared to the original case noted in Figure 4-9.

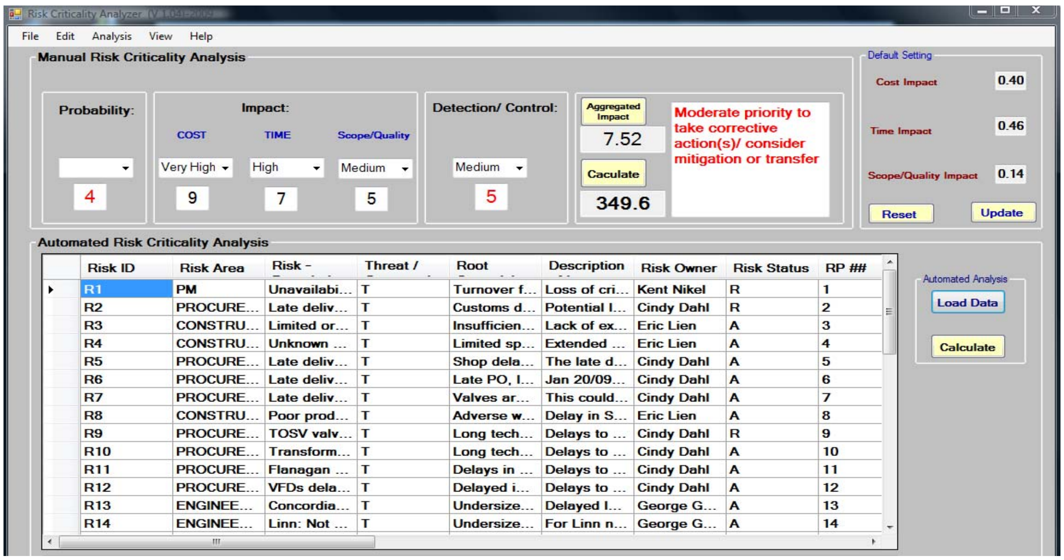

Figure 4-10. Risk Criticality Analyzer Example using the Beginner Module

The second module is the "Automated Module," and it is intended to serve advanced users. A comprehensive risk register was designed using Microsoft Excel© to support collecting data to run this module. Appendix II presents the risk register template, and chapter 6 provides a detailed explanation of each field in the risk register template. Data accumulated in the risk register are loaded automatically to the program by clicking on the "Load Data" button. After data are loaded to the software, data are presented to the user in the data grid shown in Figure 4-11. The user is advised to review and check the accuracy and consistency of all the data before proceeding with analysis. By clicking on the "Calculate" button, RCA reads P, CI, TI, SI, and D from the risk register for each risk event, calculates the aggregated impact (AI) using fuzzy AHP, exports P, AI, and D to the fuzzy expert system to calculate the RCN, and presents the resultant RCN and the recommended corrective actions to the user.

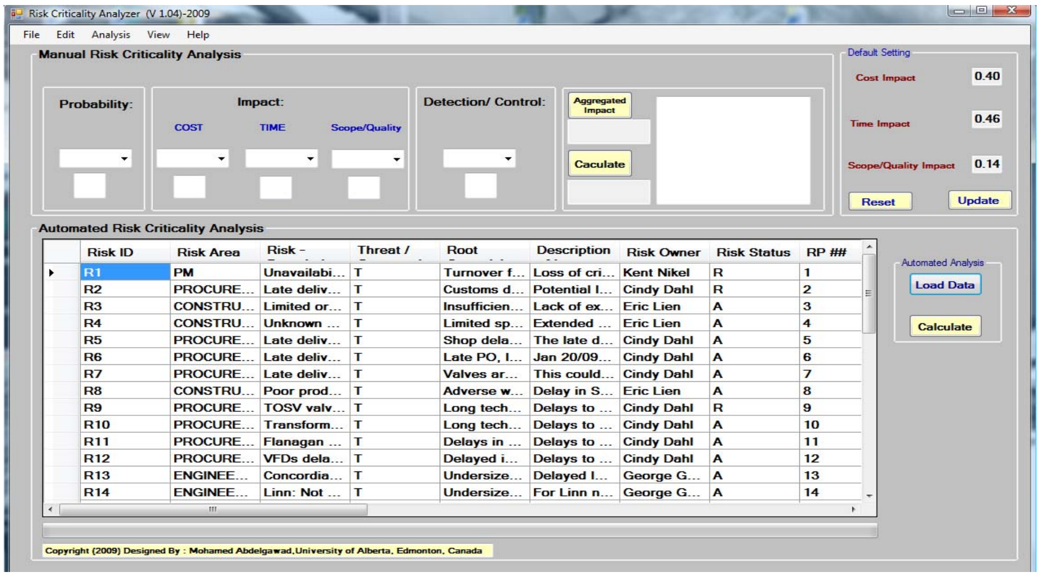

Figure 4-11. Risk Criticality Analyzer (Automated Module) (Abdelgawad and Fayek 2010a)

4.4 Risk Criticality Analyzer (RCA) - An Overview

To show how this system works, let us assume that we have the following assessments for one of the risk events:

probability of occurrence (P) = low, cost impact = medium, time impact = medium, scope/quality impact = medium, and detection/control = medium

Firstly, the AI is calculated, according to Equation 4-5, as shown in Equation 4-6:

$$AI = 0.4 * \mathbf{5} + 0.46 * \mathbf{5} + 0.14 * \mathbf{5} = 5 \qquad [4\text{-}6]$$

As can be noticed in Equation 4-6, the default setting is to represent the medium linguistic term by the element that has the highest membership value for the selected linguistic term, i.e., medium. As can be noticed in Figure 4-2, element 5 is the only element that has the highest membership degree, i.e., 1 for the medium membership function. However, the user is also allowed to select any number that falls within the medium membership function, i.e., 3–7, in case of any preference.

Secondly, the assigned values for the probability of occurrence, i.e., 3, and for detection/control, i.e., 5, together with the calculated AI are used as input to the fuzzy FMEA expert system. Input values are fuzzified according to Figure 4-1, Figure 4-2, and Figure 4-3, and the membership values $\mu(x)$ of each linguistic term are calculated. The fuzzy expert system fires the appropriate rules, performs rule implication and aggregation, and defuzzifies the result to obtain a value of RCN of 200. Thus, according to Figure 4-5 and Table 4-4, there is a "somewhat moderate priority to take corrective action(s), and the organization should consider mitigation or transfer of the risk."

To demonstrate the advantage of using the fuzzy expert system to solve the limitation of the traditional application of FMEA attributed to the use of the multiplication operator to calculate the RCN, let us consider that a risk identification workshop was arranged and two risk events were identified in which the probability, cost impact, time impact, scope/quality impact were assessed as shown in Table 4-7.

Table 4-7. Risk assessment results

Risk ID	Probability	Cost Impact	Time Impact	Scope/Quality Impact	Detection /Control
Risk #1	9	5	5	5	5
Risk #2	5	9	9	9	5

Since the cost impact is equal to time impact is equal to scope/quality impact, the overall impact of Risk #1 is equal to 5 and the overall impact of Risk #2 is equal to 9.

Based on the traditional FMEA equation, the multiplication of probability * impact * detection/control is used to calculate the RCN as shown in Table 4-8. Please note that the resultant RCN is equal for both risk events even though the impact of Risk #2 is more sever than the impact of Risk #1.

Table 4-8. Traditional FMEA calculations

Risk ID	Traditional FMEA
Risk #1	RCN=9*5*5= 225
Risk #2	RCN 5*9*9= 225

The results obtained from the traditional application of FMEA indicate that both risk events are equal in terms of their criticality. Although that there is no formal way to link between the calculated RCN and the required corrective action using the traditional FMEA, let us assume that we are going to use Table 4-4 to define the required corrective action. In this case both risk events were to be considered "somewhat moderate priority to take corrective action(s)/ consider mitigation".

To compare the results of the traditional FMEA and the proposed fuzzy FMEA approach, the aggregated impact of both risk events is calculated firstly by applying Equation 4-5 as follows:

$$AI_{Risk\ \#1} = 0.40 * 5 + 0.46 * 5 + 0.14 * 5 = 5 \quad [4\text{-}7]$$

$$AI_{Risk\ \#2} = 0.40 * 9 + 0.46 * 9 + 0.14 * 9 = 9 \quad [4\text{-}8]$$

The aggregated impact value together with the probability of occurrence and detection/control values are exported to the fuzzy expert system. For detailed example showing how fuzzy expert system performs reasoning to calculate the output, please refer to section 3.2.6. Figure 4-12 shows the inputs (Probability (P), aggregated impact (I), detection/control (D)) and the output variable (RCN) for Risk #1. As can be seen in Figure 4-12, Rule # 73 is the only rule that satisfy the input values and hence it was fired. Figure 4-13 shows the inputs and the output variables for Risk # 2. For Risk #2, Rule # 113 is the only rule that satisfy the input values and hence it was fired. The results from the fuzzy expert system are then exported to Risk Criticality Analyzer. The RCN for both risk events and the recommended corrective action are presented in Figure 4-14 and Figure 4-15 by using the Beginner Module. Table 4-9 provides detailed comparison between the calculated RCN using the traditional FMEA approach and the proposed fuzzy FMEA approach.

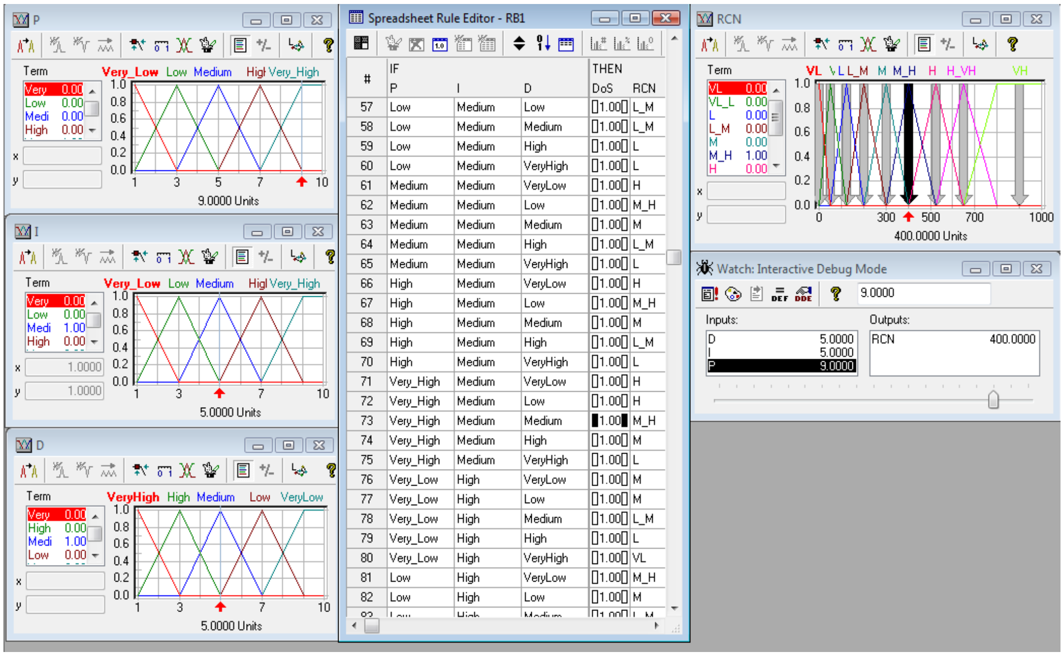

Figure 4-12. RCN calculation for Risk #1

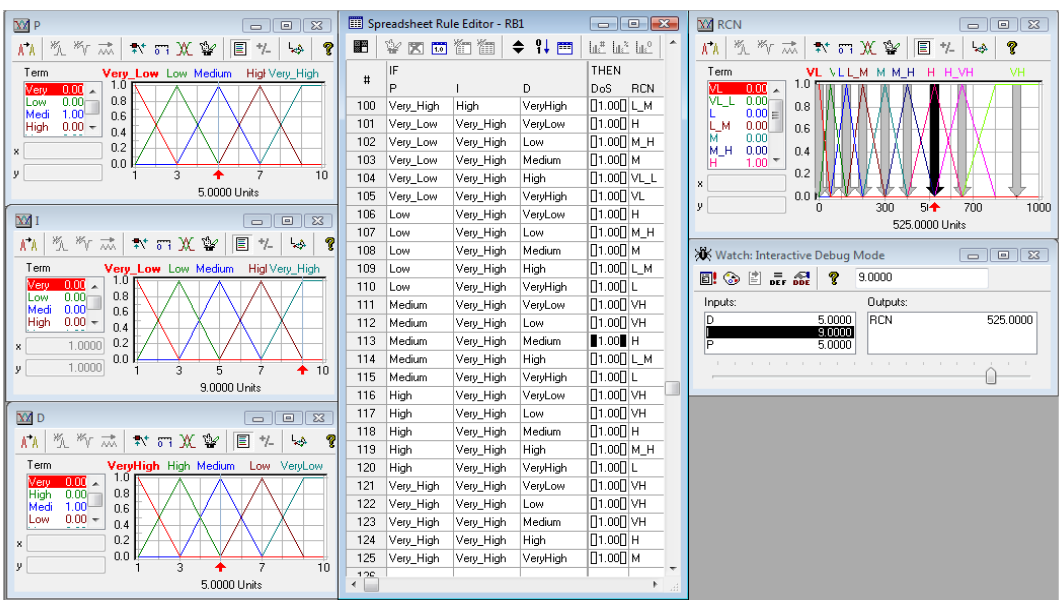

Figure 4-13. RCN calculation for Risk #2

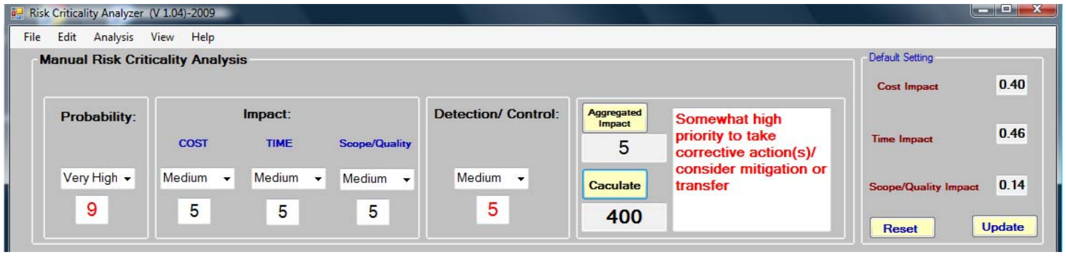

Figure 4-14. RCN calculation for Risk #1using the Beginner Module

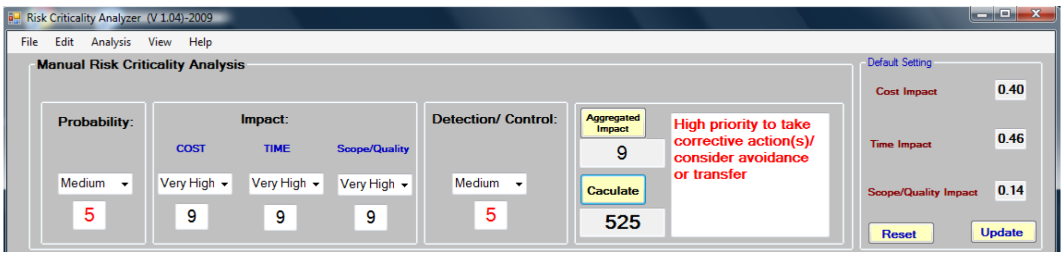

Figure 4-15. RCN calculation for Risk #2 using the Beginner Module

Table 4-9. Comparison between traditional FMEA and fuzzy FMEA

Risk ID	Traditional FMEA	Recommended Action	Fuzzy FMEA	Recommended Action
Risk #1	RCN=9*5*5= 225	somewhat moderate priority to take corrective action(s)/ consider mitigation	RCN=400	Somewhat high priority to take corrective action(s)/ consider mitigation or transfer
Risk #2	RCN 5*9*9= 225	somewhat moderate priority to take corrective action(s)/ consider mitigation	RCN=525	High priority to take corrective action(s)/ consider avoidance or transfer

To validate the proposition that Risk #1 should not be considered equal to Risk #2 in terms of its level of criticality, the results of the traditional FMEA is presented to a risk manager and to a risk analyst working for a different group at the same participating organization. The risk manager and the risk analyst were asked whether they agree that both risk events should be treated equally in terms of criticality, and if not then which risk event is to be considered more critical than the other. Both of the risk manager and the risk analyst indicated that Risk #2 should be considered more critical given that the severity of the impact of this risk is very high as compared to the first risk and the level of control of both risk events is equal. The calculated RCN for both risk events as calculated using fuzzy FMEA were then presented to the risk analyst and the risk manager. Both experts indicated an acceptance to the calculated RCN and the recommended corrective action as calculated using fuzzy FMEA and indicated that both risk events should not be treated similarly in terms of their criticality.

To utilize RCA to assess risk in a construction project, the project is broken down to its main components using the work breakdown structure (WBS), and each work package is analyzed to identify different risk events. Root cause analysis is conducted to identify root causes of different risk events. Understanding the root causes can help the risk analyst to estimate the probability of occurrence (P) of each risk event and also to suggest an appropriate risk response strategy. An evaluation of the level of detection/control (D) for each response strategy is conducted, and the RCN is calculated using the fuzzy expert system. If the risk event is assessed to have safety impact and/or environmental impact, then risk acceptability level is assessed as will be explained in chapter 6. Chapter 6 also presents the linguistic terms that are used to assess safety impact and environmental impact. If the risk event is assessed to have unacceptable risk level, then detailed quantitative risk analysis is required to be conducted as explained in chapter 5. Please note also that if the calculated RCN for any risk event is identified to fall in categories 5 to 9, then this implies that this risk event is a critical risk event (CRE) and hence detailed quantitative risk analysis is required to be conducted, as will be explained in the next chapter. All risk events are then monitored and controlled during the execution stage in which data are collected to support future risk assessment and updating the risk criticality level. Figure 4-16 shows a summary of the proposed integration between risk criticality analysis and risk analysis.

4.5 Summary

In this chapter, the concept of risk criticality analysis was investigated by combining fuzzy logic with both FMEA and AHP in a comprehensive framework that provides a practical and thorough approach for screening of critical risk events in the construction domain. Fuzzy logic was utilized to address the limitations that some combinations with lower RCN should be given more attention than others with higher RCN. The development of the fuzzy rule base has take into account the relative importance of input factors in calculating the RCN. Moreover, the framework offers the management team the ability to communicate the importance of establishing corrective actions.

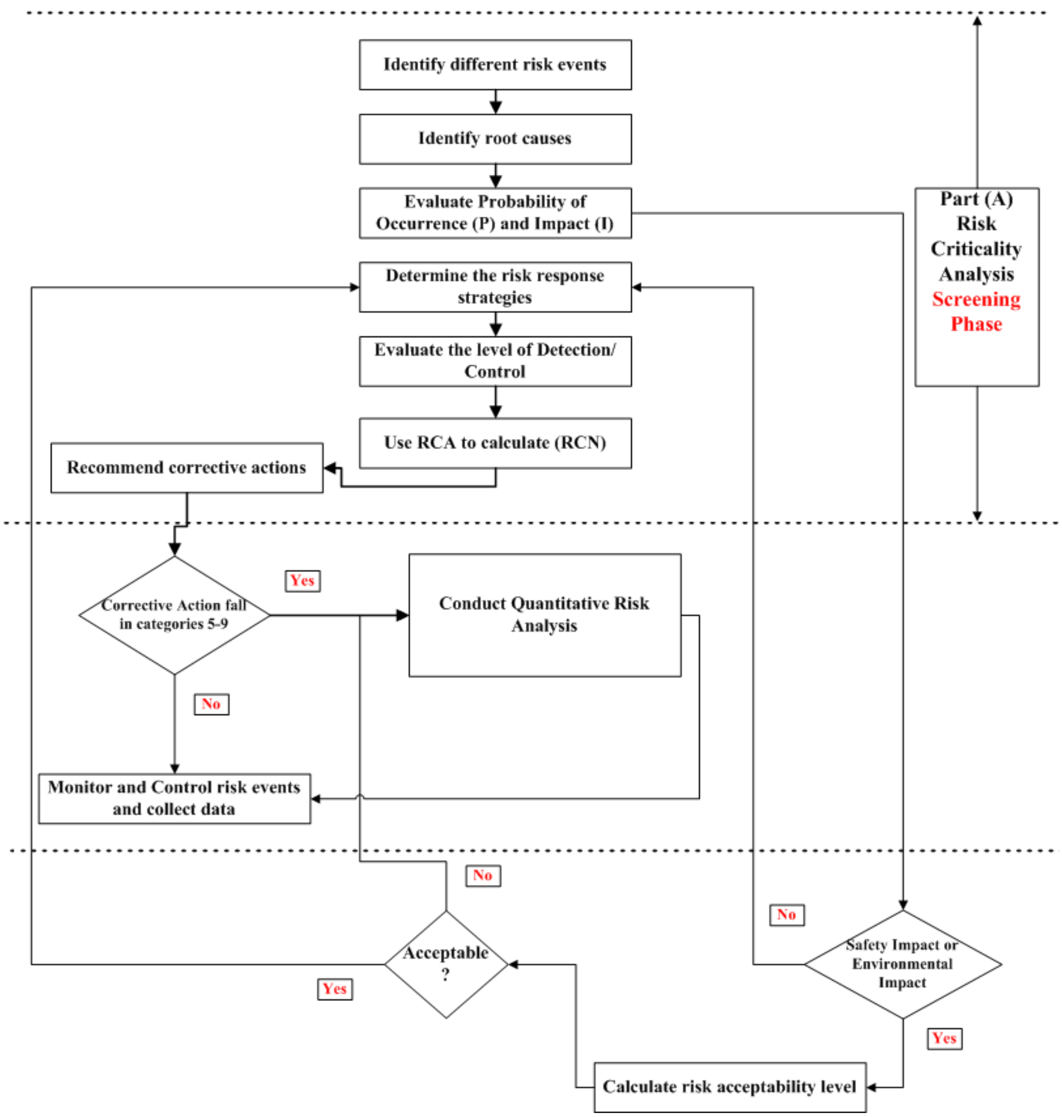

Figure 4-16. Risk criticality analysis and risk analysis

The fuzzy AHP approach has been adopted in this study to solve the multi-criteria decision-making problem by integrating cost impact, time impact, and scope/quality impact into one variable named aggregated impact (AI). The Risk Criticality Analyzer (RCA) was developed to implement the framework. Risk events that are assessed to fall in categories 5 to 9, in Figure 4-5, must undergo detailed risk analysis, as will be explained in the next chapter.

5. Quantitative Risk Analysis Using Fuzzy Fault Tree and Fuzzy Event Tree

The purpose of this chapter is to present a comprehensive framework for risk analysis in the construction industry. The proposed risk analysis model is based on integration between two commonly used techniques, i.e., fault trees and event trees, and fuzzy logic. The proposed integration between fault trees and event trees with fuzzy logic is intended to address the limitations of the traditional application of event tree and fault tree analysis presented in chapter 3. The framework also offers several advantages, as explained in this chapter and the next chapter.

5.1 Risk Analysis Using Fuzzy Fault Tree and Fuzzy Event Tree

After identifying critical risk events (CRE) using RCA, each identified CRE is required to undergo detailed risk analysis following the procedure presented in Figure 5-1. Part A of Figure 5-1 represents risk criticality analysis, which was explained in detail in the previous chapter. If the calculated RCN falls in categories 5 to 9, then the steps identified under Part B of Figure 5-1 are required to be conducted. Any risk event that is assessed to have unacceptable risk level, due to either safety or environment, is required to undergo detailed risk analysis following the steps identified under Part (B) of Figure 5-1. Further details about the risk acceptability level concept are presented in chapter 6.

According to Figure 5-1, the first step under Part B is to calculate the probability of occurrence (P) of each critical risk event using fuzzy fault tree analysis. In this regard, the probability of basic events is represented using possibility distributions, and experts can provide linguistic assessments of the probability of occurrence of basic events, which are referred to as fuzzy probabilities (FPro). Fuzzy arithmetic operations are applied to conduct a quantitative FTA, to calculate the FPro of the CRE, according to the steps that will be explained in the following sections. Fuzzy importance analysis is also established to rank different basic events according to their level of contribution to the top event, which may help in defining risk mitigation strategies.

After calculating the fuzzy probability of the identified critical risk events, team members are invited to identify mitigation strategies to control each identified CRE. It is worth noting that each CRE can have more than one mitigation strategy. Each mitigation strategy is subject to failure, and a fault tree structure can be established to represent the failure of each mitigation strategy. Fuzzy fault tree analysis is again conducted to quantify the fuzzy probability of failure of each mitigation strategy.

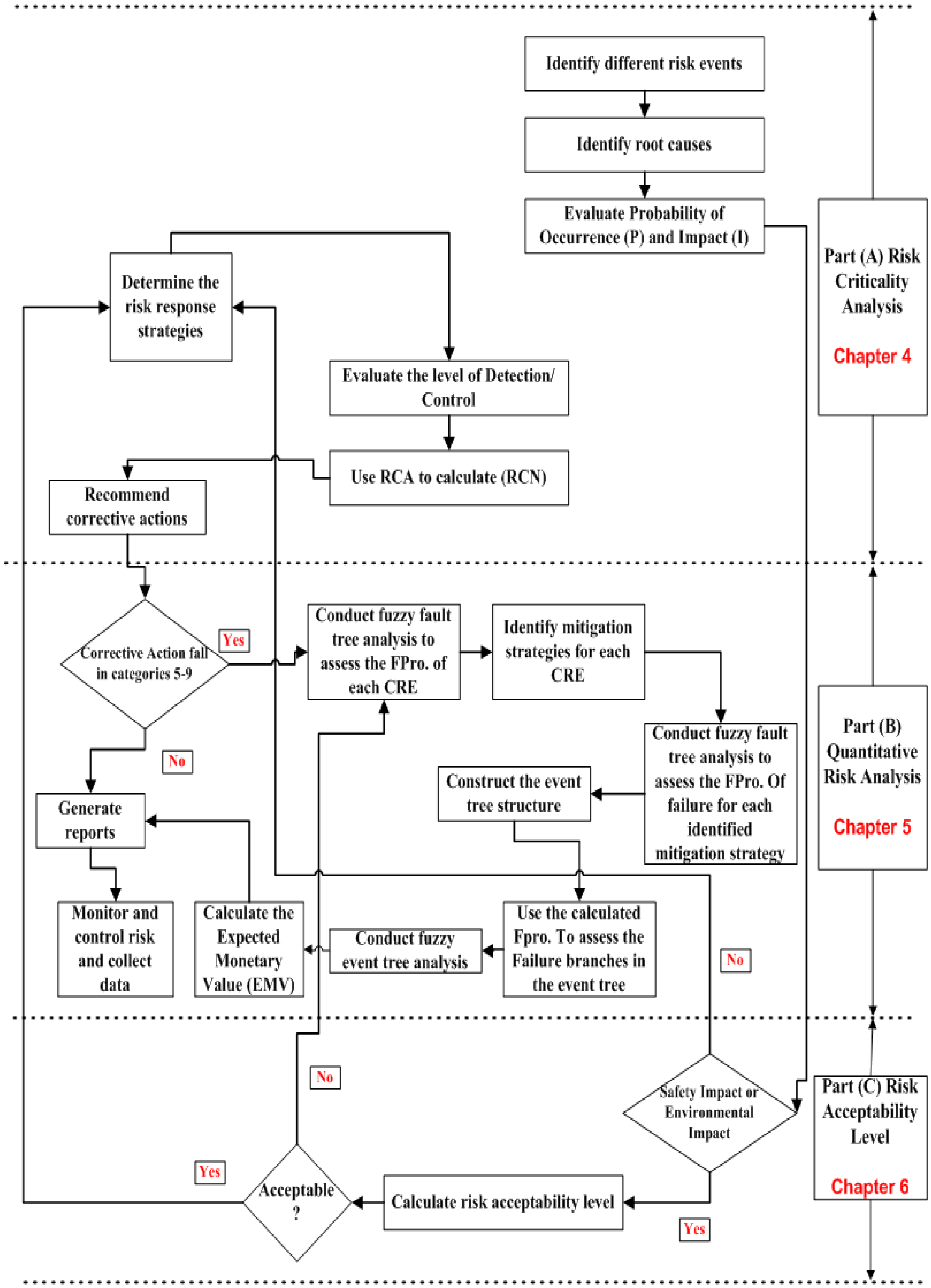

Figure 5-1. Proposed integration between FMEA, fault tree, event tree, and fuzzy logic

Given the risk event and the mitigation strategies, the event tree structure can be established. Figure 5-2 shows an example demonstrating the proposed integration between event tree and fault trees. As can be noticed in Figure 5-2, the probability of occurrence (P) of the failure branches is obtained from conducting fuzzy fault tree analysis. The probabilities of success branches are evaluated as (1 - the probability of failure). The consequence of each path is evaluated linguistically. Fuzzy event tree analysis (FETA) is then applied to estimate the expected monetary value (EMV).

