A FUZZY-BASED RISK ASSESSMENT METHODOLOGY FOR CONSTRUCTION PROJECT UNDER EPISTEMIC UNCERTAINTY

By

TARUN KUMER BISWAS

A thesis

submitted to the

Department of Industrial & Production Engineering,

Bangladesh University of Engineering and Technology

in partial fulfillment of the requirements

for the Degree

of

MASTER OF SCIENCE

in

Industrial & Production Engineering

March, 2018

Bangladesh University of Engineering and Technology, Bangladesh

CERTIFICATE OF APPROVAL

The thesis titled "**A FUZZY-BASED RISK ASSESSMENT METHODOLOGY FOR CONSTRUCTION PROJECT UNDER EPISTEMIC UNCERTAINTY**" submitted by Tarun Kumer Biswas, Student No. 1014082012, Session-October 2014, has been accepted as satisfactory in partial fulfillment of the requirements for the degree of Master of Science in Industrial & Production Engineering.

BOARD OF EXAMINERS

Kzaman

Dr. AKM Kais Bin Zaman
Professor and Head
Department of IPE, BUET, Dhaka

Chairman (Supervisor)

Parveen

Dr. Sultana Parveen
Professor
Department of IPE, BUET, Dhaka

Member

Sarwar 31.03.18

Dr. Ferdous Sarwar
Associate Professor
Department of IPE, BUET, Dhaka

Member

31-03-18

Dr. Mohammed Forhad Uddin
Professor
Department of Mathematics
BUET, Dhaka

Member (External)

ii

CANDIDATE'S DECLARATION

It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

Tarun Kumer Biswas

Date:

A FUZZY-BASED RISK ASSESSMENT METHODOLOGY FOR CONSTRUCTION PROJECT UNDER EPISTEMIC UNCERTAINTY

ABSTRACT

In this thesis, a methodology for construction projects risk assessment under epistemic uncertainty (i.e., uncertainty arising from lack of data/knowledge) has been proposed. In practice, as the sufficient data from historical sources for probabilistic analysis is quite difficult to obtain, qualitative risk assessment methodologies based on expert's judgments (i.e., using linguistic terms) are commonly used in construction industry. However, these insufficient probabilistic data combining with experts' judgments can be used in the risks evaluation process to reduce uncertainties and biasness. Since the assessment of risk is basically a measure of uncertainties, fuzzy reasoning technique can be an effective tool to deal with these uncertainties and capture the vagueness in the linguistic variables. Most of the existing risk analysis models have evaluated risks based on two factors: risk likelihood and risk severity. In all these methodologies developed so far, it has been assumed that the degrees of uncertainties (level of uncertainties) involved in individual risk event are equal. However, in practice, the degree of uncertainties that involved in each risk event may vary due to the variation in the availability or quality of data obtained from multiple sources (e.g., from experts' opinions and past data from similar projects). Therefore, evaluation of risks considering the degree of uncertainty involved in individual risk events may assist project manager in setting-up response strategies to mitigate threat to the project objectives. This thesis proposes a risk assessment methodology using triangular fuzzy numbering system to compute risk value by combining expert's opinion and insufficient historical data. A modified form of general ramp type fuzzy membership function for quantification of uncertainty range of each risk event and an extended VIKOR method for risks ranking with these uncertainty ranges have been proposed. The most notable difference with other fuzzy risk assessment methods is the use of algorithm to handle the uncertainties involved in individual risk event. An illustrative example on risk assessment of a building construction project is used to demonstrate the proposed methodology.

ACKNOWLEDGEMENT

First, the author would like to express his deepest gratefulness to the most benevolent and Almighty God, because without His grace and mercy it was quite impossible to complete this thesis. Then also would like to extend thanks to his family for their continuous inspiration, sacrifice and support to complete the thesis successfully.

The author expresses sincere respect and gratitude to his thesis supervisor Dr. AKM Kais Bin Zaman, Professor, Department of Industrial and Production Engineering, BUET, Dhaka-1000, under whose supervision this thesis has carried out. His guidance, valuable suggestions and inspirations throughout this work made the study possible.