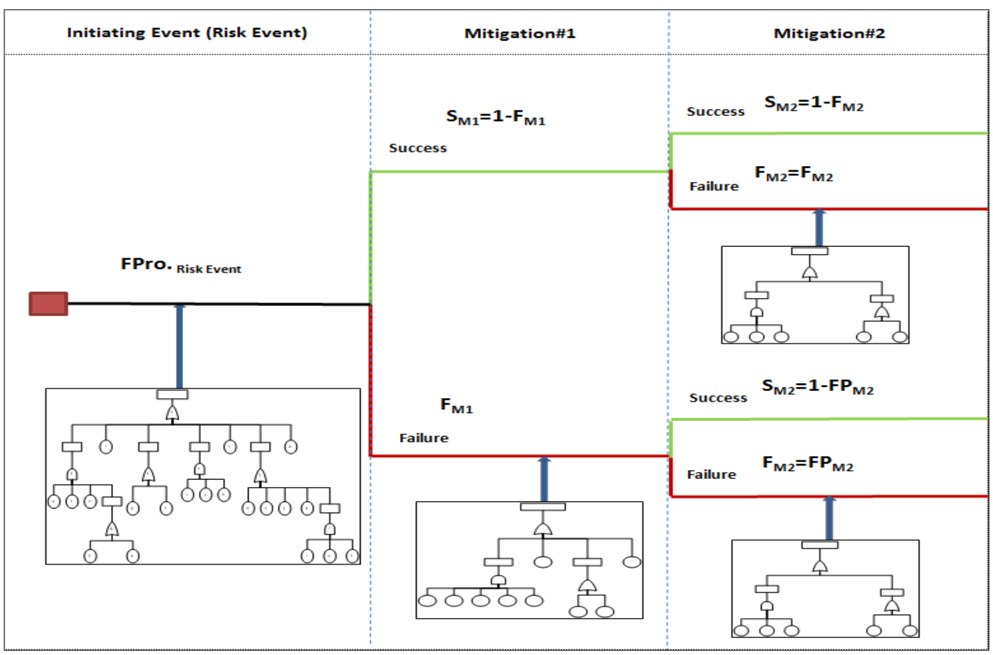

Figure 5-2. Example event tree fault tree integration using two mitigation strategies

5.2 Risk Analysis Using Fuzzy Fault Tree Analysis

After indentifying CRE, a quantitative FTA is required to be conducted. The following steps were adapted to conduct a quantitative fault tree analysis (Hauptmanns 1988, NASA 2002):

(1) Collect root causes of each CRE and use them to construct fault trees.

(2) Establish linguistic terms to assess the fuzzy probability of basic events.

(3) Use the linguistic variable in step 2 to assess the fuzzy probability of occurrence for all basic events and conduct qualitative fault tree analysis using Hauptmanns' (1988) algorithm, described in chapter 3.

(4) Conduct a quantitative fault tree analysis by calculating the top event fuzzy probability, and a sensitivity analysis by means of fuzzy importance analysis. Analyze the results and use them to develop risk response strategies.

(5) Repeat steps 1 to 4 for each identified mitigation in step 4 by considering failure of the proposed mitigation as the top event instead of the CRE. The following sections explain these steps in details.

5.2.1 Collect Root Causes

Step 1 is concerned with the elicitation of root causes of the risk event and the failure of mitigation strategies using any standard knowledge elicitation technique such as interviews, brainstorming, Delphi, or checklists. Chapman (1998) provides a comparison between some of these techniques, and the reader can refer to his work for more details. In this study, structured interviews were arranged with the same senior risk coordinator and another risk engineer to collect the required information, since face-to-face meetings were more convenient to both of them. The Delphi technique, using two rounds, was then used to reach an agreement between the two experts.

5.2.2 Establish Linguistic Terms to Assess Probability of Occurrence

To define the linguistic terms required to assess the fuzzy probability of basic events, an interview was arranged with the senior risk coordinator. After reviewing the existing risk matrix, a decision was made to continue using five linguistic terms—very low (VL), low (L), medium (M), high (H), and very high (VH)—to assess the probability of occurrence. The same expert was consulted to establish the membership function for each linguistic term. The direct method with one expert (Klir and Yuan, 1995) was used to elicit the required information to build the membership function for each linguistic term. Figure 5-3 shows the results of this elicitation process.

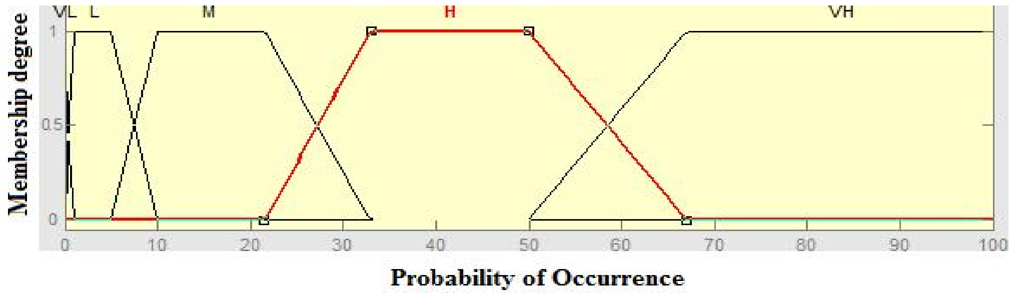

Figure 5-3. Membership function to assess probability of occurrence

5.2.3 Conduct Qualitative Fault Tree Analysis

Step 3 is intended to use the linguistic terms, established in the last step, to assess the fuzzy probability of occurrence of basic events and to identify minimal cut sets (MCS). Any standard knowledge elicitation technique such as interviews, brainstorming, Delphi, or checklists can be used for this purpose. Ayyub defined a minimal cut set (MCS) as “a cut set with the condition that the non-occurrence of any one basic event from this set results in the non-occurrence of the top event” (2003, 76).

In order to demonstrate the calculation of the minimal cut sets (MCS) concepts using Hauptmanns’ (1988) algorithm, let us consider that a risk identification workshop was conducted and a fault tree structure was established for one of the risk events as shown in Figure 5-4. This fault tree demonstrates failure of establishing of proper field process as a top event and this top event (TE) is connected by an (OR) gate to three gate events. The first gate event (GE1) is defined as “inadequate follow up training”, the second gate event (GE2) is defined as “loss of key resources”, and the third gate event (GE3) is defined as “lack of documentation of communication requirements." Each gate event is connected with a list of basic events.

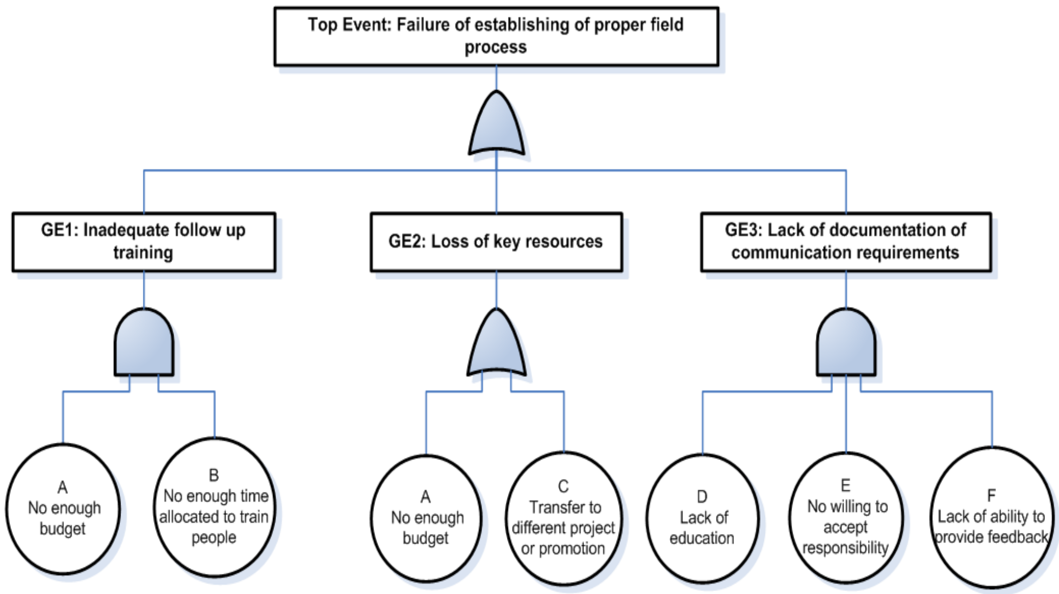

Figure 5-4. An example fault tree structure

The first step of applying Hauptmanns' (1988) algorithm is to convert the fault tree structure into a Boolean matrix (BM) composed of 0's and 1's. "0" is used to indicate that no connection exists, while "1" is used to indicate a connection between events. The rows of the BM are divided into two sections: the OR gate events (GE) in the upper part, and the AND gate events (GE) in the lower parts. The columns of the BM are divided into three blocks starting with basic events, followed by OR gate events (GE), and finally followed by AND gate events (GE). Table 5-1 shows the Boolean matrix (BM) for the fault tree shown in Figure 5-4.

Table 5-1. Boolean matrix representation of the example fault tree

Gate event ID	Gate type	Basic events						OR (GE)		AND (GE)	
		A	B	C	D	E	F	TE	GE 2	GE 1	GE 3
TE	OR	0	0	0	0	0	0	0	1	1	1
GE2	OR	1	0	1	0	0	0	0	0	0	0
GE1	AND	1	1	0	0	0	0	0	0	0	0
GE3	AND	0	0	0	1	1	1	0	0	0	0

The second step is to create another empty matrix, referred to as the working Boolean matrix (WBM), and start the analysis from the top event.

The third step is to replace the top event in the WBM with it is equivalent (basic events/gate events) from the Boolean matrix, referred to as the connection list (CL), by taking the following two rules into consideration:

3a) If the top event is connected by an OR gate with its CL, then insert each event from the CL into a separate row in the WBM.

3b) If the top event is connected by an AND gate with its CL, then insert all the events from the CL into a single row in the WBM. Table 5-2 shows the WBM after applying step 3. As shown in Table 5-2, since the top event in the BM, shown in Table 5-1, is connected by "1" with three gate events (GE1, GE2, GE3) using an OR gate, the WBM is created by inserting three separate rows, applying rule 3a, and adding a connection "1" under each gate event.

Table 5-2. Initial working Boolean matrix representation of the example fault tree

Basic events						OR (GE)		AND (GE)	
A	B	C	D	E	F	TE	GE2	GE1	GE3
0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	1

The forth step is to scan all the rows of the WBM to check if there is any connection "1" under any of the two blocks named "OR (GE)" and "AND (GE)." If so, then replace each gate event in the WBM with its equivalent (basic events/gate events) from the Boolean matrix, referred to as the connection list (CL), by taking the following two rules into consideration:

4a) If a gate event is connected by an OR gate with its CL, then insert each event from the CL into a separate row in the WBM.

4b) If a gate event is connected by an AND gate with its CL, then insert all the events from the CL into a single row in the WBM.

By doing the first scan on the initial working Boolean matrix, as defined in Table 5-2, there is a connection "1" under GE2 and it is an OR

Gate. Thus, applying rule (4a), GE2 is replaced with its equivalent (basic events), i.e., A, and C each one is in a separate raw.

Table 5-3. Second iteration of the working Boolean matrix

Basic events						OR (GE)		AND (GE)	
A	B	C	D	E	F	TE	GE2	GE1	GE3
1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	1

The fifth step is to repeat step 4 until the WBM contains 0 connections in the last two blocks, "OR (GE)" and "AND (GE)." By doing another scan on the working Boolean matrix, as defined in Table 5-3, there is a connection "1" under GE1 and it is an AND Gate. Thus, applying rule (4b), GE1 is replaced with its equivalent (basic events), i.e., A, and B both in one single raw as shown in Table 5-4.

Table 5-4. Third iteration of the working Boolean matrix

Basic events						OR (GE)		AND (GE)	
A	B	C	D	E	F	TE	GE2	GE1	GE3
1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1

By doing another scan on the working Boolean matrix, as defined in Table 5-4, there is a connection "1" under GE3 and it is an AND Gate.

Thus, applying rule (4b), GE3 is replaced with its equivalent (basic events), i.e., D, E and F all in one single raw as shown in Table 5-5. Table 5-5 shows the final working Boolean matrix since there is no connection "1" under any of the two blocks named "OR (GE)" and "AND (GE)."

Table 5-5. Forth iteration of the working Boolean matrix

Basic events						OR (GE)		AND (GE)	
A	B	C	D	E	F	TE	GE2	GE1	GE3
1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0
0	0	0	1	1	1	0	0	0	0

The six step is to use each row in the final WBM to develop the MCS equations by converting each connection "1" in a row with its related basic event, and connect basic event(s) within each row using intersection "$\cap$". For example, the first row in Table 5-5 can be read as "A". Basic event(s) in a row is/are connected with basic event(s) in another row using the union "$\cup$" operator. For example, the first and the second rows in Table 5-5, can be read as "A" $\cup$ "C". By applying step 6 to all the rows in Table 5-5, the top event is represented as shown in Equation 5-1.

$$TE= A \cup C \cup (A \cap B) \cup (D \cap E \cap F) \qquad [5\text{-}1]$$

The seventh step is to perform Boolean simplifications on the MCS equations using the rules presented in Table 3-4. The simplification of Equation 5-1 is as follows:

$$TE = A \cup C \cup (D \cap E \cap F) \quad [5\text{-}2]$$

5.2.4 Conduct Quantitative Fault Tree Analysis and Fuzzy Importance Analysis

Quantitative fault tree analysis is conducted by calculating the top event probability. To do so, the probability of occurrence of each basic event in a fault tree structure is assessed linguistically by selecting one of the linguistic terms presented in Figure 5-3. The steps followed to conduct a quantitative FTA can be summarized as follows:

(1) Represent each selected linguistic term from Figure 5-3, using the alpha-cut (α-cut) principle.

(2) Use the minimal cut set, identified in 5.2.3, to represent the top event fuzzy probability.

(3) Conduct fuzzy arithmetic operations to convert the "∪" and "∩" in the MCS equations, as shown in Equation 5-3:

The α-cut of the fuzzy probability of events connected by an "∪" gate is defined as shown in Equation 5-3 (Verma et al. 2007) for mutually exclusive events.

FPro (Top Event) $^{\alpha}$ =

$$\{1-\prod_{i=1}^{n}[1-(a_i+(b_i-a_i))^{\alpha}],1-\prod_{i=1}^{n}[1-(d_i-(d_i-c_i))^{\alpha}]\}\{1-\prod_{i=1}^{n}[1-(a_i+(b_i-a_i))^{\alpha}],1-\prod_{i=1}^{n}[1-(d_i-(d_i-c_i))^{\alpha}]\} \quad [5\text{-}3]$$

where n is the number of events connected by "$\cup$," a represents the minimum value, b and c represent the most likely value, and d represents the maximum value of the membership function (MF).

The fuzzy probability of events connected by an "$\cap$" gate is defined as shown in Equation 5-4 (Verma et al. 2007):

FPro (Top Event) $^{\alpha}$ = $\{\prod_{i=1}^{s}[a_i + (b_i - a_i)^{\alpha}], \prod_{i=1}^{s}[d_i - (d_i - c_i)^{\alpha}]\}$

[5-4]

where s is the number of events connected by "$\cap$".

The multiplication operator, $\prod$, in Equation 5-3 and 5-4 is defined as follows:

If A and B are two fuzzy sets represented over the interval $A^{\alpha} = [a_1\ d_1]$, $B^{\alpha} = [a_2\ d_2]$, then $A^{\alpha} * B^{\alpha}$ is defined as shown in Equation 5-5 (Verma et al. 2007):

$A^{\alpha} * B^{\alpha}$ = [min($a_1 * a_2$, $a_1 * d_2$, $d_1 * a_2$, $d_1 * d_2$), max ($a_1 * a_2$, $a_1 * d_2$, $d_1 * a_2$, $d_1 * d_2$)] [5-5]

(4) Defuzzify the top event fuzzy probability using the mean of maximum (MOM) method. Since the membership function at α equals 1 represents the most confident level, the mean of maximum can be viewed as the most likely estimate of probability over the most confident range.

(5) Conduct a fuzzy importance analysis to identify critical root causes using the following equation (Khan and Abbasi 1999):

FIM = $\frac{TE_1 - TE_2}{TE_1}$* 100% [5-6]

where (TE_1) is the top event fuzzy probability, assuming that all root causes will occur according to their respective fuzzy probability, and (TE_2) is the top event fuzzy probability, assuming each root cause is eliminated in turn (i.e., by setting FPro = 0 for the root cause).

(6) Analyze the results from the qualitative and quantitative FTAs and propose proper risk response strategies.

To illustrate the steps presented under section 5.2 (steps 1 to 4), the example fault tree presented in Figure 5-4 is used. Let us assume that a risk assessment workshop was arranged with experts to provide an assessment of the probability of basic events (A, B, C, D, E, and F), and the following results were obtained:

FPro(A) = medium; FPro(B) = medium; FPro(C) = medium; FPro(D) = high; FPro(E) = medium; FPro(F) = high

Each of these linguistic assessments is presented using α-cut. Table 5-6 shows the α-cut representation for the medium linguistic term, i.e., the assessment provided for A, B, C, and E.

Table 5-6. α-cut representation for “medium” probability of occurrence

α	Lower bound		Upper bound
0	0.050		0.33
0.05	0.053		0.32
0.10	0.055		0.32
0.15	0.058		0.31
0.20	0.060		0.32
0.25	0.062		0.30
0.30	0.065		0.30
0.35	0.068		0.30
0.40	0.070		0.28
0.45	0.073		0.28
0.50	0.075		0.27
0.55	0.078		0.27
0.60	0.080		0.26
0.65	0.083		0.26
0.70	0.085		0.25
0.75	0.088		0.24
0.80	0.090		0.24
0.85	0.093		0.23
0.90	0.095		0.23
0.95	0.098		0.22
1.0	0.10		0.22

Please note that the upper and the lower bound is calculated by applying Equation 5-7, and Equation 5-8 respectively at each alpha cut level

$$Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha \qquad [5\text{-}7]$$

$$Lower\ Bound = d - (d - c) * \alpha \qquad [5\text{-}8]$$

where a represents the minimum value, b and c represent the most likely value, and d represents the maximum value of the membership function (MF) as defined in Figure 5-3.

The same α-cut principle is applied to represent the probability of occurrence (P) of D, and F as shown in Table 5-7.

Table 5-7. α-cut representation for “high” probability of occurrence

α	Lower bound		Upper bound
0	0.22		0.67
0.05	0.22		0.66
0.10	0.23		0.65
0.15	0.23		0.65
0.20	0.24		0.64
0.25	0.24		0.63
0.30	0.25		0.62
0.35	0.26		0.61
0.40	0.26		0.60
0.45	0.27		0.59
0.50	0.27		0.59
0.55	0.28		0.58
0.60	0.28		0.57
0.65	0.29		0.56
0.70	0.30		0.55
0.75	0.30		0.54
0.80	0.31		0.53
0.85	0.31		0.53
0.90	0.32		0.52
0.95	0.32		0.51
1.0	0.33		0.50

By using the minimal cut equation defined in Equation 5-2 and applying Equation 5-3 and 5-4, the fuzzy probability of the top event can be represented as shown in Equation 5-9:

$FPro(TE_1)^{\alpha}$ = 1- [(1- $FPro(A)^{\alpha}$) * (1- $FPro(C)^{\alpha}$) * (1- ($FPro(D)^{\alpha}$) * $FPro(E)^{\alpha}$ * $FPro(F)^{\alpha}$)] [5-9]

Equation 5-9 is used to calculate the top event fuzzy probability by incrementally increasing the value of alpha by 0.050 increments. For instance, at α equals zero, Equation 5-9 can be written as follows in Equation 5-10:

$FPro(TE_1)^{0}$ = 1- {[(1-(0.050+(0.1-0.050))),(1-(0.33-(0.33-0.22)))] * [(1-(0.050+(0.1-0.050))),(1-(0.33-(0.33-0.22)))] * [1-{[(0.22+(0.33-0.22)), (0.67-(0.67-0.50))] * [(0.050+(0.10-0.050), (0.33-(0.33-0.22))] * [(0.22+(0.33-0.22)), (0.67-(0.67-0.50))]}] [5-10]

By using Equation 5-5 to solve the multiplication operator in Equation 5-10, the fuzzy probability of occurrence of the top event at alpha equals zero is calculated as follows in Equation 5-11:

$FPro(TE_1)^{0}$ = [10 62] [5-11]

By substituting the fuzzy probability of basic events into Equation 5-9 for different α-cuts, the fuzzy probability of the top event can be calculated, as shown in Figure 5-5 and Table 5-8.

By applying the mean of maximum (MOM) method, the top event fuzzy probability of occurrence can be estimated as shown in Equation 5-12.

$$FPro\ (TE_1) = \left(\frac{20+42}{2} \right) = 31\ \% \quad [5\text{-}12]$$

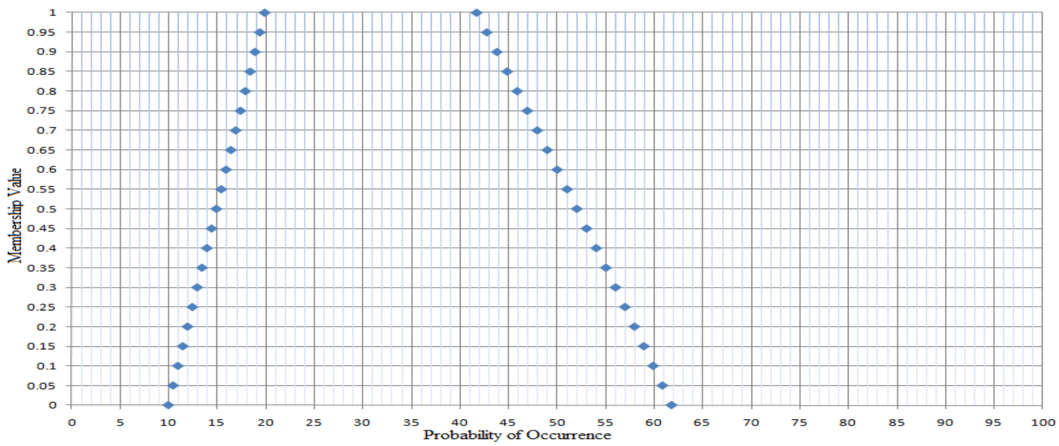

Figure 5-5. Fuzzy probability of occurrence of the top event

After conducting quantitative FTA, fuzzy importance analysis (FIM) can be applied to rank different root causes according to their level of contribution to the top event fuzzy probability by applying Equation 5-6. Appendix III shows detailed calculation of (TE_2) in Equation 5-6. Please note that TE_1 is calculated in Equation 5-12. Table 5-9 shows a summary of the fuzzy importance analysis. For example, the FIM of BE_1 can be calculated as follows:

$$FIM = \frac{31-18}{31} * 100\% = 42\% \quad [5\text{-}13]$$

Table 5-8. α-cut representation of the top event fuzzy probability

α	Lower bound (%)		Upper bound (%)
0	10		62
0.05	10		61
0.10	11		60
0.15	11		59
0.20	12		58
0.25	12		57
0.30	13		56
0.35	13		55
0.40	14		54
0.45	14		53
0.50	15		52
0.55	15		51
0.60	16		50
0.65	16		49
0.70	17		48
0.75	17		47
0.80	18		46
0.85	18		45
0.90	19		44
0.95	19		43
1.0	20		42

Table 5-9. Fuzzy importance analysis of the fault tree

Event ID	(TE_1)	(TE_2)	FIM	Rank
A	31	18	42	1
C	31	18	42	1
D	31	29	6.5	2
E	31	29	6.5	2
F	31	29	6.5	2

As can be noticed from Table 5-9, basic event A and C have the highest contribution to the top event fuzzy probability, and risk response strategies can be established to reduce or eliminate A and C to aid in reducing the overall probability of the CRE (step 5). An important conclusion that can be driven from using fuzzy importance analysis is that although D and F were identified to have a high probability of occurrence, as shown in Table 5-7, and A and C were all identified to have a medium probability of occurrence, as shown in Table 5-6, the fuzzy importance analysis results, as shown in Table 5-9, indicated that A and C are more important than D and F. The reason behind this is attributed to the logic that can leads to the occurrence of the top event, which was defined previously in the fault tree structure shown in Figure 5-4. As noted early under section 3.3.3, minimal cut sets that are composed of one basic event are critical because the occurrence of this one basic event is sufficient by itself to cause the top event to occur. According to Equation 5-2, A represents the first minimal cut, C represents the second minimal cut, D and E and F all together represent the third minimal cut. Thus, although, D and F were identified to have high probability, they have to occur all together with E to cause the top event to occur. On the other hand, A is sufficient by itself to cause the top event to occur and C is sufficient by itself to cause the top event to occur. By using the fuzzy importance analysis concept, such conclusion can be driven without the need to review the fault tree structure.

The next chapter presents a detailed application of the concepts presented in this section using a case study.

5.2.5 Conduct Fuzzy Fault Tree Analysis for each Mitigation Strategy

Each identified mitigation strategy is then analyzed by considering the failure of the selected mitigation to be the top event, and repeating steps 1 to 4 (section 5.2). To illustrate more on this step, let us assume that the project team has identified two mitigation strategies: mitigation (1) “establish proper training material”, and mitigation (2) “establish a communication protocol”. Team members can then investigate each mitigation strategy and identify the root causes that can lead to failure of each mitigation strategy. Figure 5-6 shows the fault tree to represent the failure of each mitigation strategy and the fuzzy probability of basic events. Table 5-10 shows the description of basic events in Figure 5-6.

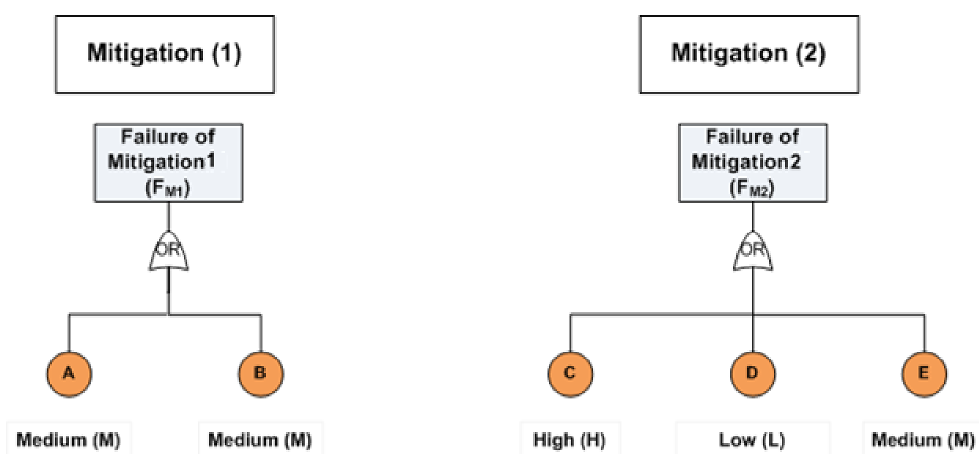

Figure 5-6. Fault tree structure of failure of mitigation 1 and mitigation 2

Table 5-10. Basic events and fuzzy probability assessment of basic events

Symbol	Description	Fuzzy probability (FPro) of occurrence
A	No enough budget	Medium (M)
B	Poor quality of produced materials	Medium (M)
C	Lack of enforce of the protocol by top management	High (H)
D	Failure to involve key personnel	Low (L)
E	Lack of time	Medium (M)

The qualitative FTA is conducted following the same steps presented in section 5.2.3. The first step of applying Hauptmanns' (1988) algorithm is to convert the fault tree structure into a Boolean matrix composed of 0's and 1's. Table 5-11 shows the Boolean matrix (BM) for the failure of mitigation (1) and Table 5-12 shows the Boolean matrix (BM) for the failure of mitigation (2).

Table 5-11. Boolean matrix representation of failure of mitigation (1)

Gate event ID	Gate type	Basic events		OR (GE)		AND (GE)	
		A	B	TE			
TE	OR	1	1	0	0	0	0

Table 5-12. Boolean matrix representation of failure of mitigation (2)

Gate event ID	Gate type	Basic events			OR (GE)		AND (GE)	
		C	D	E	TE			
TE	OR	1	1	1	0	0	0	0

The second step is to create another empty matrix, referred to as the working Boolean matrix (WBM), and start the analysis from the top event.

The third step is to replace the top event in the WBM with it is equivalent (basic events/gate events) from the Boolean matrix, referred to as the connection list (CL), by taking the following two rules into consideration:

3a) If the top event is connected by an OR gate with its CL, then insert each event from the CL into a separate row in the WBM.

3b) If the top event is connected by an AND gate with its CL, then insert all the events from the CL into a single row in the WBM. Table 5-13 shows the WBM of the failure of mitigation (1) after applying step 3. As shown in Table 5-13, since the top event in the BM, shown in Table 5-11, is connected by “1” with two basic events (A) and (B) using an OR gate, the WBM is created by inserting two separate rows, applying rule 3a, and adding a connection “1” under each gate event. The same logic is applied to establish the working Boolean matrix to represent the failure of mitigation (2) as shown in Table 5-14.

Table 5-13. Working Boolean matrix representation of failure of mitigation (1)

Basic events		OR (GE)		AND (GE)	
A	B	TE			
1	0	0	0	0	0
0	1	0	0	0	0

Table 5-14. Working Boolean matrix representation of failure of mitigation (2)

Basic events			OR (GE)		AND (GE)	
C	D	E	TE			
1	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	1	0	0	0	0

The forth step is to scan all the rows of the WBM to check if there is any connection “1” under any of the two blocks named “OR (GE)” and “AND (GE).” If so, then replace each gate event in the WBM with its equivalent (basic events/gate events) from the Boolean matrix, referred to as the connection list (CL), by taking the following two rules into consideration:

4a) If a gate event is connected by an OR gate with its CL, then insert each event from the CL into a separate row in the WBM.

4b) If a gate event is connected by an AND gate with its CL, then insert all the events from the CL into a single row in the WBM.

Since there is no connection "1" under any of the two blocks named "OR (GE)" and "AND (GE)" in Table 5-13 and Table 5-14, we can move to the next step.

The six step is to use each row in the final WBM to develop the MCS equations by converting each connection "1" in a row with its related basic event, and connect basic event(s) within each row using intersection "$\cap$". Basic event(s) in a row is/are connected with basic event(s) in another row using the union "$\cup$" operator.

By applying step 6 to all the rows in Table 5-13, the failure of mitigation (1) (F_{M1}) is represented as shown in Equation 5-14.

$$F_{M1} = A \cup B \tag{5-14}$$

By applying step 6 to all the rows in Table 5-14, the failure of mitigation (1) (F_{M1}) is represented as shown in Equation 5-15.

$$F_{M2} = C \cup D \cup E \tag{5-15}$$

After conducting qualitative FTA, quantitative FTA can be conducted following the same steps presented in section 5.2.4. The first step is to represent the fuzzy probability of failure of mitigation (1) as represented in Equation 5-14 by substituting in Equation 5-3.

$$FPro(F_{M1})^{\alpha} = 1- [(1- FPro(A)^{\alpha}) * (1- FPro(B)^{\alpha})] \quad [5\text{-}16]$$

where $FPro(A)^{\alpha}$ and $FPro(B)^{\alpha}$ are the fuzzy probability of basic event A and basic event B represented using alpha cut. Since A and B are both represented using medium probability of occurrence, Table 5-10, they are defined using the same alpha cut representation as defined in Table 5-15.