The author also expresses his sincere gratitude to Dr. Sultana Parveen, Professor, Department of IPE, BUET, Dr. Ferdous Sarwar, Associate Professor, Department of IPE, BUET and Dr. Mohammed Forhad Uddin, Professor, Department of Mathematics, BUET, for their constructive remarks and kind evaluations of this research.

Finally, the author wishes to express deepest sense of gratitude to all of his colleagues and friends for their kind co-operations and inspirations provided during this research work.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

TFN	:	Triangular Fuzzy Number
MFs	:	Membership Functions
FIS	:	Fuzzy Inference System
RL	:	Risk Likelihood
RS	:	Risk Severity
RV	:	Risk Value
ORV	:	Overall Risk Value
WDS	:	Weights to the Data Source
TMF	:	Triangular Membership Function
PIS	:	Positive Ideal Solution
NIS	:	Negative Ideal Solution

CHAPTER 1

INTRODUCTION

1.1. Background of the study

Risk assessment procedure is composed of four steps of identifying, analyzing, evaluating, and managing the risks inherent in a project (Morote and Vila, 2011). In practice, construction project contains a mixture of qualitative and quantitative data. Subjective judgment is often used in the form of linguistic variable in risk analysis due to lack of data availability (Choi et al, 2004). Therefore, uncertainties in risk analysis may be attributed both to the inherent randomness in some variables (i.e., aleatory uncertainty) and to inadequate as well as imprecise data (i.e., epistemic uncertainty) (Choi and Mahadevan, 2008). In mathematical risk analysis models, it is generally assumed that all inputs are precisely known and the influence of epistemic uncertainty to the value of risk is not explicitly considered. However, in real-world situations, this deterministic assumption about inputs may lead to poor performance or project failure. Fuzzy reasoning technique provides a systematic tool to deal with uncertainties and to capture the vagueness in the linguistic variables.

There exists a large volume of work for risk assessment of construction projects. However, most of them attempted to compute risk magnitude considering two factors: Risk Likelihood (RL) and Risk Severity (RS) (Carr and Tah, 2001; Zeng et al., 2007; Morote et al., 2011). Kuo and Lu (2013) proposed a modified Fuzzy-MCDM method to structure and evaluate the risk factors for prioritizing risk events of construction project. A methodology for incorporating knowledge and experience of many experts into conventional risk assessment framework is introduced by Yildiz et al. (2014). Cho et al. (2002) designed a new form of fuzzy membership curve to consider the ranges of uncertainties involved in both probabilistic parameter estimation and subjective judgments. Most of the existing methods of risk assessment consider only single Risk Value (RV) for prioritizing or categorizing (e.g., critical, major, minor, negligible) risks, which is helpful in risk response to mitigate threats to the project objectives (Zeng et al., 2007; Tamosaitiene et al., 2013; Sohrabinejad and Rahimi, 2015; Haghshenas et al., 2016; Asan et al., 2016). However, in practice, the degree of uncertainty that involved in each risk event may vary due to the availability of data from multiple sources (e.g., from experts' opinion and statistical data of similar projects). Uncertainty is an integral part in any risk assessment process (Dutta, 2015), thus its quantification may help project manager in taking preventive actions.

Therefore, an approach to risk assessment for construction project that can quantify the RV incorporating their associated degree of uncertainty is needed. The current research is intended to develop a risk assessment methodology that will evaluate risks in terms of uncertainty range that represents the degree of uncertainties involved in each risk event.

1.2. Objectives with specific aims

The specific objectives of this research are-

- Development of a risk assessment model using fuzzy membership functions to deal with qualitative and quantitative data and capture the vagueness in the linguistic variables.
- Development of the formulations and algorithms to compute the risk magnitudes using fuzzy inference systems and their associated degrees of uncertainties using a modified form of fuzzy membership functions.
- Development of a methodology to prioritize risks based on risk magnitude and degree of uncertainties involved in individual risk that is needed to setup risk response strategies.

Therefore, the proposed research develops and demonstrates generalized methodologies and tools for risk assessment of construction project, which will provide decision support to engineers and project managers for achieving better performance and avoiding loss of project failure.

1.3. Outline of Methodology

The proposed research methodology is outlined below:

a) A framework for the representation of qualitative and quantitative data through triangular fuzzy membership functions has been developed.

b) Formulations and algorithms for the evaluation of risks magnitude through fuzzy inference system under epistemic uncertainty has been proposed based on the framework developed in (*a*).

c) A methodology using modified form of general ramp type fuzzy membership functions for quantification of degree of uncertainties involved in each risk event has been developed based on the framework developed in (*a*).

d) Finally, a methodology to categorize risks based on risk magnitudes and their associated degrees of uncertainties has been proposed, which will help to setup response strategies.

e) The proposed methodologies have been illustrated for an example problem (a real engineering problem).

1.4. Contributions of the present study

This thesis proposes a risk assessment methodology for construction project under epistemic uncertainty using fuzzy concept. The proposed model expresses each risk event with an interval number considering the degree of uncertainties that involved in individual risk event. The following four possible factors of uncertainties are considered to represent the degree of uncertainties involved in each risk event in risks assessment process. The uncertainty involved in probabilistic parameter estimations is basically due to (*i*) unreliable/ insufficient data or (*ii*) approximation in statistical analysis methods. On the other hand, the factors influencing the uncertainties in subjective judgments are: (*iii*) the complexity of work/conditions and (*iv*) the level of education and experience of the experts.

The proposed construction project risk assessment model can be characterized as follows:

a) The proposed risk assessment model evaluates risks considering both values of risk and their associated degrees of uncertainty involved in the individual risk event.

b) All the risks are evaluated under the consideration of epistemic uncertainty.

c) This approach allows the risk assessment team to handle both quantitative and qualitative data in risk evaluation process.

d) The model provides a ranking of the project risks based on uncertainty intervals.

1.5. Organization of the Thesis

This thesis paper has been organized in following manner. The first chapter of the thesis is entitled as “Introduction” containing background of the thesis, objectives, methodologies and contributions of present study. Chapter 2 presents the literature review of all the relevant topics of the thesis. In Chapter 3, the basic theory of fuzzy logics, linguistic variables, fuzzy membership curves, uncertainties in risk assessment and extend VIKOR method are outlined. The proposed fuzzy-based risk assessment methodology for construction project under epistemic uncertainty has been described in Chapter 4. Here, the details of the formulations and algorithms of the proposed model are described step by step. Chapter 5 illustrates the proposed methodology with a numerical example (a real engineering problem). Finally, in Chapter 6, the research has been concluded with the recommendations for future work for the practitioners and researchers.

CHAPTER 2

LITERATURE REVIEW

The construction industry is plagued by various risks which are often responsible for poor performance with increasing cost and time delay, even project failure (Zeng et al., 2007). Risk is inherent in all projects and it can never be eliminate completely, although can be managed to reduce its effects to an acceptable level. Therefore, a systematic and proactive risk management framework is needed to enhance the chance of success and improve their performance. All potential risks and uncertain factors should be identified at the initial phase and managed effectively for avoiding potential loss. Risk management is essential for good project management (Baloi and Price, 2003), which is concerned with identifying and assessing risk and applying corrective actions to mitigate it to an acceptable extent (Tohidi, 2011). The successful management of risk requires the identification of risks, assessment of risk magnitude and implementation of response strategies to reduce threats to the project objectives (Dikmen et al., 2006).

A risk is an uncertain future event that has negative impact on the project objectives, such as scope, schedule, cost or quality (Morote and Vila, 2010). Other definitions of risk are available in the literature, for example, “risk is the potential barrier for project completion and achieving goal” (Mark et al., 2004; Hertz and Thomas, 1994), “the possibility of financial losses, physical damages or injuries, delays and detrimental events occurring to the project” (Baloi and Price, 2003; Chapman and Ward, 1997; Jaafari, 2001), “negative deviation from desired level” (Dziadosz and Rejment, 2015). Although various researchers define risk in various ways, some common characteristics are found in all definitions. A risk is an uncertain future event that may or may not occur and if it occurs, has negative impact on the project objectives. In other words, it can be defined as the unexpected future events with the involvement of substantial uncertainties that have detrimental effects to the project objectives.