Table 5-15. α-cut representation for the probability of basic events A and B

α	Lower bound		Upper bound
0	0.050		0.33
0.05	0.053		0.32
0.10	0.055		0.32
0.15	0.058		0.31
0.20	0.060		0.32
0.25	0.062		0.30
0.30	0.065		0.30
0.35	0.068		0.30
0.40	0.070		0.28
0.45	0.073		0.28
0.50	0.075		0.27
0.55	0.078		0.27
0.60	0.080		0.26
0.65	0.083		0.26
0.70	0.085		0.25
0.75	0.088		0.24
0.80	0.090		0.24
0.85	0.093		0.23
0.90	0.095		0.23
0.95	0.098		0.22
1.0	0.10		0.22

Please note that the upper bound and lower bound in Table 5-15 are calculated by substituting in Equation 5-7 and Equation 5-8.

The next step is to calculate the following terms in Equation 5-16 (1- $FPro(A)^{\alpha}$) and (1- $FPro(B)^{\alpha}$). Table 5-16 present the calculation of both terms (1- $FPro(A)^{\alpha}$) and (1- $FPro(B)^{\alpha}$).

Table 5-16. α-cut representation of (1- $FPro(A)^{\alpha}$), (1- $FPro(B)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.79

The next step is to use the calculated value of (1- $FPro(A)^{\alpha}$) and (1- $FPro(B)^{\alpha}$), as presented in Table 5-16, and substitute this value in

Equation 5-16 at each alpha cut. Please note that the multiplication operator in Equation 5-16 is represented as defined in Equation 5-5.

By substituting in Equation 5-16 at different alpha cuts, the fuzzy probability of failure of mitigation (1) is calculated as shown in Table 5-17.

Table 5-17. α-cut representation of failure of mitigation (1)

α	Lower Bound %		Upper Bound %
0.00	10		55
0.05	10		54
0.10	11		54
0.15	11		53
0.20	12		52
0.25	12		51
0.30	13		50
0.35	13		50
0.40	14		49
0.45	14		48
0.50	14		47
0.55	15		46
0.60	15		45
0.65	16		45
0.70	16		44
0.75	17		43
0.80	17		42
0.85	18		41
0.90	18		40
0.95	19		39
1.00	19		38

Applying the same concept, the fuzzy probability of failure of mitigation (2) is calculated as shown in Table 5-18.

Table 5-18. α-cut representation of failure of mitigation (2)

α	Lower Bound %		Upper Bound %
0.00	25		80
0.05	26		79
0.10	27		79
0.15	28		78
0.20	29		77
0.25	29		76
0.30	30		75
0.35	31		75
0.40	32		74
0.45	32		73
0.50	33		72
0.55	34		71
0.60	35		70
0.65	35		69
0.70	36		68
0.75	37		68
0.80	37		67
0.85	38		66
0.90	39		65
0.95	40		64
1.00	40		63

The fuzzy probability of failure of mitigation 1 and mitigation 2, i.e., $FPro_{FM1}$ and $FPro_{FM2}$, as represented in Table 5-17 and Table 5-18, are shown in Figure 5-7 and Figure 5-8 respectively.

The mean of maximum method is then used to defuzzify the fuzzy probability of failure of mitigation 1 and mitigation 2, as shown in Equations 5-17 and 5-18:

$$FPro.F_{M1} = \left(\frac{19+38}{2} \right) = 29\ \% \qquad [5\text{-}17]$$

$$\text{FPro.F}_{M2} = \left(\frac{40+63}{2} \right) = 52\ \% \qquad [5\text{-}18]$$

Fuzzy importance analysis can be also conducted, following the same steps presented in section 5.2.4, to identify the level of contribution of each basic event to the fuzzy probability of failure of each mitigation strategy, as summarized in Table 5-19 and Table 5-20.

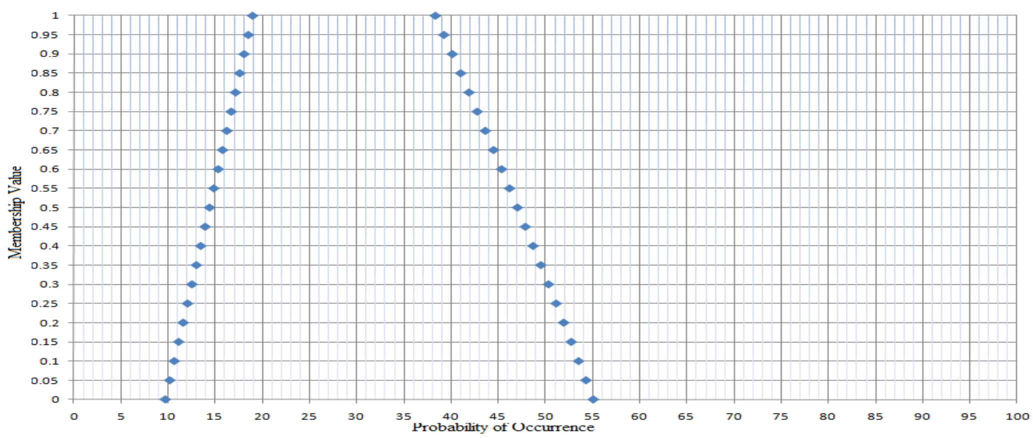

Figure 5-7. Fuzzy probability of failure of mitigation 1

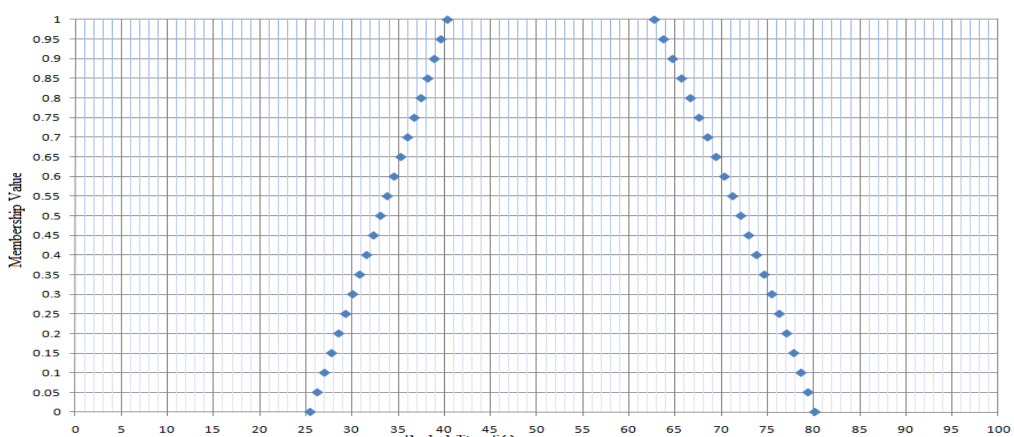

Figure 5-8. Fuzzy probability of failure of mitigation 2

Table 5-19. Fuzzy importance analysis for the failure of mitigation 1

Event ID	**(TE_1)**	**(TE_2)**	**FIM**	**Rank**
A	29	16	45	1
B	29	16	45	1

Table 5-20. Fuzzy importance analysis for the failure of mitigation 2

Event ID	**(TE_1)**	**(TE_2)**	**FIM**	**Rank**
C	52	18	65	1
D	52	50	3.8	3
E	52	43	17	2

The next chapter presents a detailed application of the concepts presented in this section using a case study.

The use of a fault tree supported explaining the logic behind how different root causes may interact to cause the risk event to occur. For example, Equation 5-2 indicates that the risk event will occur if A occurred, or C occurred, or if the following combinations between (D and E and F) occurred. The logic presented by this equation can aid in understanding the logic of how the risk event might occur, and hence, the project team can work in establishing of proactive risk response strategies. The use of fuzzy arithmetic operations on fuzzy numbers has facilitated establishing a practical approach for quantitative fault tree analysis in the construction industry. In this regard, experts are required to use linguistic terms to assess the fuzzy probability of occurrence of basic events. Thus, quantitative fault tree analysis can be established even if data do not exist or are difficult to obtain. The use of fault trees also supports explaining the logic that might lead to failure of mitigation strategies, and hence can aid further improvement of these mitigations. After calculating the fuzzy probability of the risk event, and the fuzzy probability of failure of mitigation 1 and mitigation 2, fuzzy event tree can be conducted, as explained in the next section.

5.3 Fuzzy Event Tree Analysis

After conducting quantitative FTA for the CRE under analysis, and for the failure of identified mitigation strategies, (i.e., mitigation 1 and mitigation 2), fuzzy event tree analysis can be conducted as follows:

Define the linguistic terms to assess the impact (consequence) of risk events. In this regard, more interviews were arranged with the same senior risk coordinator. The direct method with one expert (Klir and Yuan 1995) was further used to elicit the required information to build the membership function for each linguistic term. A trapezoidal membership function is selected to define each linguistic term, as shown in Table 5-21. Please note that a is the minimum impact value, b and c represent the most likely impact value, and d represents the maximum impact value defined as a percentage of the baseline cost.

I. Use the fuzzy probability of the CRE and the fuzzy probability of failure of each mitigation strategy according to the findings from the fuzzy fault tree analysis.

II. Define the fuzzy probability of success of each mitigation strategy as follows, using Equation 5-19:

Fuzzy probability of success = 1- fuzzy probability of failure [5-19]

Table 5-21. Trapezoidal representation of impact (% of baseline cost) (Abdelgawad and Fayek 2010c)

Linguistic terms	Impact (consequence)			
	a	b	c	d
Very High	6.0	10	100	100
High	1.10	2.0	6.0	10.0
Medium	0.11	0.20	1.10	2.0
Low	0.01	0.02	0.11	0.20
Very Low	0.00	0.00	0.01	0.02

III. Construct the event tree structure based on the findings from II and III. Figure 5-9 shows the event tree structure for the example explained in the last section. As can be noticed in Figure 5-9, the FPro of the risk event, FPro.F_{M1}, and FPro.$F_{M2,}$ are all obtained from the fuzzy fault tree analysis. The fuzzy probability of success of each mitigation strategy is calculated as 1—the calculated FPro. of failure.

IV. Assess the consequence (C) of each path using the linguistic terms established in the first step. Let us assume for the sake of the illustration that the consequences were assessed to be very low

(VL), low (L), low (L), and medium (M) for path 1 to path 4 respectively.

V. Determine the overall probability (OP) of each path by multiplying the fuzzy probability of all the events located on the same path. Figure 5-10 shows the OP of each path and the consequence.

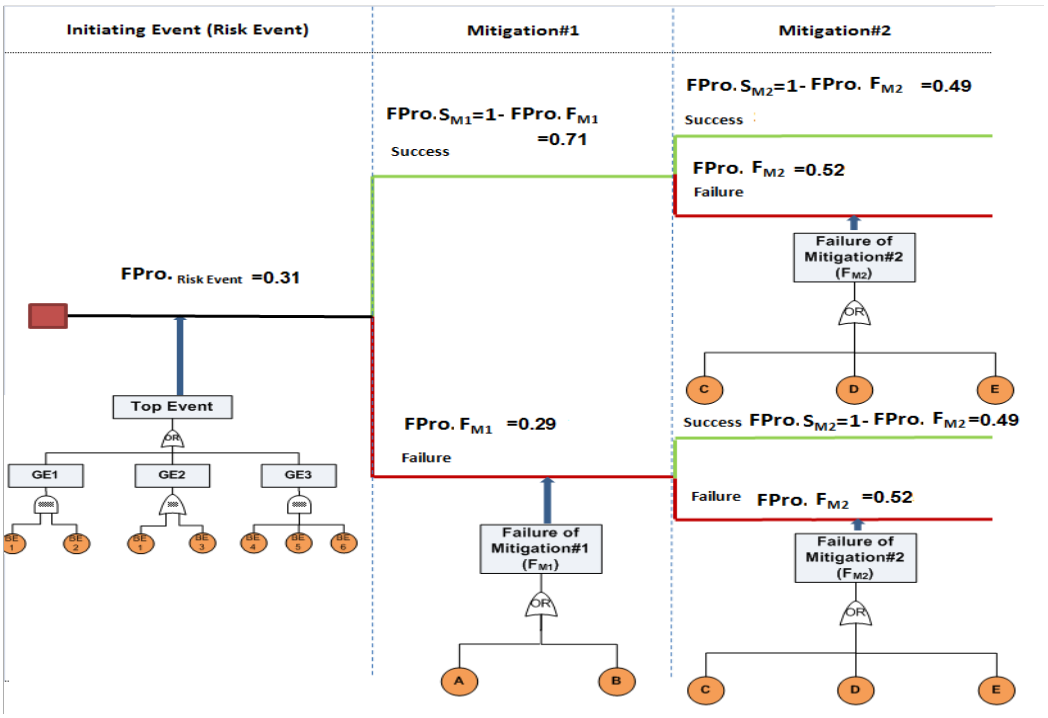

Figure 5-9. Event tree structure

VI. Multiply the OP of each path with the estimated consequence (C) of each path to calculate the expected risk magnitude (ERM) of each path.

VII. Use the fuzzy arithmetic operation on fuzzy numbers to calculate the expected monetary value (EMV) as follows:

If A and B are two trapezoidal fuzzy sets representing the ERM of two paths and is defined as follows:

$A^{\alpha} = [a_1 \; d_1]$, $B^{\alpha} = [a_2 \; d_2]$ then the EMV is defined as shown in Equation 5-20 (Verma et al. 2007).

$$A^{\alpha} + B^{\alpha} = [a_1 + a_2, b_1 + b_2, c_1 + c_2, d_1 + d_2] \qquad [5\text{-}20]$$

Steps VII and VIII are illustrated in Table 5-22.

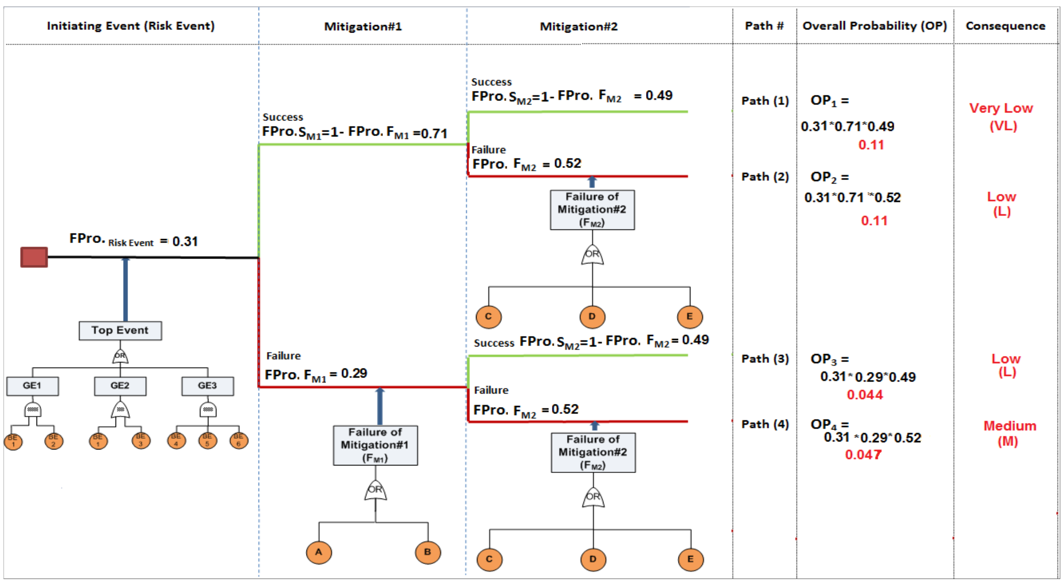

Figure 5-10. Assessment the consequence and calculating the OP

Table 5-22. Expected risk magnitude (ERM) and EMV calculations

Path	OP	Consequence (C)				Expected risk magnitude (ERM)			
		A	b	c	d	a	b	c	d
Path1	**0.11**	0.00	0.00	0.010	0.020	0	0	0.001	0.002
Path2	**0.11**	0.010	0.020	0.11	0.20	0.001	0.002	0.012	0.022
Path3	**0.044**	0.010	0.020	0.11	0.20	0	0.001	0.005	0.009
Path4	**0.047**	0.11	0.20	1.1	2.0	0.005	0.009	0.052	0.094
Expected monetary value (EMV)						**0.007**	**0.012**	**0.070**	**0.13**

VIII. Use the mean of maximum (MOM) method to provide a crisp value of the expected monetary value (EMV) of the risk event.

Equation 5-21 shows the defuzzified value of the EMV represented as a percentage of the baseline cost:

EMV = $\frac{0.012+0.070}{2} * 100$ = 4.1% [5-21]

To obtain $ value estimate of the EMV, let us assume that the baseline cost of this project is $100,000,000. Thus, the EMV is estimated as shown in Equation 5-22:

EMV = 0.041* $100,000,000 = $ 4,100,000 [5-22]

Please note that this calculation can be done since the consequences were defined as % of the baseline cost.

5.4 Fuzzy Reliability Analyzer (FRA)

In order to automate the qualitative and quantitative fuzzy fault trees analysis and fuzzy event tree analysis, a software package called Fuzzy Reliability Analyzer (FRA) was developed in Visual Studio®. FRA is composed of two modules. Figure 5-11 presents a general overview of different modules, and the components of each module.

Figure 5-11. FRA: General overview of modules and components

5.4.1 Fuzzy Reliability Analyzer (FRA): Module No. 1

The first module is used to conduct the qualitative and quantitative FTA. This module is composed of seven components. The function of each component is as follows:

I. Fuzzy probability identification: This component is used to define the MFs for different linguistic terms using a trapezoidal representation. Figure 5-12 shows how this module is used to define the linguistic term “high” probability according to the data previously presented in Figure 5-3.

II. Data input/output: This component is used to collect data to establish the fault tree logic and to support FTA. Inputs include: basic event ID, basic event description, basic event fuzzy probability, gate event ID, gate event description, top event description, gate type (OR/AND). Outputs include: Boolean matrix, working Boolean matrix, MCS, MCS equation, quantitative FTA, and fuzzy importance analysis. Figure 5-13 shows the data input/output module. The quantitative FTA and fuzzy importance analysis are exported to an Excel spreadsheet. The qualitative and quantitative FTA has not yet been conducted, and thus the “MCS” and “MCS equation” boxes are empty in Figure 5-13.

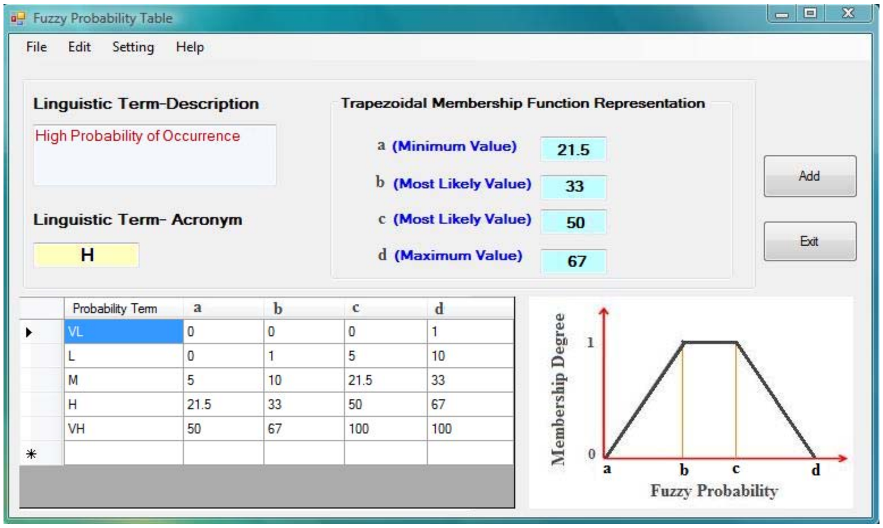

Figure 5-12. FRA: Fuzzy probability identification component

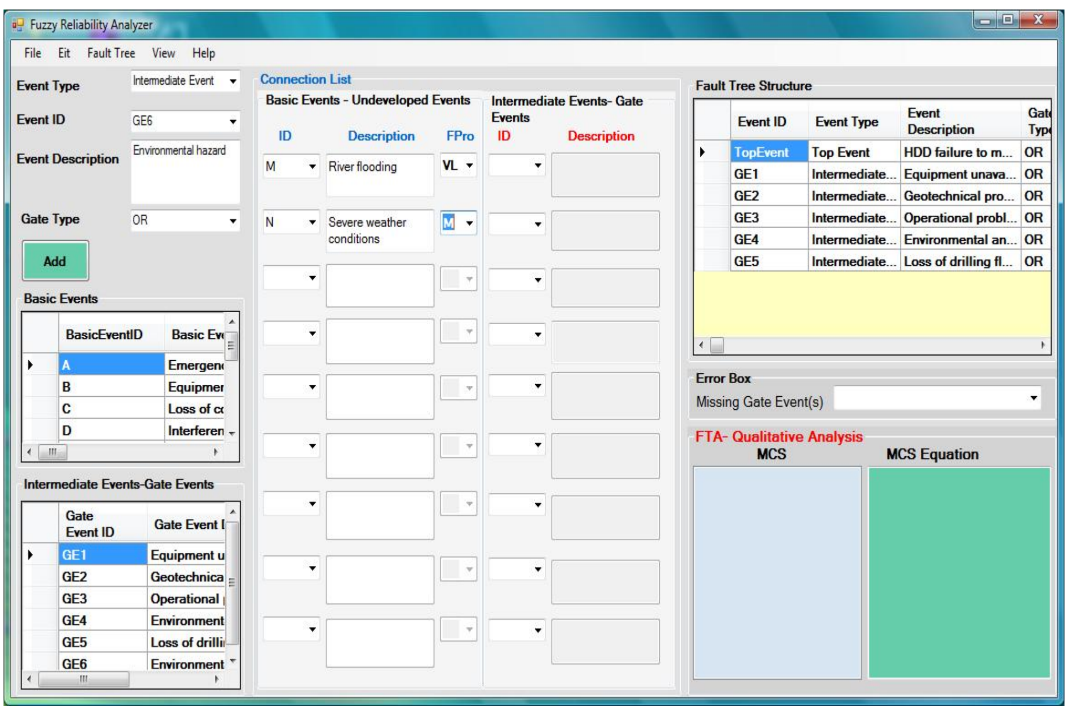

Figure 5-13. FRA: Data input/output component

III. Data integrity check: This component performs several integrity checks on the data provided by the user, including the following:

a. Check that the user cannot give the same ID for two different basic events connected to the same gate event.
b. Check that a gate event cannot be connected to itself.
c. Check FT structure integrity by ensuring that the user of the software had provided inputs for all gate events. If the user forgets to provide input for one or more of the gate events, the software creates an error message under the “Error Box” to alert the user about the missing information.
d. Check if the FT structure is composed of repeated events to direct the software to do Boolean algebra simplification before conducting a quantitative FTA.

IV. Minimum cut set generator: This component generates the Boolean matrix (BM) and the working Boolean matrix (WBM) by applying Hauptmanns’ (1988) algorithm. Summary results are presented to the user by the input/output component. Detailed calculations of BM and WBM are exported to an Excel spreadsheet.

V. Boolean algebra simplification: This component is triggered only if the fault tree contains repeated basic events (RBE). FRA interacts with MuPAD® from the symbolic math toolbox, running under the Matlab® environment, to perform Boolean simplification. FRA exports the MCS equation to MuPAD® and the Boolean simplification is conducted according to the rules presented in Table

3-4. Accordingly, FRA updates the working Boolean matrix and proceeds to the quantitative FTA.

VI. Quantitative fault tree analysis: This component generates alpha-cuts and performs a quantitative FTA according to Equations 5-3, 5-4, and 5-5. The results of the analysis are presented to the user in an Excel spreadsheet.

VII. Fuzzy importance analysis: This component is used to measure the level of importance of different basic events according to their level of contribution to the probability of occurrence of the top event. Equation 5-6 is used to perform the analysis, and detailed calculations are presented to the user in an Excel spreadsheet.

5.4.2 Fuzzy Reliability Analyzer (FRA): Module No. 2

The second module is responsible for the quantitative fuzzy event tree analysis. This module is composed of five components. The function of each component is as follows:

I. Fuzzy impact identification: This component is used to define the MFs for different linguistic terms using a trapezoidal representation according to the data previously presented in Table 5-21. Figure 5-14 shows how the linguistic term “high” impact is defined using this component.

II. Event tree structure component: This component establishes the structure of the event tree according to the number of mitigation strategies. FRA is designed to handle up to three mitigation strategies. Figure 5-15 presents an event tree structure using three mitigation scenarios. In considering the three mitigation module, the user is required to provide an assessment of the probability of the risk event, probability of failure of mitigation 1, probability of failure of mitigation 2, probability of failure of mitigation 3, and to assess the consequence column of each path as previously presented under section 5.3.

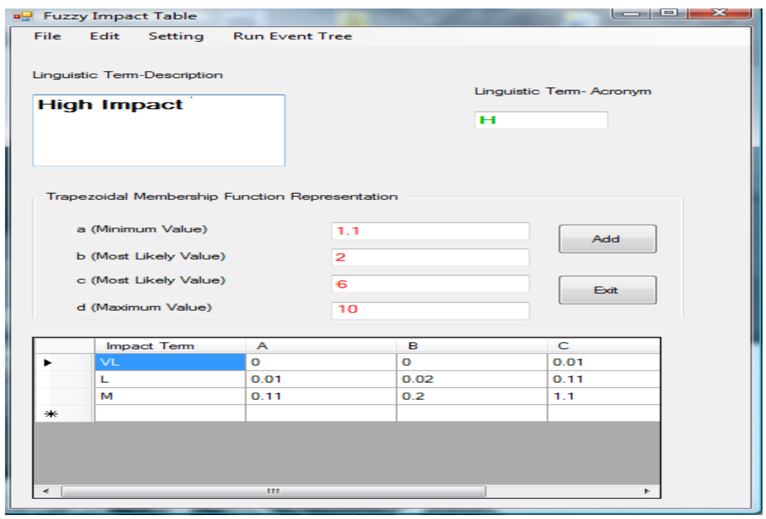

Figure 5-14. FRA: Fuzzy impact identification

III. Data integrity component: This component is responsible for verifying that all the required inputs to run ETA are entered by the user.

IV. Data input/output: This component is used to collect data to establish the event tree structure and to support fuzzy ETA. Inputs include: fuzzy probability of initiating event, fuzzy probability of failure of mitigation scenarios, and assessment of the consequence of each path. The output is the trapezoidal representation of the expected monetary value (EMV) exported to Excel.

Figure 5-15. FRA: Event tree structure (three mitigations)

V. Quantitative event tree analysis module: This module generates alpha-cuts and performs a quantitative event tree analysis according to Equations 5-19 and 5-20.

Figure 5-16 presents a screenshot showing fuzzy event tree analysis for the example presented under section 5.3. As can be noticed, the expected monetary value (EMV) obtained from FRA is similar to the one obtained from the manual calculations presented in Equation 5-21.

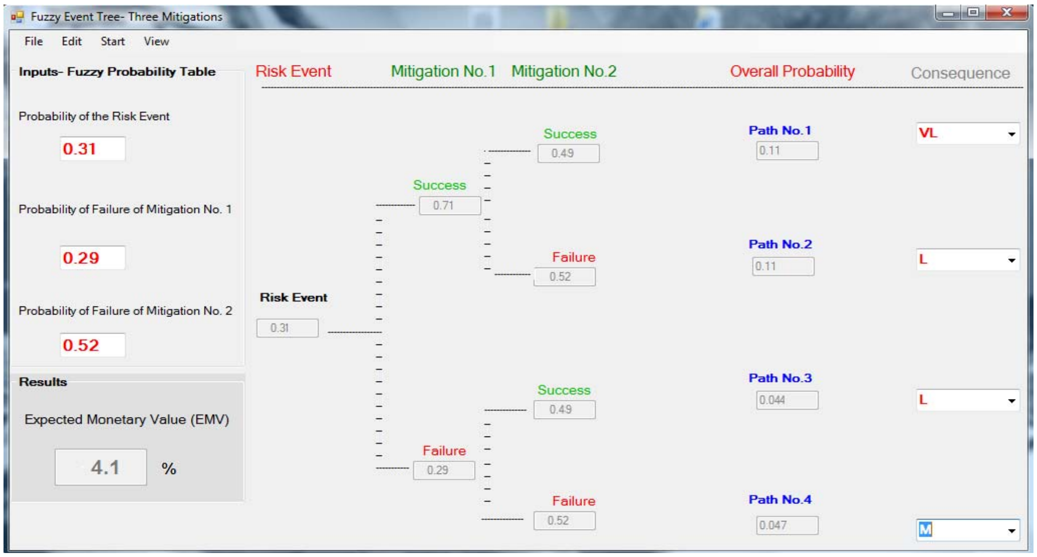

Figure 5-16. FRA: Event tree analysis

5.5 Summary

This chapter presents the proposed integration between fault trees, event trees, and fuzzy logic to provide a quantitative risk analysis of critical risk events identified in chapter 4. The proposed approach offers experts in the construction domain the ability to use linguistic terms rather than numerical values to assess the probability of occurrence of basic events and the impact of risk. Fuzzy arithmetic operations are used to perform quantitative fault tree and event tree analyses. The Fuzzy Reliability Analyzer (FRA) was developed to automate both qualitative and quantitative FTAs and ETAs. The next chapter presents a case study for validation of the framework presented in chapter 4 and chapter 5.

6. Case Study for Validation

Chapter 4 and chapter 5 present the framework to identify critical risk events and to support quantitative risk analysis using fault tree analysis and event tree analysis. The purpose of this chapter is to present the process followed to collect the required data to run Risk Criticality Analyzer (RCA) and Fuzzy Reliability Analyzer (FRA), to demonstrate the concept of risk acceptability level, and to validate the framework and the proposed contributions of this research.

6.1 Data Collection

In order to support collecting the required risk related data, a comprehensive risk register template was designed in Microsoft Excel®. The risk register is a central repository for risk-related information in a project. It captures information that supports risk identification, risk analysis, risk prioritization, risk response, and risk monitoring and control. The developed risk register went through several revisions to enhance the capabilities of the template. The latest update is version 2.00, and is designed to capture the following information:

- Risk ID: This is a unique ID to identify each risk event.
- Risk area: The risk area is obtained from the RBS, as will be explained later in this chapter.

- Risk description: This is a statement that provides a description of the uncertain event and the project objective that is at risk.
- T/O: This field is intended to differentiate threat risk events (T) from opportunity risk events (O).
- Root causes: This field is designed to capture different root causes that can lead to the occurrence of a risk event. This field is important for constructing the fault tree structure.
- Description of impact: This field is used to document the assumptions or scenarios considered to justify the impact of the risk on the project objectives.
- WBS Ref.: This field is used to document the affected work package.
- Risk owner: This field is used to document the person in charge of assessing, monitoring, and controlling the identified risk event.
- Risk status: Three available statuses are supported, including:
    - I. Active (A): a risk event that is expected to happen in the future.
    - II. Expired (E): a risk event that has expired and is no longer expected to happen.
    - III. Realized (R): a risk event that has occurred and has not yet expired.
- Next review date: This field is used to track future updates of the risk-related data, and can be used to monitor risk events.

- Probability (P): This field is used to document the assessment of the probability of occurrence (P), as described in Table 4-1.
  - Very Low (1): less than 1% chance. Event is highly unlikely to occur.
  - Low (2): between 1%–10% chance. Event is unlikely to occur.
  - Medium (3): between 10%–33% (1/3) chance. Event may occur.
  - High (4): between 33%–67% (2/3) chance.
  - Very High (5): > 67% (2/3) chance.
- Cost impact (CI): This field is used to document the assessment of the cost impact (CI), as described in Table 4-2.
- Time impact (TI): This field is used to document the assessment of the time impact (TI), as described in Table 4-2.
- Scope/quality impact (SI): This field is used to document the assessment of the scope/quality impact (SI), as described in Table 4-2.
- Safety Impact (SEI): This field is assessed using five dimensions defined as follows:
  - Very Low (1): first aid is not required.
  - Low (2): first aid is required.
  - Medium (4): medical treatment for injury/illness is required.

- High (8): disabling injury/illness and or serious health impact.
- Very high (16): One or more fatalities.

- Environmental Impact (EI): This field is assessed using five dimensions defined as follows:
  - Very Low (1): insignificant adverse effects on the environment.
  - Low (2): short-term adverse effects on the environment.
  - Medium (4): on-lease clean-up and remediation for 6 months or more.
  - High (8): off-lease clean-up and remediation for less than 6 months.
  - Very high (16): off-lease clean-up and remediation for more than 6 months.
- Risk acceptability Level (RAL): This field is used to filter any risk event that has potential effect on safety and or environment. Firstly, the risk level (RL) is calculated by multiplying probability of occurrence and the impact. Then, the risk level (RL) is compared against a threshold of 5. If the RL is less than 5, then this risk is acceptable. If the RL is greater than 5, then this risk is considered unacceptable and further investigation is required to be incorporated to bring this risk to an acceptable level. To illustrate this concept, let us assume that risk (A) is assessed to have

medium probability of occurrence and high safety impact. The risk level is equal to medium (3) * high (8) = 24 > 5. This risk should is unacceptable risk, and thus detailed risk analysis is required to be conducted using fault tree and event tree analysis as presented in chapter 5.

- Mitigation strategy: This column is used to document the proposed mitigation strategy and the specific action(s).
- Detection/control (D): This field is used to document the assessment of the detection/control (SI), as described in Table 4-3.
- Required by (date): This is the target date for the identified mitigation strategy to be fully implemented.
- Mitigation status: This date is used to document the % progress of the implementation of the mitigation strategy. The reader can refer to Appendix II for a sample risk register template.

In order to facilitate collection of the risk-related data, a risk breakdown structure (RBS) was proposed, based on literature reviews, and presented to the same senior risk coordinator and the risk engineer. The RBS is similar to the work breakdown structure (WBS), and is used to facilitate grouping of the risk-related data. To support establishing the RBS, several interviews were then conducted with both experts. The Delphi technique was utilized to reach an agreement between both experts. The first level of the RBS represents different functional areas in the organization. This level includes: planning, development, regulatory, permits, construction, commercial, corporate, engineering, environment, financial, aboriginal and community affairs, legal, project management, procurement, team, right of way (ROW), utilities, commissioning, and operation. The second and third levels represent more details under each functional area. Appendix IV provides an overview of the proposed RBS, as agreed upon by both experts.

6.2 Risk Criticality Analysis Validation

In order to validate the proposed approach presented in chapter 4, the risk register for an actual project is utilized. The approximate capacity of the chosen pipeline project is 70,000 barrels per day (bpd), and is composed of new and refurbished pump stations, metering facilities, and substations. A workshop session was arranged at the participating organization with a group of six experts, consisting of three risk analysts, the manager of the project management office, one practices and standards coordinator, and the senior risk coordinator. The purpose of the meeting was to present the traditional approach of applying FMEA, its drawbacks, the proposed approach to address these limitations, and an introduction to RCA. Following the first meeting, further meetings were arranged with the project team members to populate the risk register. The outcomes of those meetings were to populate the risk register with data related to 41 active risk events including their root cause, description of impact, WBS ref., probability of occurrence (P), cost impact, time impact, scope/quality impact, and mitigation strategies.

In order to assess the level of detection/control (D), an additional interview was conducted with the risk analyst in charge of the project. The meeting began with an introduction of the FMEA concept, and a demonstration of the Risk Criticality Analyzer (RCA).

After introducing the concept, the risk analyst was asked to evaluate the level of detection/control (D) of each risk event in accordance with the linguistic terms defined in Table 4-3. RCA was then utilized to calculate the RCN and the required corrective actions for each risk event. Figure 6-1 presents the percentage of total risk events that falls under each corrective action category. Figure 6-1 can be used to compare different projects. For instance, according to this figure, 14.63% of the risk events in this project fall under “moderate priority to take corrective action(s).” The percentage of risk events that falls under categories 5 to 9 can be used to compare different projects.

Figure 6-2 presents the risk ID versus the RCN. This figure can support management teams in identifying the most critical risk events in a project. For example, risk event No. 13 is the most critical risk event in this project. Figure 6-2 can also be used to identify risk events that are required to undergo detailed risk analysis. For example, any risk event that has an RCN equal to 250 or above, i.e., classified to fall under corrective action category 5 or above as presented in Table 4-4, is required to undergo detailed risk analysis using fault tree and event tree analyses.

Table 6-1 presents the summation of the RCN under each of the nine recommended corrective action categories. The cumulative RCN for the selected project is 5947. This number is a unitless number, and can be used to compare projects at the project level as well as at the portfolio level. For example, the cumulative RCN for category 5 for the selected project can be compared against the cumulative RCN for category 5 in other projects. The same logic can be applied to compare different categories between different projects.

Table 6-1 can be used also by the organization to compare projects at the portfolio level. For instance, the selected project has a cumulative RCN equal to 5947. This cumulative unitless number can be used by the organization to benchmark this project against other projects. For instance, this project can be considered less critical compared to another project with a cumulative RCN equal to 3000.

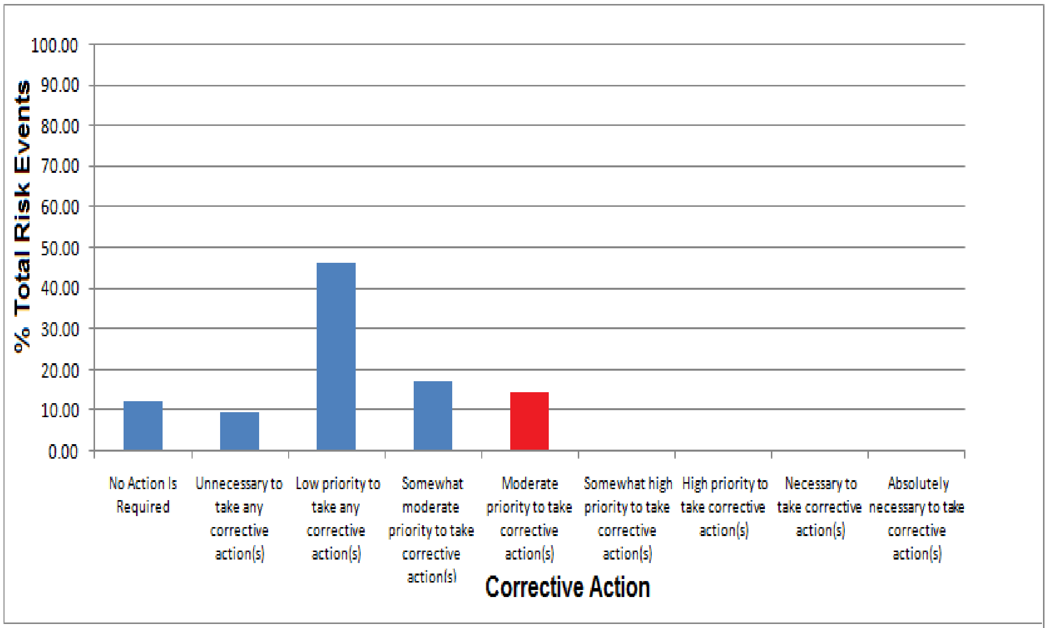

Figure 6-1. Corrective action versus % total risk events

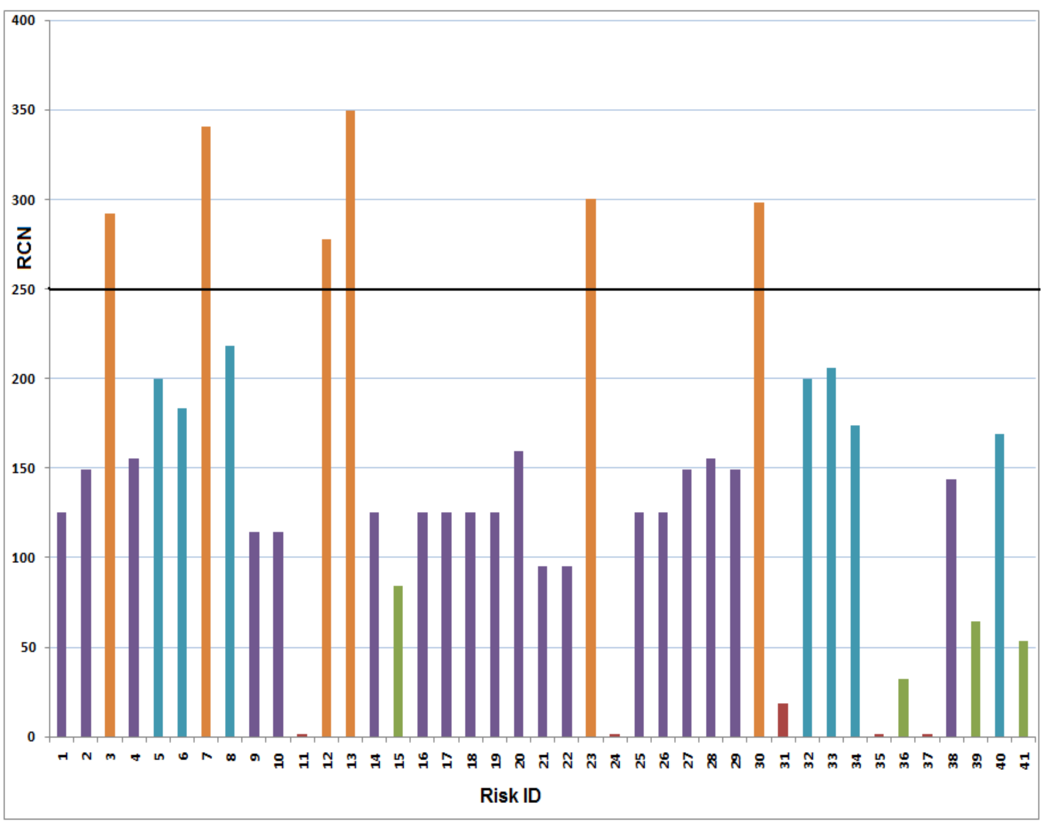

Figure 6-2. RCN versus risk ID

Table 6-1. Cumulative RCN/corrective action

Corrective action	Total RCN
No action is required	25
Unnecessary to take any corrective action(s)	235
Low priority to take any corrective action(s)	2479
Somewhat moderate priority to take corrective action(s)	1350
Moderate priority to take corrective action(s)	1858
Somewhat high priority to take corrective action(s)	0
High priority to take corrective action(s)	0
Necessary to take corrective action(s)	0
Absolutely necessary to take corrective action(s)	0
	5947

Figure 6-3 presents the percentage of risk events classified according to the first level of the RBS. As can be noticed from this figure, almost 50% of the risk events in this project are classified under procurement and construction. Some of the RBS categories are not shown in this figure, which implies that none of the 41 identified risk events were classified to fall under these categories.

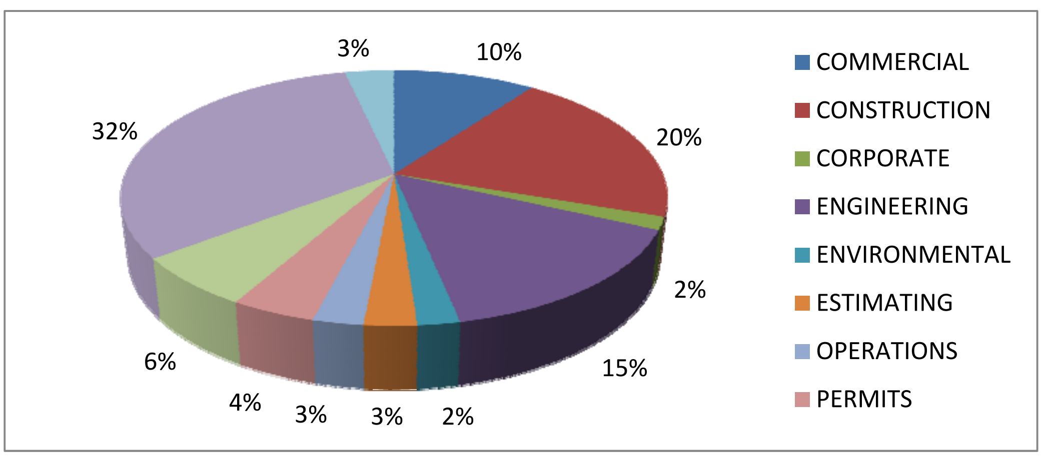

Figure 6-3. Percentage of risk event classified by RBS

In order to validate the findings using RCA, interviews were arranged with a risk analyst working for a different group within the participating organization. The objective of the first interview is to introduce the traditional FMEA concept and the proposed fuzzy FMEA approach. The second interview was intended to present the same case study and get his feedback regarding which approach, i.e., fuzzy FMEA or traditional FMEA, is producing more meaningful results. Nine risk events were randomly selected out of the 41 identified risk events and the RCN and the corrective action as calculated using the fuzzy FMEA approach and the traditional FMEA were presented to the expert as shown in Appendix V. The expert has given his opinion to the results obtained using the fuzzy FMEA for seven out of the nine selected risk events. Please note that although the expert has given his opinion to the RCN produced using the traditional FMEA approach for two cases, the fuzzy expert system can be adapted to reflect his opinion by changing the (if then) rule(s). For instance, if a consensus has been obtained within the organization to make such combinations between probability of occurrence, cost impact, time impact, scope/quality impact to produce a similar decision to the one obtained using the traditional FMEA, then this change can be accomplished in a few steps. To highlight more on the required update, let us consider that the decision for the risk entitled “poor productivity due to severe weather” is required to be updated to be similar to the one obtained using the traditional FMEA. In this case, the aggregated impact is calculated firstly using Equation 4-5 as follows:

$$AI = 0.40 * 5 + 0.46 * 7 + 0.14 * 1 = 5.4 \quad [6\text{-}1]$$

According to Figure 4-2, the calculated impact value has a membership value that falls under medium impact as well as high impact. Given that the selected probability of occurrence is medium and the selected detection/control is high, the RCN linguistic value of the two rules shown in Table 6-2 are required to be updated to reflect the selected decision. Please refer to Appendix I for all the rule base that are used to establish the fuzzy FMEA model

Table 6-2. Proposed update to the Rule Base

Rule ID	(I)	(P)	(D)	(RCN)	(RCN) Proposed Modification
64	M	M	H	L-M	VL-L
89	H	M	H	M	L-M

Figure 6-4 present the fuzzy expert system and the updated output value of rule 64 and rule 89. As can be noticed in Figure 6-4, the resultant RCN using the fuzzy expert system is 79, which fall under “low priority to take any corrective action(s)/accept.” Such flexibility to reflect expert’s opinion is not supported using the traditional FMEA approach since the resultant RCN is based on the multiplication of probability, impact, and detection. Thus, using the use of the fuzzy expert system has offer more flexibility to reflect expert opinion to support risk criticality analysis. Such flexibility offers a great advantage to reflect any change to the organization policy toward risk, i.e., (risk averse, risk neutral, risk seeking), without the need to start building the model all over again.

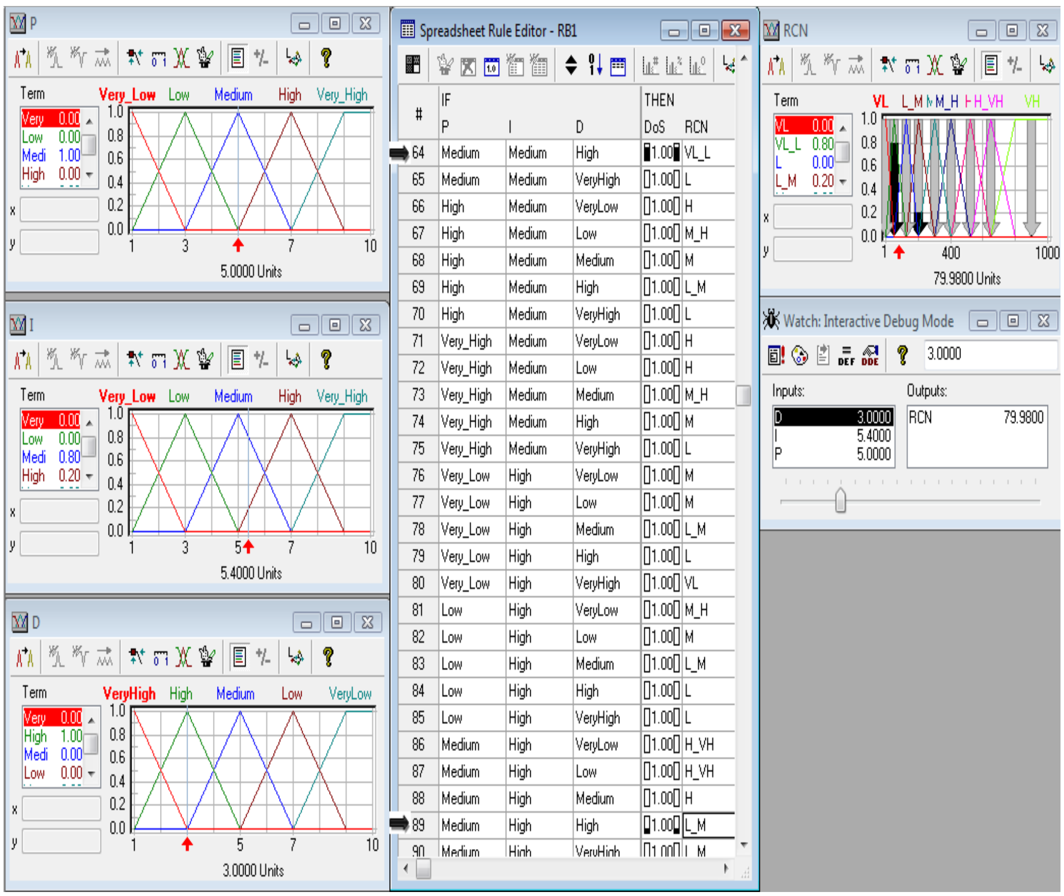

Figure 6-4. Proposed update to the fuzzy expert system

The use of the fuzzy expert system also offers the advantage of capturing the knowledge of experts in the domain of risk management and utilizes this knowledge to train new persons in the same domain.

Since the rule base are defined and utilized using language that the expert can directly understand i.e., (low, medium, high), new persons to this domain can use the fuzzy expert system, similar to the one presented in Figure 6-4, to understand how different combinations between probability, impact, and detection/control can affect the calculated RCN. Such transparency can not be established using the traditional FMEA.

"Face Validation" was used to identify practical applications of the proposed framework (Lucko and Rojas 2010). In this regard, an interview was conducted with the senior risk coordinator and the risk analyst to review the usefulness of RCA in practice. Experts noted several practical uses of RCA, which can be summarized as fallows:

- The use of fuzzy logic supported the linguistic assessment of probability of occurrence, cost impact, time impact, scope/quality impact, and detection/ control. The linguistic assessment of these terms has supported FMEA studies and offered a more convenient approach for experts to assess the level of risk criticality.
- The use of fuzzy AHP offered great ability by supporting the aggregation of the impact and by offering the ability to validate the level of consistency.
- The framework offered guidelines by connecting the RCN with the required corrective actions as defined in Table 4-4.
- RCA can aid in the comparison between projects in two levels, i.e., at the project level as well as at the portfolio level. For example,

using Figure 6-1, different projects can be compared by considering the % of total risk events that falls under categories 5 to 9. The cumulative RCN in Table 6-1, i.e., 5947, can be used to benchmark projects at the portfolio level.

- RCA can aid in identifying which risk events are required to undergo detailed risk analysis using the framework presented in Figure 5-1. All risk events that fall under categories 5 to 9 or have unacceptable risk level should be considered for detailed root cause analysis.
- RCA can aid in determining which risk events should be used for lessons learned. For example, all risk events that fall under categories 5 to 9 or have unacceptable risk level should be tracked monthly, and detailed lessons learned should be documented.
- RCA can help in determining training needs for different project teams, by identifying areas of weakness within each project that are attributed to human failure. The people responsible can then work on establishing training to mitigate those failures.
- RCA can help in identifying common areas of strength and weakness between different projects.
- RCA can support the identification of successful response strategies for future use on new projects, and weak response strategies for future avoidance and improvement.

RCA was further utilized to assess the level of risk criticality in several projects in the company. One of the criticality identified risk events in more than one project is identified as “horizontal directional drilling (HDD) failure to meet project objectives.” Referring to Figure 5-1, this risk event is required to undergo detailed risk analysis using fuzzy fault tree and fuzzy event tree analysis, as will be explained next. For confidentiality purposes, the HDD case study was selected from a different project than which one used for RCA validation, as will be explained in the next section.

6.3 Fuzzy Fault Tree Analysis Validation

The scope of the selected project for fuzzy fault tree analysis validation includes the installation of a new crude oil pipeline with an initial capacity of 350,000 bpd. The total length of the pipeline is 380 km. Horizontal directional drilling (HDD) failure to meet the project objectives was identified as a critical risk event using RCA.

In order to understand the risk involved in HDD construction, a literature review was conducted to understand the installation process and the root causes that can lead to failure. The installation process of HDD begins from the surface by launching the pilot bore at a pre-specified angle until reaching the design depth. The pilot bore can be tracked from the surface by installing a directional monitoring device. To stabilize the borehole and to reduce friction, a drilling fluid is injected under pressure ahead of the advancing bit. After reaching the design depth, the pilot bore moves horizontally until reaching the desired exit point. Once reaching this point, the pilot bore is brought to the surface along a curved path. To enlarge the hole to the design diameter and to establish the product pipe, the bit is removed and replaced by a backreamer (Ariaratnam 2001).

To establish the fault tree structure, several interviews were arranged with the same senior risk coordinator and another risk engineer. The interview started by reviewing the summary of the literature review and different root causes of failure as defined in the literature. Thereafter, the Delphi technique was used to make consensus between the two experts. Two rounds were used to establish the fault tree structure. In the first round, an interview was arranged with the risk engineer to establish the fault tree structure. The established structure was then presented to the senior risk coordinator, and further modifications were recommended to represent the fault tree structure for the selected case study. The modifications, as recommended by the senior risk coordinator, were incorporated in the fault tree structure and used for a second round. The second round started with the risk engineer aiming at reviewing the modifications as recommended by the senior risk coordinator. The risk engineer agreed with some of the modifications and added further modifications to the fault tree structure. These modifications were presented next to the senior risk coordinator, and an agreement was finally obtained for the established fault tree structure. Figure 6-5 shows the fault tree (FT) structure that connects the top event with the entire root causes, as agreed upon by both experts (Abdelgawad et al. 2010).

After establishing the FT structure, both experts were further asked to assess the fuzzy probability of different basic events. Table 6-3 presents a description of root causes and their associated linguistic assessment, in accordance with the criteria defined in Table 4-1. It is important to note that each HDD crossing is unique, and hence, the ability to collect data regarding some root causes is difficult, if not impossible, making quantitative fault tree analysis (FTA) of such fault trees not possible using probability theory. The use of fuzzy arithmetic operations on fuzzy numbers has offered more flexibility to assess the probability of occurrence of basic events and to support quantitative risk analysis. Using the linguistic assessment established in Table 4-1, both experts were able to provide an assessment of the probability of occurrence of basic events as demonstrated in Table 6-3.

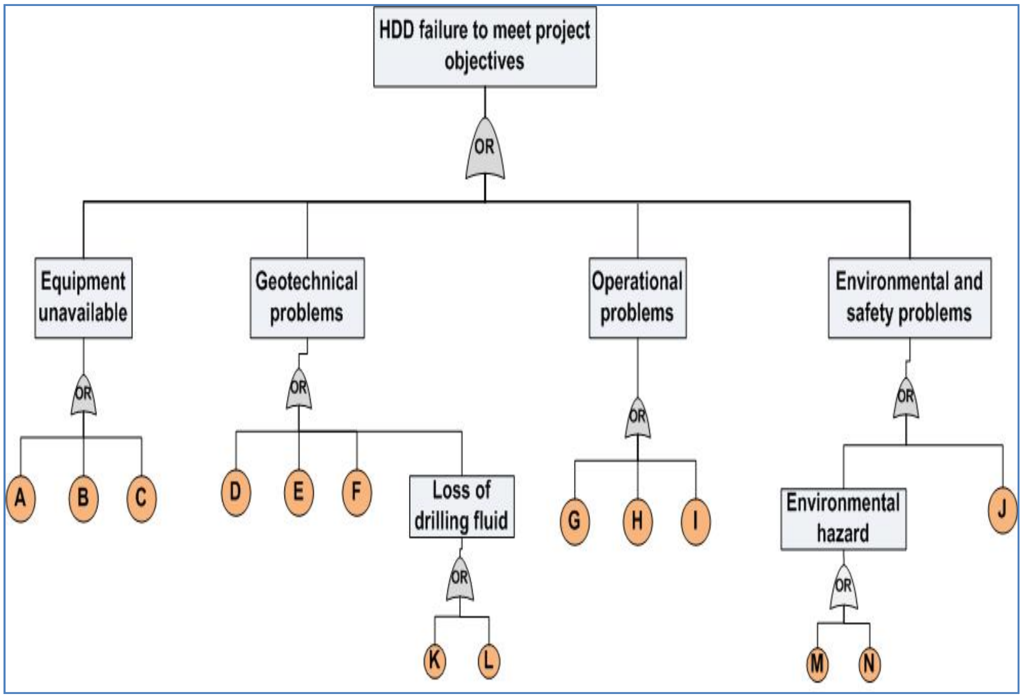

Figure 6-5. HDD failure to meet project objectives (Abdelgawad et al. 2010)

Table 6-3. Basic events and fuzzy probability assessment (Abdelgawad et al. 2010)

Symbol	Description	Fuzzy probability (FPro) of occurrence
A	Emergency shutdown system trips	High (H)
B	Equipment breakdown	Medium (M)
C	Loss of communication with drilling machine	Low (L)
D	Interference with bedrock	Medium (M)
E	Interference with aquifer	Medium (M)
F	Unstable bank	Medium (M)
G	Operator lacking required skills	Low (L)
H	Fatigue of workers	Very Low (VL)
I	Lack of proper supervision	Low (L)
J	Safety incidents on site	Low (L)
K	Seepage of drilling fluid into waterway	Low (L)
L	Seepage of drilling fluid into soil	Medium (M)
M	River flooding	Very Low (VL)
N	Severe weather conditions	Medium (M)

The Fuzzy Reliability Analyzer (FRA) is then utilized to conduct qualitative and quantitative assessment of the FT presented in Figure 6-5. The qualitative assessment of the fault tree, as presented in Appendix (VI), indicates that we have fourteen minimal cut sets MCSs defined as follows, in Equation 6-2:

M1 = (A); M2 = (B); M3 = (C); M4 = (D); M5 = (E); M6 = (F); M7 = (G); M8 = (H); M9 = (I); M10 = (J); M11 = (K); M12 = (L); M13 = (M); M14 = (N)

[6-2]

These MCS combinations indicate critical scenarios since the occurrence of any of the basic events, as identified by the MCS, is sufficient to cause the top event to occur. For instance, the occurrence of basic event A is sufficient to cause HDD to fail in meeting the project objectives. Figure 6-6 presents a screenshot of the inputs and the output minimal cut sets and minimal cut set equations.