Risk is raised when there is uncertainty and these uncertainties are integral part in any risk assessment process (Carr and Tah, 2001; Olsson, 2007; Jha and Devaya, 2008; Dutta, 2015). Therefore, without considering the uncertainty that is associated with risks, the risk assessment process will remain inefficient. The uncertainty that involved in risk assessment process can be divided into two types: aleatory uncertainty and epistemic uncertainty (Choi and Mahadevan, 2008). In real-life problems, both types of uncertainties should be accounted for in risk analysis process (Ang and Tang, 2006; Choi and Mahadevan, 2008). Aleatory uncertainty is irreducible and also known as random uncertainty. It refers to the inherent randomness that comes from natural variability. On the other hand, epistemic uncertainty is reducible and often arises from limited or imprecise data, measurement limitations and approximations in mathematical model. By gathering more information and precise data, these types of uncertainty can be reduced. In literature, epistemic uncertainty previously has been expressed by probability distributions (Zaman et al., 2011), subjective probabilities (O'Hagan and Oakley, 2004), fuzzy sets (Fetz and Oberguggenberger, 2004), etc. The construction project risk assessment methodology considering epistemic uncertainty has been developed using different paradigms to treat uncertainty including fuzzy set theory (Cho et al., 2002; Choi et al., 2004), interval probability theory (Cui and Blockley, 1990), fuzzy event tree analysis (Hadipriono et al., 1986), and merging probability theory and subjective information (Brown, 1980; Choi et al., 2008).

Construction project risk assessment

Construction project is associated with greater inherent risks due to the involvement of many stakeholders (Serpell et al., 2015). There are many risk sources and factors involved in construction projects that should be identified and assessed for effective risk managements. In risk analysis process, there exists both qualitative and quantitative data. Basically, risk related data are found from experts' opinions in the qualitative form and from historical records in the quantitative form. However, in many circumstances, for construction project, it is very hard to obtain sufficient amount of risk data from historical sources due to its non-routine and unique characteristics. Due to the scarcity of sufficient data for probabilistic analysis, construction project risks are being managed based on experts' judgments and experiences (Zeng et al., 2007). Therefore, the data type for risk studies is mostly qualitative rather quantitative (Islam and Nepal, 2016). Note that this qualitative data may induce imprecision and biasness in the decision-making process (Sadiq and Husain, 2005). Moreover, these qualitative data are often found as linguistic variables. Linguistic variable can be defined as variable which can take words in natural language as its value such as "High/Low", "Good/Bad" or "Major/Minor", etc. These linguistic variables express imprecise and vague information instead of sharp numerical values. In these situations, the risk assessment cannot be exact but approximate. Fuzzy set theory (Zadeh, 1965) provides an effective tool to quantify or capture the vagueness in the linguistic variables. However, depending on the data types, availability and sources, both probabilistic and subjective judgments can be used in risk analysis process simultaneously. Due to its suitability for handling both quantitative and qualitative data, fuzzy logic has been used in risk assessment process for a long time (Zeng et al., 2007; Morote and Vila, 2010; Choi et al., 2004; Islam and Nepal, 2016; Sadiq and Husain, 2005). Concepts other than fuzzy logic have also been used in risk management over the last two decades, such as MCDM approach, (Tamosaitene et al., 2013; Zoffani et al., 2016; Erdogan et al., 2016; Zavadskas et al., 2009), Fault tree analysis/Event tree analysis (Hadipriono et al., 1986), Influence diagram (Dikmen et al., 2006), Brain storming, Merging fuzzy with MCDM tools (Lin and Jianping, 2011; Haghshenas et al., 2016), etc. In real-life problem, though it is very hard to obtain sufficient statistical data, it may be possible to evaluate risk using these insufficient data merging with subjective judgements. A very few researchers have attempted to develop their risk assessment models using data from both sources: probabilistic analysis on historical data and subjective judgments from experts (Cho et al., 2002; Choi et al., 2008).