The right bottom corner of Figure 6-6 shows the minimal cut sets and the minimal cut set equation. The fuzzy probability of the top event can be further represented as shown in Equation 6-3:

FPro(Top Event) = FPro(A) OR FPro(B) OR FPro(C) OR FPro(D) OR FPro(E) OR FPro(F) OR FPro(G) OR FPro(H) OR FPro(I) OR FPro(G) OR FPro(K) OR FPro(L) OR FPro(M) OR FPro(N) [6-3]

Equation 6-3 can be further represented using the α-cut principle, as follows in Equation 6-4:

$$FPro(Top\ Event)^{\alpha} = FPro(A)^{\alpha} \cup FPro(B)^{\alpha} \cup FPro(C)^{\alpha} \cup FPro(D)^{\alpha} \cup FPro(E)^{\alpha} \cup FPro(F)^{\alpha} \cup FPro(G)^{\alpha} \cup FPro(H)^{\alpha} \cup FPro(I)^{\alpha} \cup FPro(G)^{\alpha} \cup FPro(K)^{\alpha} \cup FPro(L)^{\alpha} \cup FPro(M)^{\alpha} \cup FPro(N)^{\alpha} \quad [6\text{-}4]$$

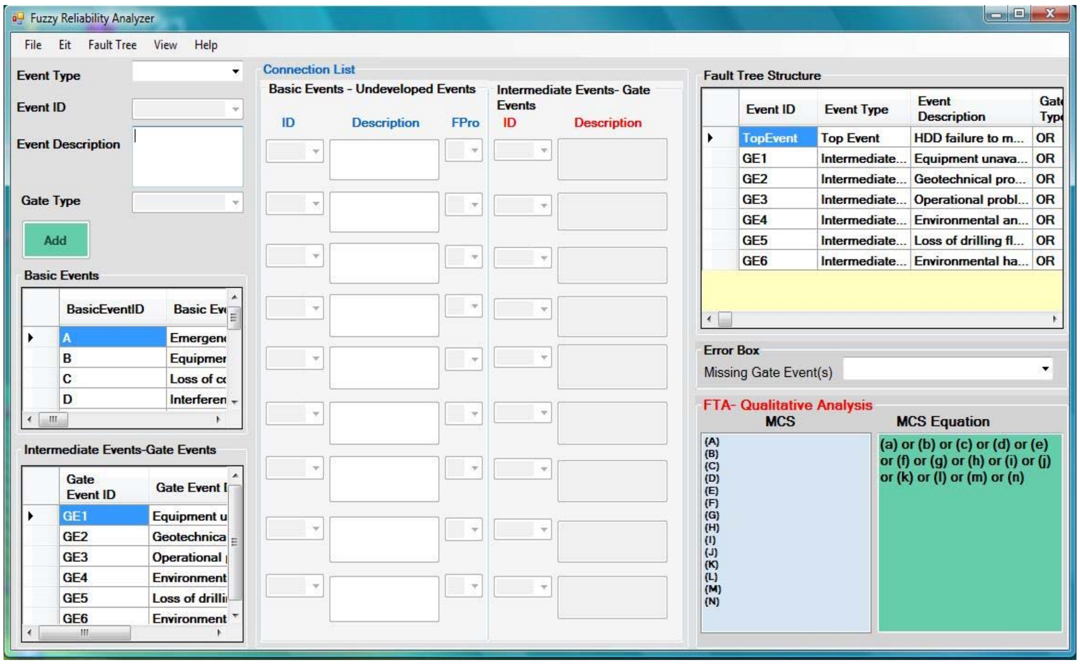

Figure 6-6. Inputs and outputs minimal cut sets for the HDD case study

The alpha cut representations of basic events A through basic event B are presented in Appendix (VII). Since the top event is connected by an OR gate with basic events, Equation 5-3 is used as follows:

$$FPro\ (Top\ Event)^{\alpha} = 1- [(1- FPro\ (A)^{\alpha}) * (1- FPro\ (B)^{\alpha}) *(1- FPro\ (C)^{\alpha}) *(1- FPro\ (D)^{\alpha}) *(1- FPro\ (E)^{\alpha}) *(1- FPro\ (F)^{\alpha}) *(1- FPro\ (G)^{\alpha}) *(1- FPro\ (H)^{\alpha}) *(1- FPro\ (I)^{\alpha}) *(1- FPro\ (J)^{\alpha}) *(1- FPro\ (K)^{\alpha}) *(1- FPro\ (L)^{\alpha}) *(1- FPro\ (M)^{\alpha}) *(1- FPro\ (N)^{\alpha})] \quad [6\text{-}5]$$

Equation 6-5 is applied to calculate the lower and upper bound of the top event fuzzy probability at each alpha cut. Appendix (VIII) shows detailed calculation of the following terms in Equation 6-5: (1- FPro $(A)^{\alpha}$), (1- FPro $(B)^{\alpha}$) , (1- FPro $(C)^{\alpha}$, (1- FPro $(DB)^{\alpha}$, (1- FPro $(E)^{\alpha}$, (1- FPro $(F)^{\alpha}$, (1- FPro $(G)^{\alpha}$, (1- FPro $(H)^{\alpha}$, (1- FPro $(I)^{\alpha}$, (1- FPro $(J)^{\alpha}$, (1- FPro $(K)^{\alpha}$, (1- FPro $(L)^{\alpha}$, (1- FPro $(M)^{\alpha}$, (1- FPro $(N)^{\alpha}$.

By multiplying all the calculated terms in Appendix (VIII) at each alpha cut using the multiplication operator, i.e., Equation 5-5, the upper and the lower bound of the top event fuzzy probability is calculated as shown in Appendix (IX).

Please note that since the probability of occurrence is always represented using positive numbers, Equation 5-5, can be simplified as follows:

$$A^{\alpha} * B^{\alpha} = [a_1 * a_2, d_1 * d_2] \qquad [6\text{-}6]$$

Where $a_1 * a_2$ represents the lower bound of multiplying two fuzzy numbers and $d_1 * d_2$ represents the upper bound of multiplying two fuzzy numbers. Figure 6-7 shows the top event fuzzy probability using the values presented in Appendix (IX).

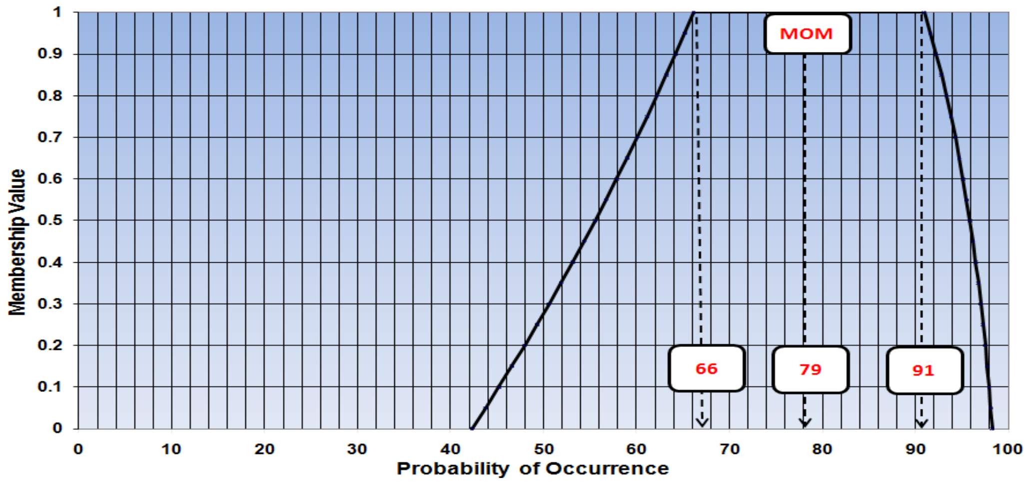

Figure 6-7. The fuzzy probability distribution for the HDD risk event (Abdelgawad and Fayek 2010b)

After calculating the fuzzy probability of the top event, the mean of maximum (MOM) method was utilized to defuzzify the results. Equation 6-7 shows the defuzzified estimate of the fuzzy probability for HDD failure using the MOM method.

$$\text{FPro (Top Event)} = \left(\frac{0.66+0.91}{2} \right) * 100 = 79\ \% \qquad [6\text{-}7]$$

"Face Validation" was used to verify the advantage of using linguistic terms to assess the fuzzy probability of failure of basic events. In this regard, an interview was conducted with both experts in which both experts has indicated the advantage of using linguistic terms to provide an assessment of the fuzzy probability of basic events versus providing numerical numbers.

After conducting qualitative and quantitative FTA, FRA was then used to conduct fuzzy importance analysis (FIM). The top event fuzzy probability (TE_1), assuming that all root causes will occur according to their respective fuzzy probability, is as calculated in Equation 6-7. Noting that there are 14 basic events in the MCS equations, the fuzzy probability of the top event has to be calculated 14 times, simply by eliminating each root cause (i.e., by setting FPro = 0 for the root cause) to calculate the top event fuzzy probability (TE_2). Appendix X shows the detailed calculation of TE_2 after removing each of the root causes. Table 6-4 shows a summary of the fuzzy importance analysis.

Table 6-4. Fuzzy importance analysis (Abdelgawad and Fayek 2010b)

Event ID	(TE_1)	(TE_2)	FIM	Rank
A	**79**	**66**	**17**	**1**
B	79	75	5.1	2
C	79	78	1.3	3
D	79	75	5.1	2
E	79	75	5.1	2
F	79	75	5.1	2
G	79	78	1.3	3
H	79	79	0	4
I	79	78	1.3	3
J	79	78	1.3	3
K	79	78	1.3	3
L	79	75	5.1	2
M	79	79	0	4
N	79	75	5.1	2

Results from FIM show that the emergency shutdown system trip (basic event A) is ranked first in contributing to the top event fuzzy probability. Altering this basic event by itself is sufficient to reduce the top event fuzzy probability to 66% (TE_2). Thus, risk response strategies can be developed specifically to mitigate this basic event.

”Face Validation” was used to verify the advantage of using fuzzy importance analysis to rank different basic events. In this regard, an interview was conducted with both experts in which both experts has indicated the advantage of using FIM to support ranking different root causes, which can support the establishment of effective risk response strategies.

In order to establish mitigation strategies for the selected risk event, further interviews were arranged with the senior risk coordinator and the risk engineer. The outcomes from these meetings indicated that three mitigation strategies can be established, as follows:

- Mitigation 1: Establish a proper prequalification strategy to select the right HDD contractor.
- Mitigation 2: Establish a proper procedure to select the right drilling location.
- Mitigation 3: Establish a contingency plan to control the risk if realized.

The two experts were asked to identify the root causes of failure of each mitigation strategy, and to assess the fuzzy probability of each basic event. Figure 6-8 depicts a summary of the findings.

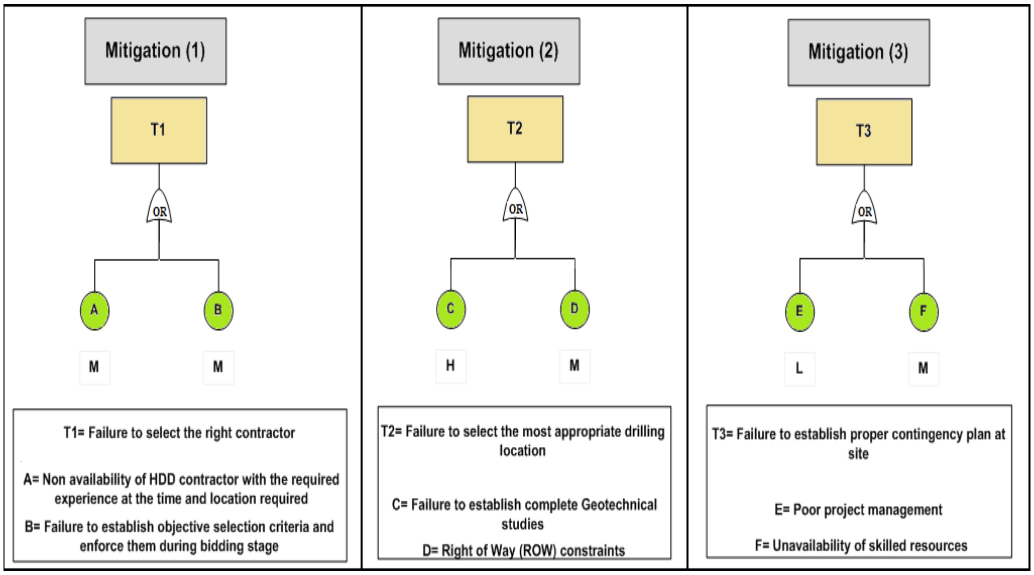

Figure 6-8. Fault tree analysis of different mitigation strategies (Abdelgawad and Fayek 2010c)

FRA is used to conduct qualitative and quantitative assessment of the fault trees presented in Figure 6-8. The fuzzy probability of failure of each mitigation strategy, following the same principle explained to calculate the top event fuzzy probability, is estimated as follows:

- FPro. failure of mitigation 1 = 29%
- FPro. failure of mitigation 2 = 50%
- FPro. failure of mitigation 3 = 18%

Please refer to Appendix (XI), (XII), and (XIII) for detailed calculations of the fuzzy probability of failure of mitigation 1, mitigation 2, and mitigation 3. Please note that the use of fuzzy logic to conduct quantitative fault tree analysis has offered an easy to understood and transparent approach to track the calculated fuzzy probability for the top event as well as the probability of failure of mitigation 1, mitigation 2, and mitigation 3.

”Face Validation” was used to verify the advantage of using fault tree analysis to calculate the fuzzy probability of the top event. In this regard, an interview was conducted with both experts and the following advantages were noted:

- The use of fault trees can help in explaining the logic behind how different root causes may interact to cause the failure of different mitigation strategies.
- Fault trees offered the ability to create proactive risk response strategies by working on eliminating critical root causes. For example, mitigation 1 can be used to reduce the probability of occurrence of basic event A.
- Fuzzy logic offers more flexibility to conduct quantitative fault tree analysis to calculate the probability of failure of different mitigation strategies by supporting the linguistic assessment of basic events.

6.4 Fuzzy Event Tree Analysis Validation

Based on the findings from fuzzy fault tree analysis, event tree structure is established considering three mitigation strategies. The fuzzy probability of the risk event and the failure of the mitigation strategies were obtained by performing fuzzy fault tree analysis, i.e., 79, 29, 50, and 18 for the risk event, mitigation 1, mitigation 2, and mitigation 3 respectively. The senior risk coordinator and the risk engineer were further asked to assess the consequence of impact for each path, considering the events located on each path, as presented in the last column of Figure 6-9. For example, path No. 1 is assessed considering the following scenario:

(1) If the risk event occurs and mitigation No. 1 was successful, mitigation No. 2 was successful, and mitigation No. 3 was successful, then what would be the residual cost impact of the risk?

    According to the feedback from experts, path No. 1 was assessed to have "Very Low (VL)" impact following the cost impact presented in Table 5-21.

The same logic of questions were used to collect experts' opinions regarding the cost impact given the sequence of events located on each path. Figure 6-9 presents the event tree structure and the expected monetary value (EMV) obtained after running FRA-event tree module. Figure 6-10 presents the defuzzified expected monetary value (EMV) after conducting event tree analysis. The mean of maximum defuzzification method was used to defuzzify the EMV. Please refer to section 5.3 for detailed explanations of the steps required to conduct fuzzy event tree analysis to calculate the EMV.

The expected monetary value is represented as a percentage of the baseline cost of the selected project. This percentage can be converted to a dollar value by multiplying this percentage and the baseline cost of the project. For example, if the baseline cost of the project is $100,000,000, then the EMV can be calculated, as shown in Equation 6-8:

EMV = 0.0027 * $100,000,000 = $267,000 [6-8]

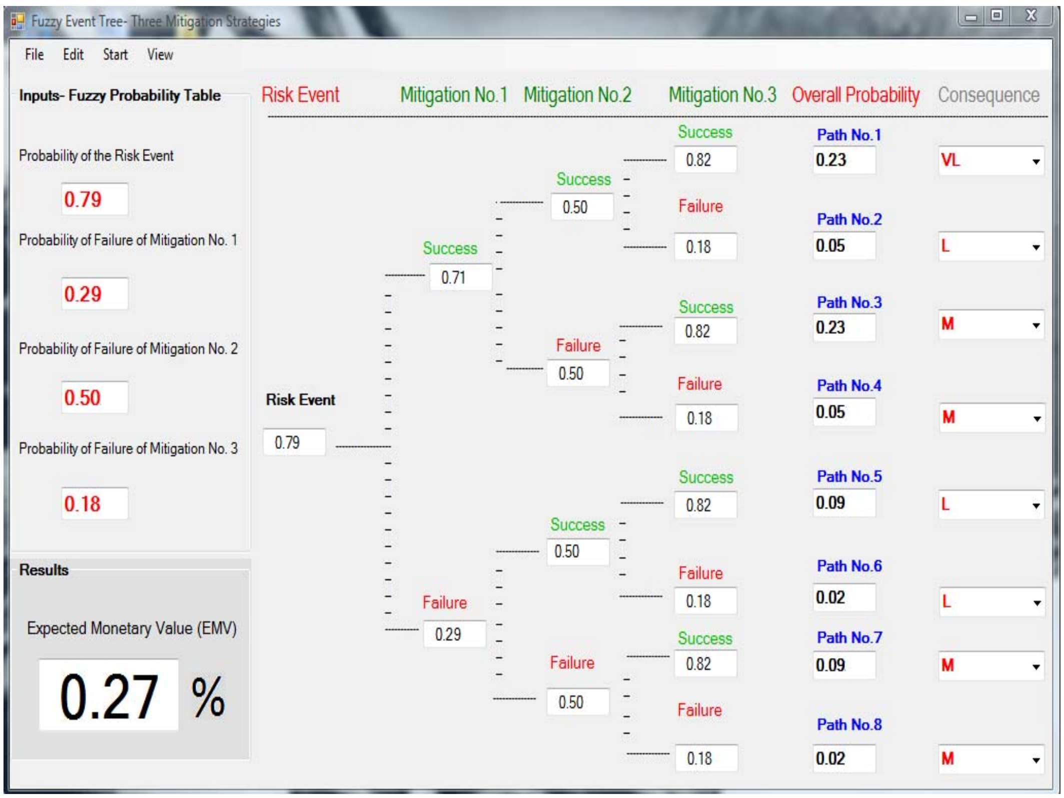

Figure 6-9. Fuzzy event tree analysis (Abdelgawad and Fayek 2010c)

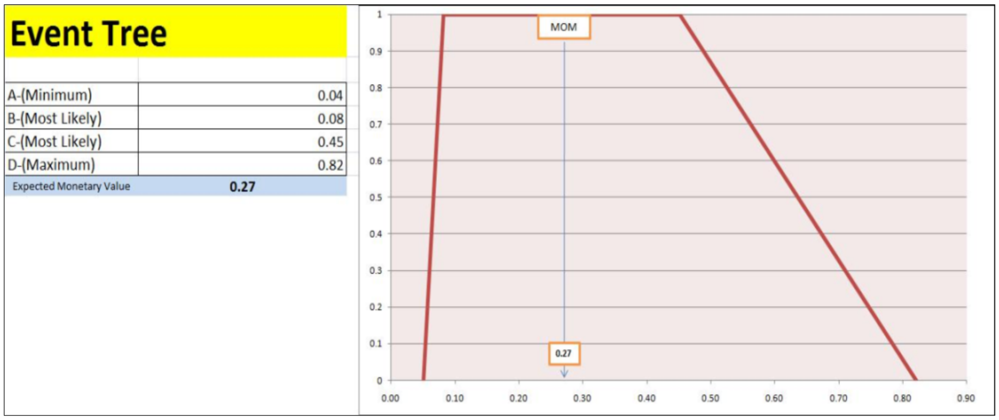

Figure 6-10. Expected monetary value (EMV)

Table 6-5 presents detailed calculation of the event tree shown in Figure 6-9. Please note that the minimum, most likely, and the maximum values are similar to the numbers presented in Figure 6-10 using Fuzzy Reliability Analyzer (FRA).

Table 6-5. Expected monetary value (EMV) calculations

Path	OP	Consequence (C)				Expected risk magnitude (ERM)			
		a	B	c	d	a	b	C	d
Path1	**0.23**	0	0	0.01	0.02	0.00	0.00	0.00	0.00
Path2	**0.05**	0.01	0.02	0.11	0.2	0.00	0.00	0.01	0.01
Path3	**0.23**	0.11	0.2	1.1	2	0.03	0.05	0.25	0.46
Path4	**0.05**	0.11	0.2	1.1	2	0.01	0.01	0.06	0.10
Path5	**0.09**	0.01	0.02	0.11	0.2	0.00	0.00	0.01	0.02
Path6	**0.02**	0.01	0.02	0.11	0.2	0.00	0.00	0.00	0.00
Path7	**0.09**	0.11	0.2	1.1	2	0.01	0.02	0.10	0.18
Path8	**0.02**	0.11	0.2	1.1	2	0.00	0.00	0.02	0.04
Expected monetary value (EMV)						**0.04**	**0.08**	**0.45**	**0.82**

The defuzzified expected monetary valve is calculated using the mean of maximum method as follows:

EMV= $\frac{0.08+0.45}{2} = 0.27\%$ [6-9]

”Face Validation” was used to verify the advantage of the proposed framework to conduct risk analysis. In this regard, an interview was conducted with both experts and both experts have noted the following advantages:

- The use of event trees supports explaining the expected cost impact of the risk event and a sequence of mitigation scenarios, as presented in Table 6-5.
- Fault trees offered the ability to explain the logic that might lead to a failure of mitigation strategies, and hence, can aid further improvement of these mitigations.
- Fuzzy logic has offered considerable flexibility to conduct quantitative event tree analysis to calculate the expected monetary value (EMV). For example, the use of the linguistic terms, presented in Table 5-21, supported conducting event tree analysis even if data do not exist.

The advantage of using fuzzy logic to solve event trees as compared to other techniques is attributed to the ability of fuzzy logic to establish transparent and easy to understood models in which the results can be traced back to understand how a certain number or conclusion is obtained. For example, Table 6-5 shows how fuzzy arithmetic operations are conducted to solve the event trees shown in Figure 6-9.

In order to validate the findings of using fuzzy fault tree analysis and fuzzy event tree analysis, an interview was arranged with a construction manager with more than 30 years of experience, during which he was in charge of the executing of more than thirty-five horizontal directional drillings. Before conducting the interview, a detailed report of the selected case study was obtained from the senior risk coordinator. The detailed report together with the fault tree structure, presented in Figure 6-5, and the fuzzy probability of basic events, presented in Table 6-3, were all presented to the construction manager. The construction manager was then asked to provide an assessment of the probability of the risk event and three point estimate of the impact representing the minimum, most likely, and maximum cost. The following scenarios were considered to represent the cost impact of the selected risk event:

1- The minimum cost impact represents the scenario that the HDD will not fail; however, extra cost will be incurred due to delays and the requirement to add extra casing to support the drilling.
2- The most likely scenario considers that HDD crossing will fail and an isolated crossing is to be used without impacting the in service date of the project.

3- The Maximum scenario considers that HDD crossing will fail and an isolated crossing is to be used; however the in service date will be delayed due to the late permitting from regulatory agencies.

Table 6-6 presents summary of the finding from the interview. Please note that for confidentiality purposes, the impact is represented as a percentage of the project baseline cost.

Table 6.6. Probability and three point estimate of the impact

Probability of Occurrence	Cost impact (min) %	Cost impact (most likely) %	Cost impact (maximum) %
0.75	0.06	0.14	0.52

A Monte Carlo simulation model was developed using Primavera Risk Analysis®. The risk event is represented using triangular distribution and 1000 iterations were conducted to calculate the expected monetary value (EMV). Figure 6-11 presented a cumulative distribution curve of the expected monetary value of the risk event. Table 6-7 shows the cumulative cost impact of the selected risk event represented as a percentage of the project baseline cost. The calculated mean cost value of this risk is equal to be 0.24% of the project baseline cost based on using Monte Carlo simulation and is used to represent the expected monetary value (EMV) of the risk event. The expected monetary value (EMV) obtained using Monte Carlo is compared against the expected monetary value (EMV) obtained using fuzzy fault tree and fuzzy event tree analysis as calculated in Equation 6-9. The results show the validity of using fuzzy fault tree and fuzzy event tree analysis to calculate the expected monetary value. Comparing the EMV indicated that the resultant EMV obtained using fuzzy fault tree and fuzzy event tree analysis, i.e., 0.27% of the baseline cost as shown in Equation 6-9, is more conservative than the value obtained using Monte Carlo simulation, 0.24% of the baseline cost.

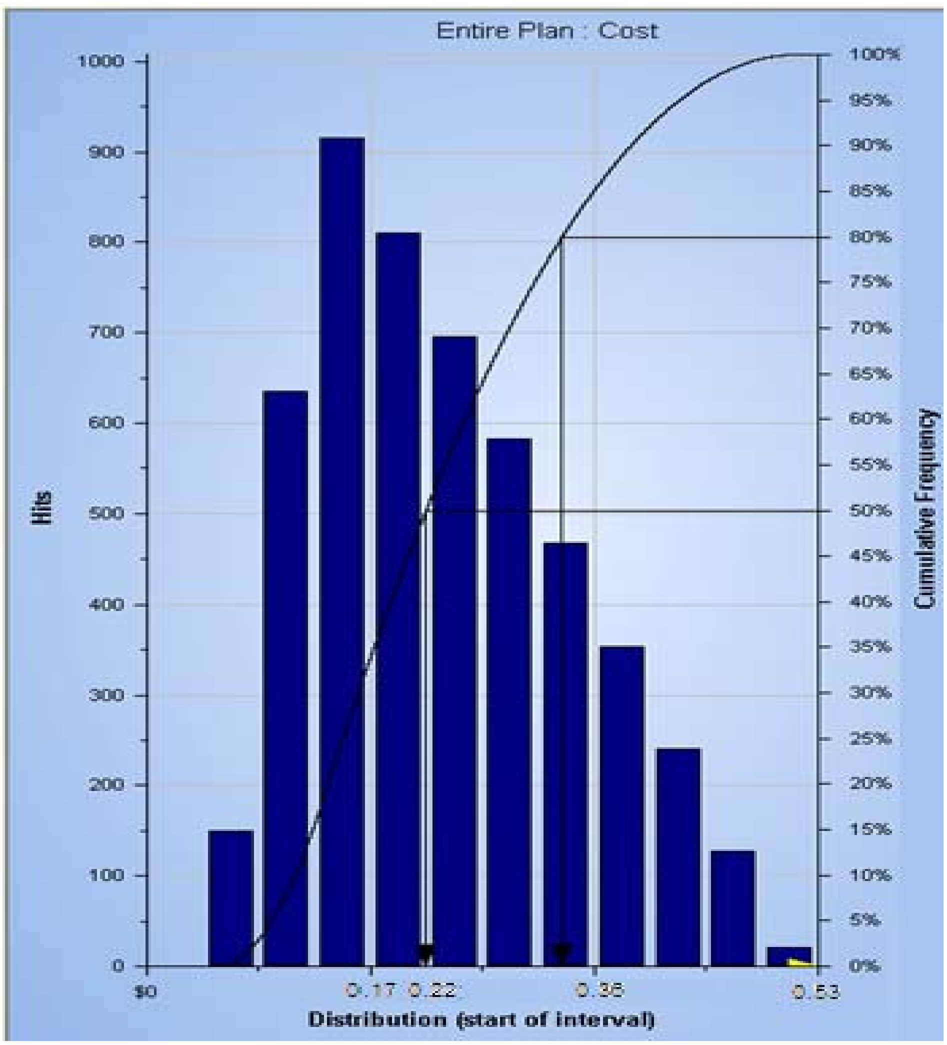

Figure 6-11. Cumulative distribution of the expected monetary value

Table 6-7. Cumulative distribution of the expected monetary value

Probability	Cost Impact (% project base budget)
0%	0.06
5%	0.10
10%	0.12
15%	0.13
20%	0.14
25%	0.16
30%	0.17
35%	0.18
40%	0.19
45%	0.21
50%	0.22
55%	0.24
60%	0.25
65%	0.27
70%	0.29
75%	0.31
80%	0.33
85%	0.35
90%	0.38
95%	0.42
100%	0.51

The absolute error between Monte Carlo simulation and the result obtained using Fuzzy Reliability Analyzer (FRA) is calculated as follow:

Absolute error = $\left|\frac{EMV_{Monte\ Carlo} - EMV_{Fuzzy\ Reliability\ Analyzer}}{EMV_{Monte\ Carlo}}\right| * 100$ [6-10]

According to Equation 6-10, the absolute error is obtained as follows:

Absolute error = $\left|\frac{0.24-0.27}{0.24}\right| * 100 = 13\%$ [6-11]

By comparing the proposed approach against Monte Carlo simulation, a list of conclusions can be derived:

1- The utilization of fuzzy logic to solve fault trees and event trees offers a transparent approach to track the calculated probability of occurrence and the expected monetary value. Such transparency can help verifying the resultant expected monetary value as compared to the value obtained using Monte Carlo simulation approach in which random numbers are created and used to calculate the results.
2- The use of fuzzy logic allows experts to comminute information about the probability of occurrence and the impact of risk events using linguistic terms, which is more convenient for experts especially when it comes to risk assessment. Such advantage is not supported using Monte Carlo simulation in which experts are asked to provide numerical values for probability and impact.
3- The utilization of fault trees to support risk analysis also offers the advantage of supporting risk identification. In this regard, the utilization of the fault tree structure, as presented in Figure 6-5, allows experts to understand the root causes of the risk event. Monte Carlo simulation model does not support such identification of the root causes.
4- The use of the fuzzy importance analysis offers the advantage of ranking different root causes and supporting experts to

understand which root causes are contributing the most to the occurrence of the risk event. Such understanding can aid risk response by working on establishing mitigation strategies that can either eliminate or reduce the chances of the occurrence of the highest ranked root causes. Monte Carlo simulation models fails to offers such mechanism to aid risk response.

5- The use of event tree analysis offers the advantage of exploring different scenarios for risk mitigation and understanding the impact on a risk event by considering the failure and success of the identified mitigation strategies. Monte Carlo simulation as compared to event tree analysis does not offer the ability of explaining how the expect monetary value (EMV) of a risk event might change as a result of revising or adding different mitigation scenarios to mitigate the risk event under analysis.

6.5 Validation of Contributions

In order to validate the contributions of the proposed framework, a survey was conducted, with two experts specialized in the field of risk analysis. The objective of this survey was to test the advantages of the proposed integration between fuzzy logic, FMEA, fault tree, and event tree versus traditional risk analysis approaches. Prior to conducting the survey, the proposed framework and its various components were presented to the two experts, and the two software packages, i.e., Risk Criticality

Analyzer and Fuzzy Reliability Analyzer were also demonstrated using the case studies presented under this section. Experts were also given the ability to experiment with both software packages by running several examples. The fuzzy expert system (FES) component of Risk Criticality Analyzer was also demonstrated to both experts and they were given the ability to notice how different rules are fired and how the FES system calculates the resultant RCN. Thereafter, a survey was conducted, by means of a questionnaire (Appendix XIV), which addressed specific questions to test whether each specific component of the proposed framework has provided an advantage(s) over other available risk analysis techniques. Not only the experts were asked to provide (Yes/No) answers to the questions but also they were asked to provide justifications of their answers. The questionnaire was composed of eleven basic questions as follows:

- Question (1) is composed or three parts targeting to address the preference of the experts of using numerical scale to assess probability of occurrence (1a), impact (1b), and detection/ control (1c) versus the linguistic scale.
- Question (2) is targeting the ability of the fuzzy expert system to provide transparent mean of obtaining the RCN and the ability of this system to educate new employees.

- Question (3) is intended to check the advantage of providing multi dimensions to assess risk events versus relaying on a mixed scale of (cost, time, scope/quality … etc) to assess the impact.
- Question (4) is intended to test if there are any advantages of using linguistic terms to assess probability of occurrence, cost impact, time impact.
- Question (5) is intended to check the value added of using fuzzy expert system versus an Excel look up table.
- Question (6) is intended to test the ability of applying the proposed framework to other projects to validate if this framework can be considered as a general framework.
- Question (7) is intended to test if there is any value added by considering the combination between fault tree and event tree.
- Question (8) is intended to verify if there is any advantage of providing the ranking of basic events according to their level of contribution to the top event fuzzy probability.
- Question (9) is intended to compare the proposed framework against one of the commonly used techniques, i.e., Monte Carlo simulation, to understand the advantages and limitations of both approaches.
- Question (10) is intended to understand which one of the following two scenarios is more appropriate to be used to calculate the

aggregated impact of cost impact, time impact, and scope/quality impact using fuzzy AHP.

- Scenario 1: use one aggregated impact equation to calculate the aggregated impact for all the risk events in one project by running the analysis at the project level.
- Scenario 2:change the aggregated impact equation for each risk event in a risk register by running the analysis at the individual risk level.

- Question (11) is intended to check if safety and environment is to be considered in the calculation of the aggregated impact rather than handling it separately through the use of risk acceptability level.

Based on the feedback of the two experts, the experts preferred using the linguistic terms to assess probability of occurrence, impact, and detection/control (refer to questions 1a, 1b, 1c), which are the method used by Risk Criticality Analyzer. In their responses to these three questions, the experts noted that linguistic terms had the advantage of: (1) providing better statistical range (0-100); (2) providing better communication; (3) solving the problem of non availability of data since probability of occurrence has to be assessed based on conditions, which is difficult to obtain; (4) using of linguistic terms is the most established practice within the construction industry.

The two experts noted the advantage of using the linguistic scale to assess the impact as described in Table 4-2. Several advantages were noted as follows: (1) it enables specific impact description of cost, time, and scope as compared to the one dimension representation of the impact as defined by the traditional FMEA method; (2) the linguistic terms provide better communication with project team members. The advantage of using linguistic scale to assess detection/control was also noted by both experts. The description of the detection/control as defined in Table 4-3 provides less subjective assessment of the level of detection/control and provides better communication.

Both experts also noted the advantage of using fuzzy expert system to educate new team members since it is based on the use linguistic terms. The common knowledge base created using linguistic terms is more transparent for experts to use and apply.

Both experts also noted the advantage of using three dimensions to represent the impact of risk. Any assessment that does not supports providing multi dimensions to asses the impact will entails an ambiguous communication mechanism of the risk related information. The management team will not able to know which dimension of the impact is the one that govern the feedback of the project team when they provided their assessment of the impact.

Allowing the experts to experiment with the fuzzy experts system supported them to understand how different if-then rules are fired, how implication, aggregation, and defuzzification are applied. Experts were then asked to compare what they have seen against establishing an Excel Look up table that takes numerical assessment of probability of occurrence, impact, and detection to calculate the RCN. Experts noted that the fuzzy expert system is more preferable for them to calculate the RCN since it is based on linguistic terms and it is transparent to visualize the results.

The framework as demonstrated to both experts shows that it can be considered to be a generic framework. Experts noted that the range of each linguistic term can be adjusted, if required, and used to fit another context.

Experts noted that the use fault tree and event tree as proposed by this study does not only support risk assessment but also it provides a general mechanism that aids risk identification, risk assessment, mitigation planning, decision making, and contingency assessment. The combination of fault tree and event tree can aid assessing of risk benefit to cost ratio and applying decision related to contingency response planning.

The ability of the framework to rank different root causes using fuzzy importance analysis was also highlighted as a contribution of this framework. This advantage can support the project team in establishing effective mitigation strategies.

The experiment demonstrated to both experts using fuzzy reliability analyzer and Monte Carlo simulation had supported them to provide a judgement about the advantages and limitations of both applications. Experts noted that fuzzy reliability analyzers shows a comprehensive framework that offer multi-advantage such as risk identification, risk assessment, and risk response planning which provide more integrated tool that can fit the needs of the construction projects.

The calculation of the aggregated impact at the project level is perceived as the most appropriate way to calculate the aggregated impact. Calculating the aggregated impact at the project level will ensure consistency in decision making. Moreover, doing this calculation for each specific risk event is a cumbersome, impractical, and will add more confusion to the risk owner since this decision is a project based rather than a risk based decision.

The utilization of the risk acceptability level concept to screen risk events that have critical impact on safety and/or environment is perceived to be sufficient. Both experts indicated that all unacceptable risk events are then must undergo detailed risk analysis using fault tree and event tree analysis and based on the application of this concept, detailed risk response strategies can be established.

6.6 Summary

In this chapter, the proposed integration between FMEA, fault trees, event trees, and fuzzy logic was explored. Fuzzy FMEA is first applied using RCA, to identify critical risk events. The failure of horizontal directional drilling (HDD) to meet project objectives was identified as a critical risk event using RCA. Detailed fuzzy fault tree analysis and event tree analysis were conducted to quantify the expected monetary value (EMV) of the selected risk event. The results were then validated by comparing the results against a Monte Carlo simulation model. The experts noted several advantages of using this framework in the construction domain to conduct a quantitative assessment of risk. For instance, the use of fuzzy logic has offered the ability to conduct a linguistic assessment of probability of occurrence, cost impact, time impact, scope/quality impact, and detection/ control. The use of fuzzy AHP offered the ability to aggregate the three dimensions of the impact and support conducting consistency analysis. The framework supports the identification of the required corrective action, as presented in Table 4-4. The use of fault trees offered the ability to explain how a risk event might occur, and supported creating proactive risk response strategies. Fuzzy logic offers more flexibility to conduct quantitative fault tree and event tree analysis to calculate the probability of a risk event, by considering the linguistic assessment of basic events, as presented in Table 4-1, and supporting the expected monetary value (EMV) calculations using of the linguistic terms presented in Table 5-21.

The proposed integration between event tree and fault tree, as presented in Figure 5-2, and demonstrated thought out a case study offers several advantages as compared to Monte Carlo simulation models. This integration between event tree and fault tree offers a compressive framework not only to support risk analysis but also to support risk identification and risk response management.

In order to validate the contributions of the proposed framework, an experiment was conducted with two experts specialized in risk analysis a long. Thereafter, a survey was conducted to test the advantages of the proposed integration between fuzzy logic, FMEA, fault tree, and event tree versus traditional risk analysis approaches and to verify the contribution of this study. The following is a summary of the results obtained from the survey.

- The framework supports judging the level of risk criticality by addressing the limitations of the conventional FMEA.
- The use of the fuzzy logic offers the advantage of capturing the knowledge of experts in the domain of risk management and help utilizing this knowledge to train new personnel in the same domain.
- The use fuzzy expert system and FMEA offers a transparent model in which the calculated RCN can be tracked.
- The use of fuzzy AHP offers the advantage of using three dimensions to represent the impact of risk. Any assessment that does not supports providing multi dimensions to asses the impact will entails an ambiguous communication mechanism of the risk related information.

- The framework offers the contribution of combining fuzzy logic, event trees, and fault trees in a comprehensive framework that does not only support risk assessment but also provides a general mechanism that aids risk identification, risk assessment, mitigation planning, decision making, and contingency assessment.
- The use of fuzzy logic to solve fault trees and event trees offers a transparent framework, in which the calculated fuzzy probability of occurrence and the expected monetary value can be easily tracked and understood.
- The use of fuzzy logic allows experts to express themselves linguistically which is more convenient for experts.
- The framework offers a generic framework that can be adapted to fit any industry or organization.
- The framework supports conducting sensitivity analysis by ranking different basic events, which can aid risk response planning.
- The concept of fuzzy AHP analysis is better being applied at the project level rather than being applied at the specific risk level, which confirms the logic used in this study.
- Safety and environmental impact are both well handled using the risk acceptability level concept.

7. Conclusions and Future Work

This chapter provides a summary of the work conducted in this research, and summarizes the contributions. Limitations of the framework and recommendations for future research are also outlined.

7.1 Summary

Risk analysis represents one of the crucial steps of any risk management framework. Conducting risk analysis using qualitative techniques such as risk matrix and AHP lacks the ability to provide an accurate estimate of the expected monetary value of risk events, since the ultimate outcomes of these techniques is to rank different risk events. On the other hand, conducting risk analysis using the probabilistic techniques, such as Monte Carlo simulation or decision trees, requires collecting a sufficient amount of data to establish probability density functions to define each risk event, which is difficult to obtain, especially in the construction industry. Eventually this difficulty of conducting risk analysis creates more need to establish a more flexible framework that can support screening of critical risk events and supporting risk analysis, even if data are not available or hard to obtain and is required to be transparent by offering the ability to trace the output obtained and understand how these models derive the outcomes. Such a framework has to consider the linguistic nature of risk events by allowing the use of linguistic terms, such as low, medium, and high, to assess risk events, rather than using numerical numbers. In addition, any proposed framework has to consider supporting the risk analyst to distinguish between critical and non-critical risk events so that more time can be dedicated to the ones that require more attention to the establishment of proper risk response strategies. Moreover, the framework is required to be comprehensive to support other risk management processes such as risk identification and risk response management.

The objective of this research is to establish a comprehensive framework to support screening of critical risk events and to facilitate conducting risk analysis in the construction industry by addressing some of the outlined limitations of the previous work conducted in this domain. The approach developed is based on combining three well-known techniques in reliability engineering, i.e., failure mode and effect analysis (FMEA), fault trees, and event trees with fuzzy logic. The framework created in this thesis is based upon using the significant capability of fuzzy logic to support linguistic assessment of risk events, which is more convenient for experts working in the field of risk analysis. During this research, FMEA is combined with fuzzy logic to create a fuzzy expert system to support screening of critical risk events in the construction industry. Inputs to the fuzzy expert system include an assessment of the probability of occurrence (P), cost impact (CI), time impact (TI), scope/quality impact (SI), and the level of detection/control (D). Fuzzy

AHP was utilized to support aggregating the multi-dimension of impact, i.e., CI, TI, SI, into one variable named aggregated impact (AI). One hundred and twenty-five rules were elicited to define the relationship between inputs P, AI, and D, and the risk criticality number (RCN). The RCN range, i.e., 1 to 1000, was then divided into nine categories, and each category was assigned a level of priority for establishing corrective actions. Corrective actions vary from accepting the risk events, when the RCN is small, to recommending the avoidance of risk events, when the RCN is high. The use of the fuzzy expert system and FMEA has offered the advantage of addressing several limitations of the conventional approach of conducting FMEA, outlined in chapter 3, and offered a transparent system that can help educating new personnel regarding the risk criticality principle. The framework also offers the advantage of associating each RCN with a corrective action, which is used to screen critical risk events. The risk acceptability level (RAL) concept is introduced to handle risk events that have safety and/or environmental impact. All risk events that have unacceptable risk level are required to undergo detailed risk analysis.

After identifying critical risk events and/or risk events with unacceptable risk level, detailed risk analysis is required to be conducted using fault tree and event tree analysis. Fault tree analysis and event tree analysis are well-established methods for risk analysis that have been used extensively in many industries. The utilization of fault trees and event trees offers several advantages compared to other risk analysis techniques. For instance, fault tree analysis (FTA) supports the decision-maker in understanding how different root causes interact to cause the top event (i.e., risk event), and provides supporting detail behind the estimated probability of occurrence of a risk event. In addition, FTA can be used as a tool to identify proactive risk response strategies. Moreover, FTA can be used as a diagnostic tool after the occurrence of a risk event to understand the logic that leads to the occurrence of the risk event. On the other hand, event tree analysis can be used to calculate the expected monetary value of each risk event by considering different scenarios to mitigate the risk event. However, due to the limited availability of data in the construction domain, few works were recognized that involve the use of such techniques.

To facilitate adapting fault tree analysis and event tree analysis in the construction industry, fuzzy logic was utilized. The use of fuzzy logic has offered the advantage of using linguistic terms to assess the probability of occurrence of basic events and to support quantitative fault tree analysis. Conducting fuzzy importance analysis offered the ability to rank different basic events according to their level of contribution to the top event's (risk event) fuzzy probability of occurrence. Hence, proactive risk response strategies can be established to address the top ranked basic events. The use of fuzzy logic has also offered the advantage of conducting event tree analysis using linguistic terms.

Since conducting fault tree analysis and event tree analysis is a cumbersome process that requires a lot of time and effort, this study has established a practical approach for conducting detailed risk analysis using both techniques. In this regard, risk events that are analyzed to fall under categories 5 to 9, defined by the RCN, are required to undergo detailed risk analysis using fault tree analysis and event tree analysis. Thus, more focus and attention can be allocated to risk events that drive more criticality to the project. By combining fuzzy logic with FMEA, fault tree, and event tree a compressive and novel framework is established that can support risk analysis as well as other risk management processes such as risk identification, and risk response planning while considering the linguistic nature of the risk related data.

The framework was implemented in two software applications, entitled Risk Criticality Analyzer (RCA) and Fuzzy Reliability Analyzer (FRA). A case study was utilized to verify the validity of the proposed framework. RCA was applied first to calculate the level of criticality of different risk events. Horizontal directional drilling failure to meet project objectives was identified as a critical risk event using RCA. Hence, fuzzy event tree and fuzzy fault tree analysis were conducted to calculate the expected monetary value (EMV). "Face validation" is applied to verify the advantage of the proposed framework. In this regard, an interview was conducted with two experts and both have noted the advantage of using the proposed framework to examine the level of risk criticality and to calculate the expected monetary value. Detailed analysis was conducted by comparing the results obtained using traditional FMEA and fuzzy FMEA and used to validate the finding and to illustrate the advantage of using fuzzy FMEA to solve some of the limitations of the traditional FMEA approach. A Monte Carlo simulation model was developed and used to validate the results obtained using fuzzy fault tree analysis and fuzzy event tree analysis. A detailed comparison was also conducted and used to highlight the advantages of using the proposed framework to conduct risk analysis.

In order to validate the contributions of the framework, an experiment was conducted with two experts specialized in risk analysis using Risk criticality Analyzer and Fuzzy Reliability Analyzer. Thereafter, a survey was conducted aiming at testing the advantages of the proposed integration between fuzzy logic, FMEA, fault tree, and event tree versus traditional risk analysis approaches and to verify the contribution of this study. The results of the survey confirmed several contributions as will be highlighted in the next section.

7.2 Contributions

The main contribution of the proposed research is the introduction of a comprehensive framework for risk management based on combining three well know techniques in reliability engineering in a novel way to support risk identification, risk analysis, and risk response while considering the subjective characteristics of the risk-related data. The framework presented in this research provides several contributions to the area of risk management. The framework supports risk analysis even in scenarios in which data are unavailable or difficult to obtain. Since the framework is based on using linguistic terms to asses risk events, risk analysts are offered a more convenient and practical framework to conduct risk analysis, especially in the construction industry. Described below are the key academic contributions offered by this research:

- The framework offers the contribution of combining fuzzy logic, FMEA, fault tree, and event tree in a novel way to support risk analysis as well as risk identification, and risk response planning.
- The framework supports judging the level of risk criticality by addressing the limitations of the conventional FMEA. Several limitations of the conventional FMEA were addressed by establishing a fuzzy expert system to support calculating the risk criticality number (RCN), and to identify the required corrective actions.
- The use of the fuzzy logic offers the advantage of capturing the knowledge of experts in the domain of risk management and help utilizing this knowledge to train new persons in the same domain. Thus, fuzzy logic has offered the ability of incorporating the subjective quality aspects of experts in decision-making.

- The use fuzzy expert system and FMEA offers a transparent model in which the calculated RCN can be tracked. Such transparency offers flexibility to reflect any change to the organization policy toward risk, i.e., (risk averse, risk neutral, risk seeking), without the need to building the model all over again. Experts can review the fuzzy rule base and identify which rules are fired and track the calculated RCN.
- The framework explores the utilization of fuzzy AHP to support risk-based multi-criteria decision-making. The utilization of the fuzzy AHP concept has supported the aggregation of the cost impact (CI), time impact (TI), and scope/quality impact (SI) into one variable named aggregated impact (AI). Such aggregation was crucial to support risk criticality analysis.
- The use of fuzzy logic to solve fault trees and event trees offers a transparent framework, in which the calculated fuzzy probability of occurrence and the expected monetary value can be easily tracked and understood. Such transparency is not guaranteed by other techniques such as Monte Carlo simulation.
- The use of fuzzy logic allows experts to comminute information regarding the probability of occurrence and the impact of risk events using linguistic terms, which is more convenient for experts.
- The use of event tree analysis offers the advantage of exploring different scenarios for risk mitigation and understanding the impact

on a risk event by considering the failure and success of the identified mitigation strategies.

- The framework offers a generic framework that can be adapted to fit any industry or organization. Calibrations of the membership functions were considered during this study to support probability and impact assessment as shown in Figure 5-12 and Figure 5-14.
- The framework supports conducting sensitivity analysis and ranking different basic events according to their level of contribution to the top event. Thus, the framework can aid risk response planning by working on establishing mitigation strategies that can either eliminate or reduce the chances of the occurrence of the highest ranked root causes.

In addition to the academic contributions, the framework also offers several industrial contributions, which can be summarized as follows:

- The framework offers risk analysts a framework that can reason about and calculate the level of risk criticality, calculate the probability of occurrence, and calculate the expected monetary value even if data are not available or are hard to obtain, and allow experts to express themselves linguistically.
- Risk criticality analysis offers the advantages of judging the level of risk criticality at the project level as well as at the portfolio level, as illustrated in Figure 6-1, Figure 6-2, Figure 6-3, and Table 6-1.

- Risk criticality analysis aids the decision of identifying which risk events are required to undergo detailed root cause analysis. In this regard, any risk event that was assessed to fall in categories 5 to 9, described in Table 4-4, is required to undergo detailed root cause analysis.
- Risk criticality analysis helps in identifying training requirements for different risk owners. Risk events that were assessed as critical risk events at the portfolio level are required to be further analyzed to define the root causes. If the root causes were attributed to the lack of required training, then organizations can work on establishing training for different risk owners to close the gap.
- Risk criticality analysis aids in the identification of effective response strategies for future usage in new projects, and weak response strategies for future avoidance and improvement. By monitoring the deviation of the RCN of each risk event from one reporting period to another, analyzing the findings, and documenting the reason behind the deviation, the organization can identify effective and weak risk response strategies.
- Fault trees offer the contribution of explaining the logic behind how different root causes may interact to cause the risk event.
- Fault trees offer the contribution of supporting decision-makers to work on creating proactive risk response strategies by working on eliminating critical root causes.

7.3 Recommendations for Future Work

The methodology presented in this research and the findings obtained have created more interest for future research by incorporating FMEA, fault trees, and event tree. Future work can be conducted by building upon the findings from this study, and can be summarized as follows:

- The rule base of the fuzzy expert system reflects the participant organization's perspective toward risk. More testing and validation is required to be conduct in the future in case of any change of the organizational policy toward risk or if it is required to use this model within other organization.
- The membership functions of probability of occurrence, cost impact, time impact, and scope/quality impact were all represented using trapezoidal and triangular membership functions. Other forms of the membership function can be used in the future and sensitivity analysis can be conducted to verify the sensitivity of the model to the change of the membership function shape.
- More sensitivity analysis is also required to be conducted to explore changes of the t-norm operator to represent an (AND) logic, change of the s-norms operator to represent an (OR) logic, change of the implication, aggregation, and the defuzzification

method, and also to explore which rules are fired and which are unnecessary and can be eliminated from the rule base.

- The proposed application of fuzzy fault tree and fuzzy event tree has been tested and validated by using one critical risk event. To generalize the applicability, the framework should be tested using more risk events.
- The direct method with one expert is used to elicit the membership functions for probability of occurrence (P), impact (I), and detection/control (D). Other methods, such as direct methods with multiple experts or indirect methods with one or multiple experts, can be investigated and the results can be compared.
- The fuzzy fault tree analysis and fuzzy event tree analysis were both conducted using trapezoidal membership functions to represent the fuzzy probability of basic events and the impact of risk, as shown in Figure 5-3 and Table 5-21. Future research can be conducted to investigate the use of other shapes of membership functions, and the results can be compared.
- The impact table for the event tree analysis is represented using the cost impact. Other dimensions of the impact can be used in the future such as; time, safety, and environment to represent the impact and to calculate the expected monetary value.
- The framework considers defuzzifying the expected monetary value (EMV) using the mean of maximum to provide an estimated

dollar value of the risk magnitude. Future research can be conducted to investigate different possibility-probability transformation approaches to provide probabilistic assessment of the EMV.

- The framework can be further enhanced by collecting a database for root causes of critical risk events and establishing a framework to automate the creation of the fault tree structure out of the collected root causes.
- The probability of occurrence of risk events were assessed using subjective numerical terms such as: low, medium, high. More objective terms can be used in the future by using terms such as "expected to occur once per (year/decade/lifetime) within (this project/this company/this country/anywhere in the industry)".
- The Beginner module of RCA support updating the weighting of cost, time, and scope/quality impact at the individual risk event while the automated module does not. Future work can be carried to support automating the calculation of the aggregated impact at the individual risk level.

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Appendix I – Fuzzy Expert System Rule Base for RCN Calculations

Rule ID	Impact (I)	Probability of Occurrence (P)	Detection/Control (D)	Risk Criticality Number (RCN)
1	VL	VL	VL	**VL**
2	VL	VL	L	**VL**
3	VL	VL	M	**VL**
4	VL	VL	H	**VL**
5	VL	VL	VH	**VL**
6	VL	L	VL	**VL-L**
7	VL	L	L	**VL-L**
8	VL	L	M	**VL-L**
9	VL	L	H	**VL**
10	VL	L	VH	**VL**
11	VL	M	VL	**L**
12	VL	M	L	**L**
13	VL	M	M	**VL-L**
14	VL	M	H	**VL**
15	VL	M	VH	**VL**
16	VL	H	VL	**L**
17	VL	H	L	**L**
18	VL	H	M	**L**
19	VL	H	H	**L**
20	VL	H	VH	**VL**

Rule ID	Impact (I)	Probability of Occurrence (P)	Detection/Control (D)	Risk Criticality Number (RCN)
21	VL	VH	VL	**L-M**
22	VL	VH	L	**L-M**
23	VL	VH	M	**L**
24	VL	VH	H	**VL-L**
25	VL	VH	VH	**VL**
26	L	VL	VL	**L**
27	L	VL	L	**VL-L**
28	L	VL	M	**VL-L**
29	L	VL	H	**VL**
30	L	VL	VH	**VL**
31	L	L	VL	**L-M**
32	L	L	L	**L-M**
33	L	L	M	**L**
34	L	L	H	**VL**
35	L	L	VH	**VL**
36	L	M	VL	**L-M**
37	L	M	L	**L-M**
38	L	M	M	**L**
39	L	M	H	**L**
40	L	M	VH	**VL**
41	L	H	VL	**M**
42	L	H	L	**L-M**
43	L	H	M	**L-M**

Rule ID	Impact (I)	Probability of Occurrence (P)	Detection/Control (D)	Risk Criticality Number (RCN)
44	L	H	H	**L**
45	L	H	VH	**L**
46	L	VH	VL	**M**
47	L	VH	L	**M**
48	L	VH	M	**L-M**
49	L	VH	H	**L**
50	L	VH	VH	**L**
51	M	VL	VL	**L-M**
52	M	VL	L	**L**
53	M	VL	M	**VL-L**
54	M	VL	H	**VL**
55	M	VL	VH	**VL**
56	M	L	VL	**L-M**
57	M	L	L	**L-M**
58	M	L	M	**L-M**
59	M	L	H	**L**
60	M	L	VH	**L**
61	M	M	VL	**H**
62	M	M	L	**M-H**
63	M	M	M	**M**
64	M	M	H	**L-M**
65	M	M	VH	**L**
66	M	H	VL	**H**

Rule ID	Impact (I)	Probability of Occurrence (P)	Detection/Control (D)	Risk Criticality Number (RCN)
67	M	H	L	**M-H**
68	M	H	M	**M**
69	M	H	H	**L-M**
70	M	H	VH	**L**
71	M	VH	VL	**H**
72	M	VH	L	**H**
73	M	VH	M	**M-H**
74	M	VH	H	**M**
75	M	VH	VH	**L**
76	H	VL	VL	**M**
77	H	VL	L	**M**
78	H	VL	M	**L-M**
79	H	VL	H	**L**
80	H	VL	VH	**VL**
81	H	L	VL	**M-H**
82	H	L	L	**M**
83	H	L	M	**L-M**
84	H	L	H	**L**
85	H	L	VH	**L**
86	H	M	VL	**H-VH**
87	H	M	L	**H-VH**
88	H	M	M	**H**
89	H	M	H	**M**

Rule ID	Impact (I)	Probability of Occurrence (P)	Detection/Control (D)	Risk Criticality Number (RCN)
90	H	M	VH	**L-M**
91	H	H	VL	**VH**
92	H	H	L	**H**
93	H	H	M	**M-H**
94	H	H	H	**M**
95	H	H	VH	**L**
96	H	VH	VL	**VH**
97	H	VH	L	**VH**
98	H	VH	M	**H**
99	H	VH	H	**M-H**
100	H	VH	VH	**L-M**
101	VH	VL	VL	**H**
102	VH	VL	L	**M-H**
103	VH	VL	M	**M**
104	VH	VL	H	**VL-L**
105	VH	VL	VH	**VL**
106	VH	L	VL	**H**
107	VH	L	L	**M-H**
108	VH	L	M	**M**
109	VH	L	H	**L-M**
110	VH	L	VH	**L**
111	VH	M	VL	**VH**
112	VH	M	L	**VH**

Rule ID	Impact (I)	Probability of Occurrence (P)	Detection/Control (D)	Risk Criticality Number (RCN)
113	VH	M	M	**H**
114	VH	M	H	**L-M**
115	VH	M	VH	**L**
116	VH	H	VL	**VH**
117	VH	H	L	**VH**
118	VH	H	M	**H**
119	VH	H	H	**M-H**
120	VH	H	VH	**L**
121	VH	VH	VL	**VH**
122	VH	VH	L	**VH**
123	VH	VH	M	**VH**
124	VH	VH	H	**H**
125	VH	VH	VH	**M**

Appendix II-Sample Risk Register

Risk ID	Risk Area	Risk Description	T/O	Root Causes	Description of Impact.	WBS Ref.	Risk Owner	Risk Status	Next Review	P	CI	TI	SI	SEI	EI	RAL	Mitigation	D	Required By	Mitigation Status

Appendix III- Fuzzy Importance Analysis Detailed Calculation

Top event fuzzy probability (TE_2) after removing basic event (A)

$FPro(TE_2)^{\alpha}$ = 1- [(1- 0) * (1- $FPro(C)^{\alpha}$) * (1- ($FPro(D)^{\alpha}$) * $FPro(E)^{\alpha}$ * $FPro(F)^{\alpha}$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	5		43
0.05	5		42
0.10	6		41
0.15	6		40
0.20	6		39
0.25	7		38
0.30	7		38
0.35	7		37
0.40	7		36
0.45	8		35
0.50	8		34
0.55	8		33
0.60	9		32
0.65	9		31
0.70	9		31
0.75	9		30
0.80	10		29
0.85	10		28
0.90	10		27
0.95	11		27
1.00	11		26

$TE_2 = \frac{11+26}{2} = 18\%$

Top event fuzzy probability (TE_2) after removing basic event (C)

$FPro(TE_2)^{\alpha}$ = 1- [(1- $FPro(A)^{\alpha}$) * (1- 0) * (1- ($FPro(D)^{\alpha}$) * $FPro(E)^{\alpha}$ * $FPro(F)^{\alpha}$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	5		43
0.05	5		42
0.10	6		41
0.15	6		40
0.20	6		39
0.25	7		38
0.30	7		38
0.35	7		37
0.40	7		36
0.45	8		35
0.50	8		34
0.55	8		33
0.60	9		32
0.65	9		31
0.70	9		31
0.75	9		30
0.80	10		29
0.85	10		28
0.90	10		27
0.95	11		27
1.00	11		26

$TE_2 = \frac{11+26}{2} = 18\%$

Top event fuzzy probability (TE_2) after removing basic event (D)

$FPro(TE_2)^{\alpha}$ = 1- [(1- $FPro(A)^{\alpha}$) * (1- $FPro(C)^{\alpha}$) * (1- (0) * $FPro(E)^{\alpha}$ * $FPro(F)^{\alpha}$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	10		55
0.05	10		54
0.10	11		54
0.15	11		53
0.20	12		52
0.25	12		51
0.30	13		50
0.35	13		50
0.40	14		49
0.45	14		48
0.50	14		47
0.55	15		46
0.60	15		45
0.65	16		45
0.70	16		44
0.75	17		43
0.80	17		42
0.85	18		41
0.90	18		40
0.95	19		39
1.00	19		38

$TE_2 = \frac{19+38}{2} = 29\%$

Top event fuzzy probability (TE_2) after removing basic event (E)

$FPro(TE_2)^{\alpha}$ = 1- [(1- $FPro(A)^{\alpha}$) * (1- $FPro(C)^{\alpha}$) * (1- ($FPro(D)^{\alpha}$) * 0 * $FPro(F)^{\alpha}$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	10		55
0.05	10		54
0.10	11		54
0.15	11		53
0.20	12		52
0.25	12		51
0.30	13		50
0.35	13		50
0.40	14		49
0.45	14		48
0.50	14		47
0.55	15		46
0.60	15		45
0.65	16		45
0.70	16		44
0.75	17		43
0.80	17		42
0.85	18		41
0.90	18		40
0.95	19		39
1.00	19		38