In literature, different researchers have proposed different models or techniques for assessing, handling and managing risk in construction project. All these methodologies developed so far use different algorithms and theories for formulating risk assessment models, which are applicable to different situations and conditions. A statistical risk assessment model for construction project based on quantitative data obtained as a result of questionnaire survey is proposed by Khodeir et al. (2015). Beside this, numerous researches based on statistical analysis are also available in the literature (Zubaidi and Otaibi, 2008; Deng and Zhou, 2010; Andi, 2006; Dada and Jagboro, 2007; Zou and Zhang, 2009; Kululanga and Koutcha, 2010; Manelele and Muya, 2008). These models provide quite good results but they require high quality and sufficient data. Islam and Nepal (2016) proposed a Fuzzy-Bayesian model for making realistic budget and avoiding cost overrun by identifying the critical risk in the preliminary stage of the project life-cycle. They used expert's judgments for developing the model with Bayesian belief networks, which overcome the drawback of biasness in subjective judgments. Another risk evaluating methodology was developed by Park et al. (2016) considering degree of change for mega projects. They showed how risk factors are changed simultaneously over time and its impact on projects. Belay et al. (2016) introduced a knowledge management algorithm based on conceptual learning and sharing matrix for concurrent construction projects. Zoffani et al. (2016)

developed a hybrid Multi-Criteria Decision Making (MCDM) model to evaluate construction project risk regarding environmental sustainability. Purnus and Bodea (2015) described an educational simulation-based method to assess financial risk of a construction project. Toth and Sebestyen (2015) formulated a model to control the risk changing with time, based on value-based risk monitoring. Wang and Elhag (2007) proposed a risk assessment methodology that allows experts to evaluate risk factors, in terms of occurrence probabilities and consequences of risks. All these existing models are developed under aleatory uncertainty alone, which leads poor performance in practice as real-life problem includes both aleatory and epistemic uncertainty. These models are also found incapable of handling epistemic uncertainty and complex relationship among the risk factors properly. Therefore, as the epistemic uncertainty is reducible, this must be incorporated into risk assessment framework for better performance in practice.

Risk assessment models considering uncertainty

Several studies on the construction project risk assessment are reported in the literature to deal with uncertainty. A model for risk assessment considering associated uncertainty was developed by Zeng et al. (2007), based on fuzzy reasoning and Analytic Hierarchy Process (AHP). A Factor Index was introduced in this risk analysis process to evaluate all possible uncertainty associated with two parameters: risk likelihood and risk severity. However, the biasness in subjective judgments is ignored in this model, therefore, evaluation of uncertainty is still not fully covered. Asan et al. (2014) proposed a fuzzy prioritizing approach to project risk management considering the uncertainty raised from subjective judgments. This model gives satisfactory results in respect of handling biasness in subjectivities but still incapable to handle modeling uncertainty. Lu and Tzeng (2002) formulated a risk assessment model based on AHP and Fuzzy-MCDM approach. This work employed AHP to determine the weights of risk factors and Fuzzy-MCDM approach to synthesize the degree of risk of each activity. The uncertainties factors were not explicitly considered in this risk analysis model. A risk assessment framework for construction projects was proposed by Wang et al. (2004), particularly for developing countries. The research utilized literature review, international survey, interviews and discussions to interpret statistical analysis, mean criticality and standard deviation to develop the model. The model is capable of categorizing risks better and represents the influence relationship among risks at different hierarchy levels. Morote and Vila (2010) developed a risk assessment methodology using trapezoidal fuzzy membership function to capture the vagueness in the linguistic variable obtained from expert's judgments. They used an algorithm to handle the inconsistencies in the fuzzy preference relation when pair-wise comparison judgments are necessary. Though in this model, uncertainties in subjective judgments are considered in computing risk value, its uncertainty factors are still not explicitly expressed. Cho et al. (2002) designed a new form of fuzzy membership curve to represent the degree of uncertainty involved with occurrence probability of a risk event. However, uncertainties or subjectivities are involved in computation of both RL and RS. Therefore, the risk values are calculated ignoring the uncertainties that are associated with the evaluation of risk severity. Choi et al. (2008) developed a risk assessment model for construction projects by combining existing data and project specific information. This model minimizes the uncertainty to a certain level but not significantly because sources of uncertainty in risk analysis are not unique. Choi and Mahadevan, (2008) pointed that the uncertainties are involved in both probabilistic parameter estimations and subjective judgments. The uncertainty involved in probabilistic parameter estimations is basically due to (*a*) unreliable/ insufficient data or (*b*) approximation in statistical analysis methods. On the other hand, the factors influencing the uncertainties in subjective judgments are: (*a*) the complexity of work/conditions and (*b*) the level of education and experience of the experts.