$TE_2 = \frac{19+38}{2} = 29\%$

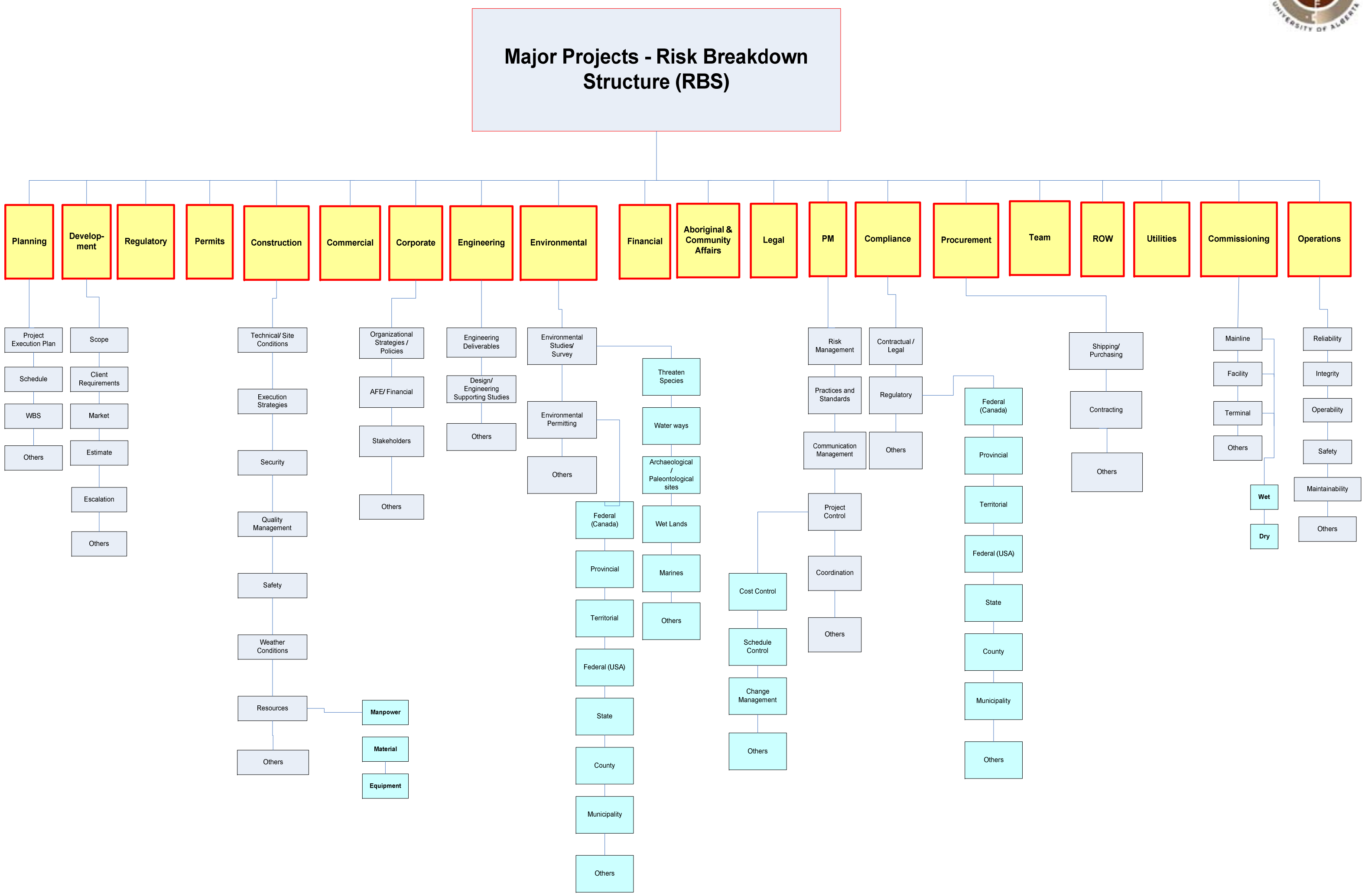
Top event fuzzy probability (TE_2) after removing basic event (F)

$FPro(TE_2)^{\alpha}$ = 1- [(1- $FPro(A)^{\alpha}$) * (1- $FPro(C)^{\alpha}$) * (1- ($FPro(D)^{\alpha}$) * $FPro(E)^{\alpha}$ * 0)]

α	Lower Bound (%)		Upper Bound (%)
0.00	10		55
0.05	10		54
0.10	11		54
0.15	11		53
0.20	12		52
0.25	12		51
0.30	13		50
0.35	13		50
0.40	14		49
0.45	14		48
0.50	14		47
0.55	15		46
0.60	15		45
0.65	16		45
0.70	16		44
0.75	17		43
0.80	17		42
0.85	18		41
0.90	18		40
0.95	19		39
1.00	19		38

$TE_2 = \frac{19+38}{2} = 29\%$

Appendix IV- Risk Breakdown Structure (RBS) for Pipeline Projects



Appendix V- Risk Criticality Analysis Validation

	RCN using Fuzzy FMEA (Option A)							RCN using Traditional FMEA (Option B)								Selection Option	
Risk Description	P	CI	TI	SI	D	RCN	Corrective Action	P	CI	TI	SI	AI	D	RCN	Corrective Action	RCN	Action
Unavailability of critical resources - project team	M	L	L	L	H	125	Low priority to take any corrective action(s)/Accept	5	3	3	3	3	3	45	Unnecessary to take any corrective action(s)/Accept	A	A
Late delivery of valve actuators to manufacturer in Italy	L	L	M	VL	M	149	Low priority to take any corrective action(s)/Accept	3	3	5	1	5	5	75	Unnecessary to take any corrective action(s)/Accept	A	A
Limited or insufficient construction inspection resources	M	L	M	VL	H	149	Low priority to take any corrective action(s)/Accept	5	3	5	1	5	3	75	Unnecessary to take any corrective action(s)/Accept	A	A
Unknown underground utilities and	M	M	L	L	H	155	Low priority to take any corrective	5	5	3	3	5	3	75	Unnecessary to take any corrective	A	A

obstructions							action(s)/Accept								action(s)/Accept		
Late delivery of pumps	L	L	L	L	VL	200	Somewhat moderate priority to take corrective action(s) /consider mitigation	3	3	3	3	3	9	81	Unnecessary to take any corrective action(s)/Accept	A	A
Late delivery of motors	L	L	H	VL	M	183	Somewhat moderate priority to take corrective action(s) /consider mitigation	3	3	7	1	7	5	105	Low priority to take any corrective action(s)/Accept	A	A
Late delivery of Triple off valves	M	M	H	VL	M	340	Moderate priority to take corrective action(s)/ consider mitigation or transfer	5	5	7	1	7	5	175	Somewhat moderate priority to take corrective action(s) /consider mitigation	A	A
Poor productivity due to	M	M	H	VL	H	218	Somewhat moderate priority to take	5	5	7	1	7	3	105	Low priority to take any corrective	B	B

severe weather							corrective action(s) /consider mitigation								action(s)/Accept		
Transformers late procurement	L	L	L	VL	M	114	Low priority to take any corrective action(s)/Accept	3	3	3	1	3	5	45	Unnecessary to take any corrective action(s)/Accept	B	B

Appendix VI- Minimal Cut Calculations for the Case Study Using (Hauptmanns 1988) Algorithm

1- Boolean matrix representation for the case study fault tree (Figure 6-5) using (Hauptmanns 1988) algorithm

Gate event ID	Gate type	**Basic events**														**OR (GE)**							**AND (GE)**
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	TE	GE1	GE2	GE3	GE4	GE5	GE6	
TE	OR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
GE1	OR	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GE2	OR	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
GE3	OR	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
GE4	OR	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0
GE5	OR	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0

TE= HDD failure to meet project objectives, GE1= Equipment unavailability, GE2= Geotechnical problems, GE3= Operational problems, GE4= Environmental and safety problems, GE5= Loss of drilling fluid, GE6= Environmental hazard. Basic events A to N are defined in Table 6-3.

2- Initial working Boolean matrix (WBM) representation for the case study fault tree (Figure 6-5) using (Hauptmanns 1988) algorithm

Start the analysis from the top event. Replace the top event in the WBS with its equivalent (basic events/ gate events) from the Boolean matrix. In this case study, the top event is connected by an OR gate with (GE1, GE2, GE3, GE4). Thus, rule (3a), refer to section 3.3.3.1, is applied.

Basic events														**OR (GE)**							**AND (GE)**
A	B	C	D	E	F	G	H	I	J	K	L	M	N	TE	GE1	GE2	GE3	GE4	GE5	GE6	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

3- Working Boolean matrix iteration (1) for the case study fault tree (Figure 6-5) using (Hauptmanns 1988) algorithm

Scan all the rows of the WBM to check if there is any connection “1” under any of the two blocks named “OR (GE)” and “AND (GE). If so, then replace each gate event in the WBM with its equivalent (basic events/gate events) from the Boolean matrix. By doing the first scan on the initial working Boolean matrix, as defined in the previous step, there is a connection “1” under GE1 and it is an OR Gate. Thus, applying rule (4a), GE1 is replaced with its equivalent (basic events), i.e., A, B, and C, each one is in a separate raw.

Basic events														**OR (GE)**							**AND(GE)**
A	B	C	D	E	F	G	H	I	J	K	L	M	N	TE	GE1	GE2	GE3	GE4	GE5	GE6	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

4- Working Boolean matrix iteration (2) for the case study fault tree (Figure 6-5) using (Hauptmanns 1988) algorithm

Scan all the rows of the WBM to check if there is any connection “1” under any of the two blocks named “OR (GE)” and “AND (GE). If so, then replace each gate event in the WBM with its equivalent (basic events/gate events) from the Boolean matrix. By scanning the working Boolean matrix, as defined in the previous step, there is a connection “1” under GE2 and it is an OR Gate. Thus, applying rule (4a), GE2 is replaced with its equivalent (basic events/ gate events), i.e., D, E, F and GE5, each one is in a separate raw.

Basic events														**OR (GE)**							**AND(GE)**
A	B	C	D	E	F	G	H	I	J	K	L	M	N	TE	GE1	GE2	GE3	GE4	GE5	GE6	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

5- Working Boolean matrix iteration (3) for the case study fault tree (Figure 6-5) using (Hauptmanns 1988) algorithm

Scan all the rows of the WBM to check if there is any connection “1” under any of the two blocks named “OR (GE)” and “AND (GE). If so, then replace each gate event in the WBM with its equivalent (basic events/gate events) from the Boolean matrix. By scanning the working Boolean matrix, as defined in the previous step, there is a connection “1” under GE5 and it is an OR Gate. Thus, applying rule (4a), GE5 is replaced with its equivalent (basic events), i.e., K, and L each one is in a separate raw.

Basic events														OR (GE)							AND(GE)
A	B	C	D	E	F	G	H	I	J	K	L	M	N	TE	GE1	GE2	GE3	GE4	GE5	GE6	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0

6- Working Boolean matrix iteration (4) for the case study fault tree (Figure 6-5) using (Hauptmanns 1988) algorithm

Scan all the rows of the WBM to check if there is any connection “1” under any of the two blocks named “OR (GE)” and “AND (GE). If so, then replace each gate event in the WBM with its equivalent (basic events/gate events) from the Boolean matrix. By scanning the working Boolean matrix, as defined in the previous step, there is a connection “1” under GE3 and it is an OR Gate. Thus, applying rule (4a), GE3 is replaced with its equivalent (basic events), i.e., G, H, and I each one is in a separate raw.

Basic events														OR (GE)							AND(GE)
A	B	C	D	E	F	G	H	I	J	K	L	M	N	TE	GE1	GE2	GE3	GE4	GE5	GE6	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0

7- Working Boolean matrix iteration (5) for the case study fault tree (Figure 6-5) using (Hauptmanns 1988) algorithm

Scan all the rows of the WBM to check if there is any connection “1” under any of the two blocks named “OR (GE)” and “AND (GE). If so, then replace each gate event in the WBM with its equivalent (basic events/gate events) from the Boolean matrix. By scanning the working Boolean matrix, as defined in the previous step, there is a connection “1” under GE4 and it is an OR Gate. Thus, applying rule (4a), GE4 is replaced with its equivalent (basic events/ gate events), i.e., GE6, and J each one is in a separate raw.

Basic events														**OR (GE)**							**AND(GE)**
A	B	C	D	E	F	G	H	I	J	K	L	M	N	TE	GE1	GE2	GE3	GE4	GE5	GE6	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0

8- Working Boolean matrix iteration (6) for the case study fault tree (Figure 6-5) using (Hauptmanns 1988) algorithm

Scan all the rows of the WBM to check if there is any connection "1" under any of the two blocks named "OR (GE)" and "AND (GE). If so, then replace each gate event in the WBM with its equivalent (basic events/gate events) from the Boolean matrix. By scanning the working Boolean matrix, as defined in the previous step, there is a connection "1" under GE6 and it is an OR Gate. Thus, applying rule (4a), GE6 is replaced with its equivalent (basic events), i.e., M, and N each one is in a separate raw.

Basic events														**OR (GE)**							**AND(GE)**
A	B	C	D	E	F	G	H	I	J	K	L	M	N	TE	GE1	GE2	GE3	GE4	GE5	GE6	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0

9- Working Boolean matrix iteration (7) for the case study fault tree (Figure 6-5) using (Hauptmanns 1988) algorithm

Scan all the rows of the WBM to check if there is any connection “1” under any of the two blocks named “OR (GE)” and “AND (GE). Further scanning for the working Boolean matrix indicates that there is “No” connection, i.e., “0”s in the last two blocks, i.e., “OR (GE)” and “AND (GE)”. Thus, the last matrix represents the final WBM and the MCS equations can be written by converting each connection “1” in a row with its related basic event, and connect basic event(s) within each row using intersection “∩”. For example, the first row in can be read as “A”. Basic event(s) in a row is/are connected with basic event(s) in another row using the union “∪” operator. For example, the first and the second rows in the final WBM can be read as “A” ∪ “B”. By applying the above mentioned rules to all the rows in the final WBM, the following MCS equations are obtained.

TE= $A \cup B \cup C \cup D \cup E \cup F \cup K \cup L \cup G \cup H \cup I \cup J \cup M \cup N$

M1= (A), M2= (B), M3=(C), M4= (D), M5= (E), M6=(F), M7= (K), M8= (L), M9= (G), M10= (H), M11= (I), M12=(J), M13=(M), M14= (N)

Where M1, M2, M3, M4, M5, M6, M7, M8, M9, M10, M11, M12, M13, M14 are the minimal cut sets.

Appendix VII- Alpha Cut Representation for Basic Events

Alpha cut representation of basic event (A)

α	Lower Bound *		Upper Bound **
0.00	0.22		0.67
0.05	0.22		0.66
0.10	0.23		0.65
0.15	0.23		0.64
0.20	0.24		0.64
0.25	0.24		0.63
0.30	0.25		0.62
0.35	0.26		0.61
0.40	0.26		0.60
0.45	0.27		0.59
0.50	0.27		0.59
0.55	0.28		0.58
0.60	0.28		0.57
0.65	0.29		0.56
0.70	0.30		0.55
0.75	0.30		0.54
0.80	0.31		0.53
0.85	0.31		0.53
0.90	0.32		0.52
0.95	0.32		0.51
1.00	0.33		0.50

$* \, Upper \ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower \ Bound = \ d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “high” probability is represented as follows:

	a	b	c	d
Basic Event A	0.22	0.33	0.50	0.67

Alpha cut representation of basic event (B)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$$

$$** \, Lower\ Bound = \ d - (d - c) * \alpha$$

According to Figure 5-3, the membership function of “medium” probability is represented as follows:

	a	b	c	d
Basic Event B	0.05	0.10	0.22	0.33

Alpha cut representation of basic event (C)

α	Lower Bound *		Upper Bound **
0.00	0.00		0.10
0.05	0.00		0.10
0.10	0.00		0.10
0.15	0.00		0.09
0.20	0.00		0.09
0.25	0.00		0.09
0.30	0.00		0.09
0.35	0.00		0.08
0.40	0.00		0.08
0.45	0.00		0.08
0.50	0.01		0.08
0.55	0.01		0.07
0.60	0.01		0.07
0.65	0.01		0.07
0.70	0.01		0.07
0.75	0.01		0.06
0.80	0.01		0.06
0.85	0.01		0.06
0.90	0.01		0.06
0.95	0.01		0.05
1.00	0.01		0.05

$* \, Upper \; Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower \; Bound = \; d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “low” probability is represented as follows:

	a	b	c	d
Basic Event C	0.00	0.01	0.05	0.10

Alpha cut representation of basic event (D)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$$

$$** \, Lower\ Bound = \ d - (d - c) * \alpha$$

According to Figure 5-3, the membership function of “medium” probability is represented as follows:

	a	b	c	d
Basic Event D	0.05	0.10	0.22	0.33

Alpha cut representation of basic event (E)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$$

$$** \, Lower\ Bound = \ d - (d - c) * \alpha$$

According to Figure 5-3, the membership function of “medium” probability is represented as follows:

	a	b	c	d
Basic Event E	0.05	0.10	0.22	0.33

Alpha cut representation of basic event (F)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower\ Bound = \ d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “medium” probability is represented as follows:

	a	b	c	d
Basic Event F	0.05	0.10	0.22	0.33

Alpha cut representation of basic event (G)

α	Lower Bound *		Upper Bound **
0.00	0.00		0.10
0.05	0.00		0.10
0.10	0.00		0.10
0.15	0.00		0.09
0.20	0.00		0.09
0.25	0.00		0.09
0.30	0.00		0.09
0.35	0.00		0.08
0.40	0.00		0.08
0.45	0.00		0.08
0.50	0.01		0.08
0.55	0.01		0.07
0.60	0.01		0.07
0.65	0.01		0.07
0.70	0.01		0.07
0.75	0.01		0.06
0.80	0.01		0.06
0.85	0.01		0.06
0.90	0.01		0.06
0.95	0.01		0.05
1.00	0.01		0.05

$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower\ Bound = \ d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “low” probability is represented as follows:

	a	b	c	d
Basic Event G	0.00	0.01	0.05	0.10

Alpha cut representation of basic event (H)

α	Lower Bound *		Upper Bound **
0.00	0.00		0.01
0.05	0.00		0.01
0.10	0.00		0.01
0.15	0.00		0.01
0.20	0.00		0.01
0.25	0.00		0.01
0.30	0.00		0.01
0.35	0.00		0.01
0.40	0.00		0.01
0.45	0.00		0.01
0.50	0.00		0.01
0.55	0.00		0.00
0.60	0.00		0.00
0.65	0.00		0.00
0.70	0.00		0.00
0.75	0.00		0.00
0.80	0.00		0.00
0.85	0.00		0.00
0.90	0.00		0.00
0.95	0.00		0.00
1.00	0.00		0.00

$$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$$

$$** \, Lower\ Bound = \ d - (d - c) * \alpha$$

According to Figure 5-3, the membership function of “vey low” probability is represented as follows:

	a	b	c	d
Basic Event H	0.00	0.00	0.00	0.01

Alpha cut representation of basic event (I)

α	Lower Bound *		Upper Bound **
0.00	0.00		0.10
0.05	0.00		0.10
0.10	0.00		0.10
0.15	0.00		0.09
0.20	0.00		0.09
0.25	0.00		0.09
0.30	0.00		0.09
0.35	0.00		0.08
0.40	0.00		0.08
0.45	0.00		0.08
0.50	0.01		0.08
0.55	0.01		0.07
0.60	0.01		0.07
0.65	0.01		0.07
0.70	0.01		0.07
0.75	0.01		0.06
0.80	0.01		0.06
0.85	0.01		0.06
0.90	0.01		0.06
0.95	0.01		0.05
1.00	0.01		0.05

$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower\ Bound = \ d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “low” probability is represented as follows:

	a	b	c	d
Basic Event I	0.00	0.01	0.05	0.10

Alpha cut representation of basic event (J)

α	Lower Bound *		Upper Bound **
0.00	0.00		0.10
0.05	0.00		0.10
0.10	0.00		0.10
0.15	0.00		0.09
0.20	0.00		0.09
0.25	0.00		0.09
0.30	0.00		0.09
0.35	0.00		0.08
0.40	0.00		0.08
0.45	0.00		0.08
0.50	0.01		0.08
0.55	0.01		0.07
0.60	0.01		0.07
0.65	0.01		0.07
0.70	0.01		0.07
0.75	0.01		0.06
0.80	0.01		0.06
0.85	0.01		0.06
0.90	0.01		0.06
0.95	0.01		0.05
1.00	0.01		0.05

$$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$$

$$** \, Lower\ Bound = \ d - (d - c) * \alpha$$

According to Figure 5-3, the membership function of “low” probability is represented as follows:

	a	b	c	d
Basic Event J	0.00	0.01	0.05	0.10

Alpha cut representation of basic event (K)

α	Lower Bound *		Upper Bound **
0.00	0.00		0.10
0.05	0.00		0.10
0.10	0.00		0.10
0.15	0.00		0.09
0.20	0.00		0.09
0.25	0.00		0.09
0.30	0.00		0.09
0.35	0.00		0.08
0.40	0.00		0.08
0.45	0.00		0.08
0.50	0.01		0.08
0.55	0.01		0.07
0.60	0.01		0.07
0.65	0.01		0.07
0.70	0.01		0.07
0.75	0.01		0.06
0.80	0.01		0.06
0.85	0.01		0.06
0.90	0.01		0.06
0.95	0.01		0.05
1.00	0.01		0.05

$$* \, Upper \ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$$

$$** \, Lower \ Bound = \ d - (d - c) * \alpha$$

According to Figure 5-3, the memberships function of ““low” probability is represented as follows:

	a	b	c	d
Basic Event K	0.00	0.01	0.05	0.10

Alpha cut representation of basic event (L)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$$* \, Upper \ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$$

$$** \, Lower \ Bound = \ d - (d - c) * \alpha$$

According to Figure 5-3, the membership function of “medium” probability is represented as follows:

	a	b	c	d
Basic Event L	0.05	0.10	0.22	0.33

Alpha cut representation of basic event (M)

α	Lower Bound *		Upper Bound **
0.00	0.00		0.01
0.05	0.00		0.01
0.10	0.00		0.01
0.15	0.00		0.01
0.20	0.00		0.01
0.25	0.00		0.01
0.30	0.00		0.01
0.35	0.00		0.01
0.40	0.00		0.01
0.45	0.00		0.01
0.50	0.00		0.01
0.55	0.00		0.00
0.60	0.00		0.00
0.65	0.00		0.00
0.70	0.00		0.00
0.75	0.00		0.00
0.80	0.00		0.00
0.85	0.00		0.00
0.90	0.00		0.00
0.95	0.00		0.00
1.00	0.00		0.00

$* \, Upper \ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower \ Bound = \ d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “very low” probability is represented as follows:

	a	b	c	d
Basic Event M	0.00	0.00	0.00	0.01

Alpha cut representation of basic event (N)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$$

$$** \, Lower\ Bound = d - (d - c) * \alpha$$

According to Figure 5-3, the membership function of “medium” probability is represented as follows:

	a	b	c	d
Basic Event N	0.05	0.10	0.22	0.33

Appendix VIII- Detailed Calculation of the Term (1- FPro (Basic event)$^{\alpha}$) for the Case Study

(1- FPro (A)$^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.78		0.33
0.05	0.78		0.34
0.10	0.77		0.35
0.15	0.77		0.36
0.20	0.76		0.36
0.25	0.76		0.37
0.30	0.75		0.38
0.35	0.74		0.39
0.40	0.74		0.40
0.45	0.73		0.41
0.50	0.73		0.42
0.55	0.72		0.42
0.60	0.72		0.43
0.65	0.71		0.44
0.70	0.70		0.45
0.75	0.70		0.46
0.80	0.69		0.47
0.85	0.69		0.47
0.90	0.68		0.48
0.95	0.68		0.49
1.00	0.67		0.50

(1- FPro (B)$^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.79

$(1- \text{FPro}(C)^{\alpha})$

α	Lower Bound		Upper Bound
0.00	1.00		0.90
0.05	1.00		0.90
0.10	1.00		0.91
0.15	1.00		0.91
0.20	1.00		0.91
0.25	1.00		0.91
0.30	1.00		0.92
0.35	1.00		0.92
0.40	1.00		0.92
0.45	1.00		0.92
0.50	1.00		0.93
0.55	0.99		0.93
0.60	0.99		0.93
0.65	0.99		0.93
0.70	0.99		0.94
0.75	0.99		0.94
0.80	0.99		0.94
0.85	0.99		0.94
0.90	0.99		0.95
0.95	0.99		0.95
1.00	0.99		0.95

(1- FPro $(D)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.78

$(1\text{- FPro }(E)^{\alpha})$

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.78

(1- FPro $(F)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.78

(1- FPro $(G)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	1.00		0.90
0.05	1.00		0.90
0.10	1.00		0.91
0.15	1.00		0.91
0.20	1.00		0.91
0.25	1.00		0.91
0.30	1.00		0.92
0.35	1.00		0.92
0.40	1.00		0.92
0.45	1.00		0.92
0.50	1.00		0.93
0.55	0.99		0.93
0.60	0.99		0.93
0.65	0.99		0.93
0.70	0.99		0.94
0.75	0.99		0.94
0.80	0.99		0.94
0.85	0.99		0.94
0.90	0.99		0.95
0.95	0.99		0.95
1.00	0.99		0.95

$(1\text{- FPro }(H)^{\alpha})$

α	Lower Bound		Upper Bound
0.00	1.00		0.99
0.05	1.00		0.99
0.10	1.00		0.99
0.15	1.00		0.99
0.20	1.00		0.99
0.25	1.00		0.99
0.30	1.00		0.99
0.35	1.00		0.99
0.40	1.00		0.99
0.45	1.00		0.99
0.50	1.00		1.00
0.55	1.00		1.00
0.60	1.00		1.00
0.65	1.00		1.00
0.70	1.00		1.00
0.75	1.00		1.00
0.80	1.00		1.00
0.85	1.00		1.00
0.90	1.00		1.00
0.95	1.00		1.00
1.00	1.00		1.00

$(1- FPro (I)^{\alpha})$

α	Lower Bound		Upper Bound
0.00	1.00		0.90
0.05	1.00		0.90
0.10	1.00		0.91
0.15	1.00		0.91
0.20	1.00		0.91
0.25	1.00		0.91
0.30	1.00		0.92
0.35	1.00		0.92
0.40	1.00		0.92
0.45	1.00		0.92
0.50	1.00		0.93
0.55	0.99		0.93
0.60	0.99		0.93
0.65	0.99		0.93
0.70	0.99		0.94
0.75	0.99		0.94
0.80	0.99		0.94
0.85	0.99		0.94
0.90	0.99		0.95
0.95	0.99		0.95
1.00	0.99		0.95

(1- FPro $(J)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	1.00		0.90
0.05	1.00		0.90
0.10	1.00		0.91
0.15	1.00		0.91
0.20	1.00		0.91
0.25	1.00		0.91
0.30	1.00		0.92
0.35	1.00		0.92
0.40	1.00		0.92
0.45	1.00		0.92
0.50	1.00		0.93
0.55	0.99		0.93
0.60	0.99		0.93
0.65	0.99		0.93
0.70	0.99		0.94
0.75	0.99		0.94
0.80	0.99		0.94
0.85	0.99		0.94
0.90	0.99		0.95
0.95	0.99		0.95
1.00	0.99		0.95

(1- FPro $(K)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	1.00		0.90
0.05	1.00		0.90
0.10	1.00		0.91
0.15	1.00		0.91
0.20	1.00		0.91
0.25	1.00		0.91
0.30	1.00		0.92
0.35	1.00		0.92
0.40	1.00		0.92
0.45	1.00		0.92
0.50	1.00		0.93
0.55	0.99		0.93
0.60	0.99		0.93
0.65	0.99		0.93
0.70	0.99		0.94
0.75	0.99		0.94
0.80	0.99		0.94
0.85	0.99		0.94
0.90	0.99		0.95
0.95	0.99		0.95
1.00	0.99		0.95

$(1- FPro (L)^{\alpha})$

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.78

$(1\text{- FPro }(M)^{\alpha})$

α	Lower Bound		Upper Bound
0.00	1.00		0.99
0.05	1.00		0.99
0.10	1.00		0.99
0.15	1.00		0.99
0.20	1.00		0.99
0.25	1.00		0.99
0.30	1.00		0.99
0.35	1.00		0.99
0.40	1.00		0.99
0.45	1.00		0.99
0.50	1.00		1.00
0.55	1.00		1.00
0.60	1.00		1.00
0.65	1.00		1.00
0.70	1.00		1.00
0.75	1.00		1.00
0.80	1.00		1.00
0.85	1.00		1.00
0.90	1.00		1.00
0.95	1.00		1.00
1.00	1.00		1.00

(1- FPro $(N)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.78

Appendix IX- Top Event Fuzzy Probability (TE1) for the Case Study

FPro (Top Event)$^{\alpha}$ = 1- [(1- FPro (A)$^{\alpha}$) * (1- FPro (B)$^{\alpha}$) *(1- FPro (C)$^{\alpha}$) *(1- FPro (D)$^{\alpha}$) *(1- FPro (E)$^{\alpha}$) *(1- FPro (F)$^{\alpha}$) *(1- FPro (G)$^{\alpha}$) *(1- FPro (H)$^{\alpha}$) *(1- FPro (I)$^{\alpha}$) *(1- FPro (J)$^{\alpha}$) *(1- FPro (K)$^{\alpha}$) *(1- FPro (L)$^{\alpha}$) *(1- FPro (M)$^{\alpha}$) *(1- FPro (N)$^{\alpha}$)]

α	Lower Bound %		Upper Bound %
0.00	42		98
0.05	44		98
0.10	45		98
0.15	47		98
0.20	48		98
0.25	49		97
0.30	51		97
0.35	52		97
0.40	53		97
0.45	54		96
0.50	56		96
0.55	57		96
0.60	58		95
0.65	59		95
0.70	60		94
0.75	61		94
0.80	62		93
0.85	63		93
0.90	64		92
0.95	65		92
1.00	66		91

TE1 = $\frac{66+98}{2}$ = 79%

Appendix X- Top Event Fuzzy Probability Calculations for Fuzzy Importance Analysis

Top event fuzzy probability (TE_2) after removing basic event (A)

$FPro\ (TE_2)^{\alpha}$ = 1- [(1- 0) * (1- $FPro\ (B)^{\alpha}$) *(1- $FPro\ (C)^{\alpha}$) *(1- $FPro\ (D)^{\alpha}$) *(1- $FPro\ (E)^{\alpha}$) *(1- $FPro\ (F)^{\alpha}$) *(1- $FPro\ (G)^{\alpha}$) *(1- $FPro\ (H)^{\alpha}$) *(1- $FPro\ (I)^{\alpha}$) *(1- $FPro\ (J)^{\alpha}$) *(1- $FPro\ (K)^{\alpha}$) *(1- $FPro\ (L)^{\alpha}$) *(1- $FPro\ (M)^{\alpha}$) *(1- $FPro\ (N)^{\alpha}$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	26		95
0.05	28		94
0.10	29		94
0.15	30		94
0.20	32		93
0.25	33		93
0.30	34		92
0.35	35		92
0.40	37		91
0.45	38		91
0.50	39		90
0.55	40		89
0.60	41		89
0.65	42		88
0.70	43		87
0.75	44		87
0.80	45		86
0.85	46		85
0.90	47		84
0.95	48		83
1.00	49		82

$TE_2 = \frac{49+82}{2} = 66\%$

Top event fuzzy probability (TE_2) after removing basic event (B)

$FPro\ (TE_2)^{\alpha} = 1 - [(1 - FPro\ (A)^{\alpha}) * (1 - 0) * (1 - FPro\ (C)^{\alpha}) * (1 - FPro\ (D)^{\alpha}) * (1 - FPro\ (E)^{\alpha}) * (1 - FPro\ (F)^{\alpha}) * (1 - FPro\ (G)^{\alpha}) * (1 - FPro\ (H)^{\alpha}) * (1 - FPro\ (I)^{\alpha}) * (1 - FPro\ (J)^{\alpha}) * (1 - FPro\ (K)^{\alpha}) * (1 - FPro\ (L)^{\alpha}) * (1 - FPro\ (M)^{\alpha}) * (1 - FPro\ (N)^{\alpha})]$

α	Lower Bound (%)		Upper Bound (%)
0.00	39		97
0.05	40		97
0.10	42		97
0.15	43		97
0.20	45		96
0.25	46		96
0.30	47		96
0.35	48		95
0.40	50		95
0.45	51		95
0.50	52		94
0.55	53		94
0.60	54		93
0.65	55		93
0.70	56		92
0.75	57		92
0.80	58		91
0.85	59		91
0.90	60		90
0.95	61		89
1.00	62		88

$TE_2 = \frac{82+88}{2} = 75\%$

Top event fuzzy probability (TE_2) after removing basic event (C)

$FPro\ (TE_2)^{\alpha} = 1- [(1- FPro\ (A)^{\alpha}) * (1- FPro\ (B)^{\alpha}) *(1- 0) *(1- FPro\ (D)^{\alpha}) *(1- FPro\ (E)^{\alpha}) *(1- FPro\ (F)^{\alpha}) *(1- FPro\ (G)^{\alpha}) *(1- FPro\ (H)^{\alpha}) *(1- FPro\ (I)^{\alpha}) *(1- FPro\ (J)^{\alpha}) *(1- FPro\ (K)^{\alpha}) *(1- FPro\ (L)^{\alpha}) *(1- FPro\ (M)^{\alpha}) *(1- FPro\ (N)^{\alpha})]$

α	Lower Bound (%)		Upper Bound (%)
0.00	42		98
0.05	44		98
0.10	45		98
0.15	47		98
0.20	48		97
0.25	49		97
0.30	50		97
0.35	52		97
0.40	53		96
0.45	54		96
0.50	55		96
0.55	56		95
0.60	58		95
0.65	59		94
0.70	60		94
0.75	61		93
0.80	62		93
0.85	63		92
0.90	64		92
0.95	65		91
1.00	66		90

$TE_2 = \frac{66+90}{2} = 78\%$

Top event fuzzy probability (TE_2) after removing basic event (D)

$FPro\ (TE_2)^\alpha = 1- [(1- FPro\ (A)^\alpha) * (1- FPro\ (B)^\alpha) *(1- FPro\ (C)^\alpha) *(1- 0) *(1- FPro\ (E)^\alpha) *(1- FPro\ (F)^\alpha) *(1- FPro\ (G)^\alpha) *(1- FPro\ (H)^\alpha) *(1- FPro\ (I)^\alpha) *(1- FPro\ (J)^\alpha) *(1- FPro\ (K)^\alpha) *(1- FPro\ (L)^\alpha) *(1- FPro\ (M)^\alpha) *(1- FPro\ (N)^\alpha)]$

α	Lower Bound (%)		Upper Bound (%)
0.00	39		97
0.05	41		97
0.10	42		97
0.15	43		97
0.20	45		96
0.25	46		96
0.30	47		96
0.35	48		95
0.40	50		95
0.45	51		95
0.50	52		94
0.55	53		94
0.60	54		93
0.65	55		93
0.70	56		92
0.75	57		92
0.80	58		91
0.85	59		91
0.90	60		90
0.95	61		89
1.00	62		88

$TE_2 = \frac{62+88}{2} = 75\%$

Top event fuzzy probability (TE_2) after removing basic event (E)

$FPro\ (TE_2)^{\alpha} = 1- [(1- FPro\ (A)^{\alpha}) * (1- FPro\ (B)^{\alpha}) *(1- FPro\ (C)^{\alpha}) *(1- FPro\ (D)^{\alpha}) *(1- 0) *(1- FPro\ (F)^{\alpha}) *(1- FPro\ (G)^{\alpha}) *(1- FPro\ (H)^{\alpha}) *(1- FPro\ (I)^{\alpha}) *(1- FPro\ (J)^{\alpha}) *(1- FPro\ (K)^{\alpha}) *(1- FPro\ (L)^{\alpha}) *(1- FPro\ (M)^{\alpha}) *(1- FPro\ (N)^{\alpha})]$

α	Lower Bound (%)		Upper Bound (%)
0.00	39		97
0.05	41		97
0.10	42		97
0.15	43		97
0.20	45		96
0.25	46		96
0.30	47		96
0.35	48		95
0.40	50		95
0.45	51		95
0.50	52		94
0.55	53		94
0.60	54		93
0.65	55		93
0.70	56		92
0.75	57		92
0.80	58		91
0.85	59		91
0.90	60		90
0.95	61		89
1.00	62		88

$TE_2 = \frac{62+88}{2} = 75\%$

Top event fuzzy probability (TE_2) after removing basic event (F)

$FPro\ (TE_2)^{\alpha} = 1- [(1- FPro\ (A)^{\alpha}) * (1- FPro\ (B)^{\alpha}) *(1- FPro\ (C)^{\alpha}) *(1- FPro\ (D)^{\alpha}) *(1- FPro\ (E)^{\alpha}) *(1- 0) *(1- FPro\ (G)^{\alpha}) *(1- FPro\ (H)^{\alpha}) *(1- FPro\ (I)^{\alpha}) *(1- FPro\ (J)^{\alpha}) *(1- FPro\ (K)^{\alpha}) *(1- FPro\ (L)^{\alpha}) *(1- FPro\ (M)^{\alpha}) *(1- FPro\ (N)^{\alpha})]$

α	Lower Bound (%)		Upper Bound (%)
0.00	39		97
0.05	41		97
0.10	42		97
0.15	43		97
0.20	45		96
0.25	46		96
0.30	47		96
0.35	48		95
0.40	50		95
0.45	51		95
0.50	52		94
0.55	53		94
0.60	54		93
0.65	55		93
0.70	56		92
0.75	57		92
0.80	58		91
0.85	59		91
0.90	60		90
0.95	61		89
1.00	62		88

$TE_2 = \frac{62+88}{2} = 75\%$

Top event fuzzy probability (TE_2) after removing basic event (G)

FPro $(TE_2)^{\alpha}$ = 1- [(1- FPro $(A)^{\alpha}$) * (1- FPro $(B)^{\alpha}$) *(1- FPro $(C)^{\alpha}$) *(1- FPro $(D)^{\alpha}$) *(1- FPro $(E)^{\alpha}$) *(1- FPro $(F)^{\alpha}$) *(1- 0) *(1- FPro $(H)^{\alpha}$) *(1- FPro $(I)^{\alpha}$) *(1- FPro $(J)^{\alpha}$) *(1- FPro $(K)^{\alpha}$) *(1- FPro $(L)^{\alpha}$) *(1- FPro $(M)^{\alpha}$) *(1- FPro $(N)^{\alpha}$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	42		98
0.05	44		98
0.10	45		98
0.15	47		98
0.20	48		97
0.25	49		97
0.30	50		97
0.35	52		97
0.40	53		96
0.45	54		96
0.50	55		96
0.55	56		95
0.60	58		95
0.65	59		94
0.70	60		94
0.75	61		93
0.80	62		93
0.85	63		92
0.90	64		92
0.95	65		91
1.00	66		90

$TE_2 = \frac{66+90}{2} = 78\%$

Top event fuzzy probability (TE_2) after removing basic event (H)

FPro $(TE_2)^{\alpha}$ = 1- [(1- FPro $(A)^{\alpha}$) * (1- FPro $(B)^{\alpha}$) *(1- FPro $(C)^{\alpha}$) *(1- FPro $(D)^{\alpha}$) *(1- FPro $(E)^{\alpha}$) *(1- FPro $(F)^{\alpha}$) *(1- FPro $(G)^{\alpha}$) *(1- 0) *(1- FPro $(I)^{\alpha}$) *(1- FPro $(J)^{\alpha}$) *(1- FPro $(K)^{\alpha}$) *(1- FPro $(L)^{\alpha}$) *(1- FPro $(M)^{\alpha}$) *(1- FPro $(N)^{\alpha}$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	42		98
0.05	44		98
0.10	45		98
0.15	47		98
0.20	48		98
0.25	49		97
0.30	51		97
0.35	52		97
0.40	53		96
0.45	54		96
0.50	56		96
0.55	57		96
0.60	58		95
0.65	59		95
0.70	60		94
0.75	61		94
0.80	62		93
0.85	63		93
0.90	64		92
0.95	65		92
1.00	66		91

$TE_2 = \frac{66+91}{2} = 79\%$

Top event fuzzy probability (TE_2) after removing basic event (I)

$FPro\ (TE_2)^{\alpha}$ = 1- [(1- $FPro\ (A)^{\alpha}$) * (1- $FPro\ (B)^{\alpha}$) *(1- $FPro\ (C)^{\alpha}$) *(1- $FPro\ (D)^{\alpha}$) *(1- $FPro\ (E)^{\alpha}$) *(1- $FPro\ (F)^{\alpha}$) *(1- $FPro\ (G)^{\alpha}$) *(1- $FPro\ (H)^{\alpha}$) *(1- 0) *(1- $FPro\ (J)^{\alpha}$) *(1- $FPro\ (K)^{\alpha}$) *(1- $FPro\ (L)^{\alpha}$) *(1- $FPro\ (M)^{\alpha}$) *(1- $FPro\ (N)^{\alpha}$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	42		98
0.05	44		98
0.10	45		98
0.15	47		98
0.20	48		97
0.25	49		97
0.30	50		97
0.35	52		97
0.40	53		96
0.45	54		96
0.50	55		96
0.55	56		95
0.60	58		95
0.65	59		94
0.70	60		94
0.75	61		93
0.80	62		93
0.85	63		92
0.90	64		92
0.95	65		91
1.00	66		90

$TE_2 = \frac{66+90}{2} = 78\%$

Top event fuzzy probability (TE_2) after removing basic event (J)

FPro $(TE_2)^{\alpha}$ = 1- [(1- FPro $(A)^{\alpha}$) * (1- FPro $(B)^{\alpha}$) *(1- FPro $(C)^{\alpha}$) *(1- FPro $(D)^{\alpha}$) *(1- FPro $(E)^{\alpha}$) *(1- FPro $(F)^{\alpha}$) *(1- FPro $(G)^{\alpha}$) *(1- FPro $(H)^{\alpha}$) *(1- FPro $(I)^{\alpha}$) *(1- 0) *(1- FPro $(K)^{\alpha}$) *(1- FPro $(L)^{\alpha}$) *(1- FPro $(M)^{\alpha}$) *(1- FPro $(N)^{\alpha}$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	42		98
0.05	44		98
0.10	45		98
0.15	47		98
0.20	48		97
0.25	49		97
0.30	50		97
0.35	52		97
0.40	53		96
0.45	54		96
0.50	55		96
0.55	56		95
0.60	58		95
0.65	59		94
0.70	60		94
0.75	61		93
0.80	62		93
0.85	63		92
0.90	64		92
0.95	65		91
1.00	66		90

$TE_2 = \frac{66+90}{2} = 78\%$

Top event fuzzy probability (TE_2) after removing basic event (K)

$FPro\ (TE_2)^{\alpha} = 1- [(1- FPro\ (A)^{\alpha}) * (1- FPro\ (B)^{\alpha}) *(1- FPro\ (C)^{\alpha}) *(1- FPro\ (D)^{\alpha}) *(1- FPro\ (E)^{\alpha}) *(1- FPro\ (F)^{\alpha}) *(1- FPro\ (G)^{\alpha}) *(1- FPro\ (H)^{\alpha}) *(1- FPro\ (I)^{\alpha}) *(1- FPro\ (J)^{\alpha}) *(1- 0) *(1- FPro\ (L)^{\alpha}) *(1- FPro\ (M)^{\alpha}) *(1- FPro\ (N)^{\alpha})]$

α	Lower Bound (%)		Upper Bound (%)
0.00	42		98
0.05	44		98
0.10	45		98
0.15	47		98
0.20	48		97
0.25	49		97
0.30	50		97
0.35	52		97
0.40	53		96
0.45	54		96
0.50	55		96
0.55	56		95
0.60	58		95
0.65	59		94
0.70	60		94
0.75	61		93
0.80	62		93
0.85	63		92
0.90	64		92
0.95	65		91
1.00	66		90

$TE_2 = \frac{66+90}{2} = 78\%$

Top event fuzzy probability (TE_2) after removing basic event (L)

FPro $(TE_2)^\alpha$ = 1- [(1- FPro $(A)^\alpha$) * (1- FPro $(B)^\alpha$) *(1- FPro $(C)^\alpha$) *(1- FPro $(D)^\alpha$) *(1- FPro $(E)^\alpha$) *(1- FPro $(F)^\alpha$) *(1- FPro $(G)^\alpha$) *(1- FPro $(H)^\alpha$) *(1- FPro $(I)^\alpha$) *(1- FPro $(J)^\alpha$) *(1- FPro $(K)^\alpha$) *(1- 0) *(1- FPro $(M)^\alpha$) *(1- FPro $(N)^\alpha$)]

α	Lower Bound (%)		Upper Bound (%)
0.00	39		97
0.05	41		97
0.10	42		97
0.15	43		97
0.20	45		96
0.25	46		96
0.30	47		96
0.35	48		95
0.40	50		95
0.45	51		95
0.50	52		94
0.55	53		94
0.60	54		93
0.65	55		93
0.70	56		92
0.75	57		92
0.80	58		91
0.85	59		91
0.90	60		90
0.95	61		89
1.00	62		88

$TE_2 = \frac{62+88}{2} = 75\%$

Top event fuzzy probability (TE_2) after removing basic event (M)

$FPro\,(TE_2)^{\alpha} = 1- [(1- FPro\,(A)^{\alpha}) * (1- FPro\,(B)^{\alpha}) *(1- FPro\,(C)^{\alpha}) *(1- FPro\,(D)^{\alpha}) *(1- FPro\,(E)^{\alpha}) *(1- FPro\,(F)^{\alpha}) *(1- FPro\,(G)^{\alpha}) *(1- FPro\,(H)^{\alpha}) *(1- FPro\,(I)^{\alpha}) *(1- FPro\,(J)^{\alpha}) *(1- FPro\,(K)^{\alpha}) *(1- FPro\,(L)^{\alpha}) *(1- 0) *(1- FPro\,(N)^{\alpha})]$

α	Lower Bound (%)		Upper Bound (%)
0.00	42		98
0.05	44		98
0.10	45		98
0.15	47		98
0.20	48		98
0.25	49		97
0.30	51		97
0.35	52		97
0.40	53		96
0.45	54		96
0.50	56		96
0.55	57		95
0.60	58		95
0.65	59		95
0.70	60		94
0.75	61		94
0.80	62		93
0.85	63		93
0.90	64		92
0.95	65		92
1.00	66		91

$TE_2 = \frac{66+91}{2} = 79\%$

Top event fuzzy probability (TE_2) after removing basic event (N)

FPro $(TE_2)^{\alpha}$ = 1- [(1- FPro $(A)^{\alpha}$) * (1- FPro $(B)^{\alpha}$) *(1- FPro $(C)^{\alpha}$) *(1- FPro $(D)^{\alpha}$) *(1- FPro $(E)^{\alpha}$) *(1- FPro $(F)^{\alpha}$) *(1- FPro $(G)^{\alpha}$) *(1- FPro $(H)^{\alpha}$) *(1- FPro $(I)^{\alpha}$) *(1- FPro $(J)^{\alpha}$) *(1- FPro $(K)^{\alpha}$) *(1- FPro $(L)^{\alpha}$) *(1- FPro $(M)^{\alpha}$) *(1- 0)]

α	Lower Bound (%)		Upper Bound (%)
0.00	39		97
0.05	41		97
0.10	42		97
0.15	43		97
0.20	45		96
0.25	46		96
0.30	47		96
0.35	48		95
0.40	50		95
0.45	51		95
0.50	52		94
0.55	53		94
0.60	54		93
0.65	55		93
0.70	56		92
0.75	57		92
0.80	58		91
0.85	59		91
0.90	60		90
0.95	61		89
1.00	62		88

$TE_2 = \frac{62+88}{2}$ = 75%

Appendix XI- Failure of Mitigation (1) – (T1) Fuzzy Probability Calculations

Alpha cut representation of basic event (A)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$* \, Upper \; Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower \; Bound = \; d - (d - c) * \alpha$

According to Figure 5-3, the membership function of "medium" probability is represented as follows:

	a	b	c	d
Basic Event A	0.05	0.10	0.22	0.33

Alpha cut representation of basic event (B)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$$

$$** \, Lower\ Bound = \ d - (d - c) * \alpha$$

According to Figure 5-3, the membership function of “medium” probability is represented as follows:

	a	b	c	d
Basic Event B	0.05	0.10	0.22	0.33

(1- FPro $(A)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.79

(1- FPro (B)$^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.79

$$FPro(T1)^{\alpha} = 1- [(1- FPro(A)^{\alpha}) * (1- FPro(B)^{\alpha})]$$

α	Lower Bound %		Upper Bound %
0.00	10		55
0.05	10		54
0.10	11		54
0.15	11		53
0.20	12		52
0.25	12		51
0.30	13		50
0.35	13		50
0.40	14		49
0.45	14		48
0.50	14		47
0.55	15		46
0.60	15		45
0.65	16		45
0.70	16		44
0.75	17		43
0.80	17		42
0.85	18		41
0.90	18		40
0.95	19		39
1.00	19		38

$$T1 = \frac{19+38}{2} = 29\%$$

Appendix XII- Failure of Mitigation (2) – (T2) Fuzzy Probability Calculations

Alpha cut representation of basic event (C)

α	Lower Bound *		Upper Bound **
0.00	0.22		0.67
0.05	0.22		0.66
0.10	0.23		0.65
0.15	0.23		0.64
0.20	0.24		0.64
0.25	0.24		0.63
0.30	0.25		0.62
0.35	0.26		0.61
0.40	0.26		0.60
0.45	0.27		0.59
0.50	0.27		0.59
0.55	0.28		0.58
0.60	0.28		0.57
0.65	0.29		0.56
0.70	0.30		0.55
0.75	0.30		0.54
0.80	0.31		0.53
0.85	0.31		0.53
0.90	0.32		0.52
0.95	0.32		0.51
1.00	0.33		0.50

$* \, Upper \; Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower \; Bound = \; d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “high” probability is represented as follows:

	a	b	c	d
Basic Event A	0.22	0.33	0.50	0.67

Alpha cut representation of basic event (D)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower\ Bound = \ d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “medium” probability is represented as follows:

	a	b	c	d
Basic Event B	0.05	0.10	0.22	0.33

(1- FPro $(C)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.78		0.33
0.05	0.78		0.34
0.10	0.77		0.35
0.15	0.77		0.36
0.20	0.76		0.36
0.25	0.76		0.37
0.30	0.75		0.38
0.35	0.74		0.39
0.40	0.74		0.40
0.45	0.73		0.41
0.50	0.73		0.42
0.55	0.72		0.42
0.60	0.72		0.43
0.65	0.71		0.44
0.70	0.70		0.45
0.75	0.70		0.46
0.80	0.69		0.47
0.85	0.69		0.47
0.90	0.68		0.48
0.95	0.68		0.49
1.00	0.67		0.50

(1- FPro $(D)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.79

$$FPro\ (T2)^{\alpha} = 1- [(1- FPro\ (C)^{\alpha}) * (1- FPro\ (D)^{\alpha})\ ]$$

α	Lower Bound %		Upper Bound %
0.00	25		78
0.05	26		77
0.10	27		76
0.15	28		76
0.20	28		75
0.25	29		74
0.30	30		73
0.35	31		72
0.40	31		72
0.45	32		71
0.50	33		70
0.55	33		69
0.60	34		68
0.65	35		67
0.70	36		66
0.75	36		65
0.80	37		64
0.85	38		64
0.90	38		63
0.95	39		62
1.00	40		61

$$T2 = \frac{40+61}{2} = 50\%$$

Appendix XIII- Failure of Mitigation (3) – (T3) Fuzzy Probability Calculations

Alpha cut representation of basic event (E)

α	Lower Bound *		Upper Bound **
0.00	0.00		0.10
0.05	0.00		0.10
0.10	0.00		0.10
0.15	0.00		0.09
0.20	0.00		0.09
0.25	0.00		0.09
0.30	0.00		0.09
0.35	0.00		0.08
0.40	0.00		0.08
0.45	0.00		0.08
0.50	0.01		0.08
0.55	0.01		0.07
0.60	0.01		0.07
0.65	0.01		0.07
0.70	0.01		0.07
0.75	0.01		0.06
0.80	0.01		0.06
0.85	0.01		0.06
0.90	0.01		0.06
0.95	0.01		0.05
1.00	0.01		0.05

$* \, Upper \ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower \ Bound = \ d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “low” probability is represented as follows:

	a	b	c	d
Basic Event A	0	0.01	0.05	0.10

Alpha cut representation of basic event (F)

α	Lower Bound *		Upper Bound **
0.00	0.05		0.33
0.05	0.05		0.32
0.10	0.06		0.32
0.15	0.06		0.31
0.20	0.06		0.31
0.25	0.06		0.30
0.30	0.07		0.30
0.35	0.07		0.29
0.40	0.07		0.28
0.45	0.07		0.28
0.50	0.08		0.27
0.55	0.08		0.27
0.60	0.08		0.26
0.65	0.08		0.26
0.70	0.09		0.25
0.75	0.09		0.24
0.80	0.09		0.24
0.85	0.09		0.23
0.90	0.10		0.23
0.95	0.10		0.22
1.00	0.10		0.22

$* \, Upper\ Bound = \mathrm{a} + (\mathrm{b} - \mathrm{a}) * \alpha$

$** \, Lower\ Bound = \ d - (d - c) * \alpha$

According to Figure 5-3, the membership function of “medium” probability is represented as follows:

	a	b	c	d
Basic Event B	0.05	0.10	0.22	0.33

(1- FPro $(E)^{\alpha}$)

α	Lower Bound		Upper Bound
0.00	1.00		0.90
0.05	1.00		0.90
0.10	1.00		0.91
0.15	1.00		0.91
0.20	1.00		0.91
0.25	1.00		0.91
0.30	1.00		0.92
0.35	1.00		0.92
0.40	1.00		0.92
0.45	1.00		0.92
0.50	1.00		0.93
0.55	0.99		0.93
0.60	0.99		0.93
0.65	0.99		0.93
0.70	0.99		0.94
0.75	0.99		0.94
0.80	0.99		0.94
0.85	0.99		0.94
0.90	0.99		0.95
0.95	0.99		0.95
1.00	0.99		0.95

$(1- FPro (F)^{\alpha})$

α	Lower Bound		Upper Bound
0.00	0.95		0.67
0.05	0.95		0.68
0.10	0.95		0.68
0.15	0.94		0.69
0.20	0.94		0.69
0.25	0.94		0.70
0.30	0.94		0.70
0.35	0.93		0.71
0.40	0.93		0.72
0.45	0.93		0.72
0.50	0.93		0.73
0.55	0.92		0.73
0.60	0.92		0.74
0.65	0.92		0.74
0.70	0.92		0.75
0.75	0.91		0.76
0.80	0.91		0.76
0.85	0.91		0.77
0.90	0.91		0.77
0.95	0.90		0.78
1.00	0.90		0.79

$$FPro(T3)^{\alpha} = 1 - [(1 - FPro(E)^{\alpha}) * (1 - FPro(F)^{\alpha})]$$

α	Lower Bound %		Upper Bound %
0.00	5		40
0.05	5		39
0.10	6		38
0.15	6		38
0.20	6		37
0.25	6		36
0.30	7		36
0.35	7		35
0.40	7		34
0.45	8		33
0.50	8		33
0.55	8		32
0.60	9		31
0.65	9		31
0.70	9		30
0.75	9		29
0.80	10		28
0.85	10		28
0.90	10		27
0.95	11		26
1.00	11		25

$$T3 = \frac{11+25}{2} = 18\%$$

Appendix XIV- Risk Criticality Analyzer and Fuzzy Reliability Analyzer Contribution Validation

Name (Optional):

Position:

Years of Experience:

You were given the following two options (numerical scale versus linguistic scale) to assess probability of occurrence, impact, and level of detection/ control of risk. Please select which option that is more preferable to conduct your assessment and provide reason behind your choice.

Table 1. Option 1- Probability of occurrence (P) rating evaluation criteria

Rating	Description
1	Failure is unlikely.
2–3	Only isolated failures associated with almost identical
4–6	Failure of similar processes that have experienced occasional failures, but not in minor operations.
7–8	Failure associated with similar processes that have often
9–10	Failure is almost inevitable.

Table 2. Option2- Probability of occurrence

Linguistic term	Probability of occurrence (P)
Very High (VH)	> 67% (2/3) chance.
High (H)	Between 33%–67% (2/3) chance.
Medium (M)	Between 10%–33% (1/3) chance. Event may occur.
Low (L)	Between 1%–10% chance. Event is unlikely to occur.
Very Low (VL)	Less than 1% chance. Event is highly unlikely to occur.

Answer:

Why?

Table 3. Option1- Impact (I) rating evaluation criteria

Rating	Description
1	No effect
2–3	Slightly noticeable
4–6	Noticeable effect on subsystem
7–8	Effects on major system, but not on safety or government regulated compliance items
9–10	Effects on safety or involving noncompliance with government regulation

Table 4. Option 2-Impact (I) rating evaluation criteria

Terms	Impact categories		
	Cost	Time	Scope/quality
Very High (VH)	Cost increase is ≥ 10% of project cost.	In service date delayed ≥ 10% of project duration.	Project scope or quality does not meet business
High (H)	Cost increase is ≥ 7% and < 10% of project cost.	In service date delayed ≥ 7% and < 10% of project duration.	Scope changes or quality are unacceptable to project sponsor.
Medium (M)	Cost increase is ≥ 4% and < 7% of project cost.	In service date delayed ≥ 4% and < 7% of project duration.	Major areas of scope or quality are affected.
Low (L)	Cost increase is ≥ 1% and < 4% of project cost.	In service date delayed ≥ 1% and < 4% of project duration.	Few areas of scope or quality are affected.
Very Low (VL)	< 1% of project cost.	Insignificant schedule slippage.	Scope change is not noticeable/quality degradation is not noticeable.

Answer:

Why?

Table 5. Option 1-detection rating evaluation criteria

Rating	Description
10	Controls will not detect a defect.
9	Controls probably will not detect a defect.
7–8	Controls have a poor chance of detecting a defect.
5–6	Controls may detect a defect.
3–4	Controls have a good chance of detecting a defect.
1–2	Controls certainly will detect a defect.

Table 6. Option 2-Linguistic definition of detection/control (D)

Terms	Detection/control
Very Low (VL)	The project team was unable to identify a risk response strategy capable of detecting the risk event, controlling root causes, and controlling the consequence of the risk event.
Low (L)	The project team has identified a risk response strategy with a low chance of detecting the risk event, controlling the root causes, and controlling the consequence of the risk event.
Moderate (M)	The project team has identified a risk response strategy with a moderate chance of detecting the risk event, controlling the root causes, and controlling the consequence of the risk event.
High (H)	The project team has identified a risk response strategy with a high chance of detecting the risk event, controlling the root causes, and controlling the consequence of the risk event.
Very High (VH)	The project team has identified a risk response strategy that has been proven in the past to have high effectiveness in detecting the risk event, controlling the root causes, and controlling the consequence of the risk event.

Answer:

Why?

2- Given what we have presented so far, do you think that this system is transparent to track the results? Can we use this fuzzy expert system to educate new employees in this field?

3- Do you see any advantage of adding three dimensions, i.e., cost, time and quality to measure the impact versus using one dimension to assess the impact?

4- Is there is any value added of using linguistic scale to assess probability of occurrence, cost impact, time impact? What do you think about using numerical scale?

5- Consider that the (if then) rules in appendix (I) were changed to an Excel lookup table and used to calculate the RCN. Do you think that there is any value added of considering the use of a fuzzy expert system?

6- Do you think that this framework is a generic framework that can be applied elsewhere? If not, what is required to be modified to enhance this framework?

7- Do you think that combining event tree with fault tree can support other risk management activities? If so, can you please list some?

8- Do you think that ranking of root causes using fuzzy importance analysis is a value added compared to other approaches?

9- Please provide a comparison between Monte Carlo simulations to the concept presented using fuzzy reliability analyzer? Any value added?

10- In your view, do you think that the aggregated impact, i.e., the combination of cost, time, and quality, is better being calculated at the project level or the risk level? In other words, do we need to run fuzzy AHP analysis and revise the aggregated impact equation for every risk event in the risk register before calculating the risk criticality number (RCN) or just use a consistent weighting to calculate the aggregated impact for all the risk events? Why?

11- Risk criticality Analyzer does not consider safety impact and environmental impact in calculating the aggregated impact value. Do you consider this as one of the limitations of this study? Please support your answer with more details.