Risks are basically assessed for prioritizing them in order to set-up risk response strategies against only to the higher order risks because of the limitations of time and cost. The risk response strategies are concerned with developing options and actions to enhance opportunities and to reduce threats to the project objectives (Morote and Vila, 2010). Most of the researchers attempted to compute risk magnitude to prioritize them considering two factors: occurrence probability and severity of risk (Zeng et al. 2007; Morote and Vila, 2010; Choi et al., 2004). None of the proposed risk assessment methodologies take into account the degree of uncertainty involved in the individual risk event. However, in practice, the degree of uncertainty that involved in each independent risk event may vary due to the availability of data from multiple sources (e.g., from experts' opinion and statistical data from similar projects). Therefore, computation of uncertainty range of individual risk event and ranking with uncertainty range may help project manager in better understanding of risk and taking preventive actions to mitigate risk impacts.

Decision with uncertainty intervals

In the uncertain environment where exist imprecise and insufficient data, interval-valued numbers are the simplest way of representing uncertainty in the decision-making problems. Since the assessment of risk is basically the measure of uncertainty, it is difficult or even impossible to express the risk with exact point value. Therefore, in this situation, it is more appropriate to express them as intervals. When a risk parameter is specified by an interval, it does not indicate which value is most likely to occur but it can take any value from within the interval (Sayadi et al., 2009). Numerous methods for ranking with interval numbers are available in the literature. Song et al. (2012) proposed a two-grade approach for ranking with interval data using a dominance degree and an entire dominance degree. Here, in a dominance degree, two objects are compared under an attribute whereas in entire dominance degree, all considered attributes are used to compare them. Another method for ranking interval data using Monte Carlo concept is developed by Jahanshaloo et al. (2008). Various methods are developed over the last decade for finding best alternative in multicriteria decision making problems based on interval-valued intuitionistic fuzzy sets theory (Nayagam et al., 2011; Chen et al., 2011; Sivaraman et al., 2014). Jahanshaloo et al. (2014) proposed an extension on TOPSIS (i.e. Technique for Order of Preference by Similarity to Ideal Solution) method to solve multicriteria decision making problems with interval data. This method is more suitable for the risk avoider (i.e., pessimist) decision makers, because it is based on the principle that optimal point should have the farthest distance from negative ideal solution (NIS). Another extension on VIKOR method based on the particular measure of "closeness" to the positive ideal solution (PIS) is proposed by Sayadi et al. (2009). This method is a bit different from the extended TOPSIS method based on the principle and it is more suitable for profit seeking (i.e., optimist) decision maker.

Although there is now an extensive volume of work available for ranking methods with interval numbers, all these methods have only been studied with respect to the decision-making problems. However, this concept may also be employed in construction project risk assessment process. Since the construction project is associated with the substantial epistemic uncertainties, interval number can be the way of representing the degree of uncertainties involved in each risk event. In all the risk assessment methodologies developed so far, it has been assumed that the degrees of uncertainties involved in individual risk event are equal. However, in practice, the degrees of uncertainties involved in each risk event may vary due to the variations in availability or quality of data. None of the existing risk assessment methods take into account the degree of uncertainties that involved among different risk events as a variable factor and interval number to express risk value. Therefore, there is a need for an efficient risk assessment methodology that evaluates construction project risks with interval numbers considering the degree of uncertainty involved in each risk event.

This research proposes a methodology for risk assessment of construction project using fuzzy concept under epistemic uncertainty. The proposed method evaluates construction project risks in terms of uncertainty interval that represents the degree of uncertainties involved in individual risk. It also provides a risk ranking based on these uncertainty intervals. In the following chapters, this study develops and demonstrates generalized methodologies and tools for risk assessment of construction projects that will provide decision support to the engineers and project managers to mitigate threat to the project objectives.

CHAPTER 3

THEORETICAL FRAMEWORK

3.1. Fuzzy Set Theory

The fuzzy set theory was first introduced by Professor Lotfi A. Zadeh in 1965. Later in 1973, he introduced linguistic variables into fuzzy sets in order to capture the fuzziness that exists in human judgment, evaluation and decisions. The notion of fuzzy set theory provides a mathematical framework in which the vague conceptual phenomena can be precisely and rigorously studied. It is well suited for the situation where there is no sharp boundary between success and failure (e.g., vagueness), for example, "less than" or "more than" type rather than "yes/no" types. Instead of determining the sharp boundary as an ordinary set, fuzzy set defines no exact boundary.

Mathematically, a fuzzy set A within the universal set U in the interval [0, 1] can be defined as

$$A = \{(x, \mu_A(x)) | (x \in U\} \qquad (1)$$

where, $\mu_A(x)$ is called membership function, which maps each element x in U to a real number in the interval [0, 1]. The large function value of $\mu_A(x)$ indicates that the grade of membership of x in A is strong (Morote and Vila, 2011).

In the framework of fuzzy set theory, Zadeh (1973) introduced the concept of possibility measure and a possibility distribution. The axioms of fuzzy possibility measure for the finite universal sets (Nikolaidis et al. 2004) are given below:

a) The possibility of an event could be either 0 or 1. If false then $\pi(\o) = 0$, and if true then $\pi(\Omega) = 1$.

b) If two event A and B in the sample space satisfy the following condition $A \leq B$, then the possibility of even A is less or equal to the possibility of event B, that is $\pi(A) \leq \pi(B)$.

c) The possibility of union of mutually exclusive events (A_1, A_2, A_3, ….., A_n) is equal to the maximum value of these events' individual possibilities. That is.
$\prod (A_1 \text{ U } A_2 \text{ U } A_3 \ldots\ldots \text{U } A_n) = \text{Max } \{\pi (A_i)\}$, where $i = 1, 2, 3 \ldots\ldots n$.

d) Similarly, the possibility of intersection of mutually exclusive events (A_1, A_2, A_3, ….., A_n) is equal to the minimum value of these events' individual possibilities. That is,

$\prod (A_1 \cap A_2 \cap A_3 \ldots\ldots \cap A_n) = \text{Min } \{\pi (A_i)\}$, where i =1, 2, 3……n.

By the extension principle of fuzzy set theory (Zadeh, 1965), the arithmetic operations of any two Triangular Fuzzy Numbers (TFNs) are as follow:

Fuzzy addition operation:

$$A_1 \oplus A_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \qquad (2)$$

For fuzzy subtraction operation:

$$A_1 \Theta A_2 = (a_1 - c_2, b_1 + b_2, c_1 - a_2) \qquad (3)$$

For fuzzy multiplication operation:

$$A_1 \otimes A_2 = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2) \qquad (4)$$

For fuzzy division operation:

$$A_1 \phi A_2 = (a_1/c_2, b_1/b_2, c_1/a_2) \qquad (5)$$

In case of fuzzy addition or subtraction of any Triangular Fuzzy Number (TFN), the resulting fuzzy number is also a TFN. However, fuzzy multiplication and fuzzy division operations provide only an approximate of a TFN.

3.2. Fuzzy Membership Function

Every fuzzy set contains values of a fuzzy variable and its membership function. This membership function is basically a curve that defines how the values of a fuzzy variable are mapped to a degree of membership to an interval of [0, 1]. Membership Functions (MFs) can take any form, but there are some common examples that appear in real applications. There are various types or shapes of fuzzy membership curves- Gaussian, triangular, trapezoidal, piecewise-linear, S-shaped, bell-shaped, etc. These fuzzy membership curves or functions may either be arbitrarily chosen by the user, based on the user's experience or be designed using machine learning methods (e.g., artificial neural networks, genetic algorithms, etc.). In Figure 1, a Triangular Membership Function (TMF) is shown, where a, b and c represent the x coordinates of the three vertices of $\mu_A(x)$ in a fuzzy set A. Here, a and c represent the lower and upper bounds, respectively, where the degree of membership is zero and b denotes the peak point at centre where the degree of membership is 1.

$$\mu_A(x)=\begin{cases} 0 & if\ x \le a \\ \dfrac{x-a}{b-a} & if\ a \le x \le b \\ \dfrac{c-x}{c-b} & if\ b \le x \le c \\ 0 & if\ x \ge c \end{cases}$$

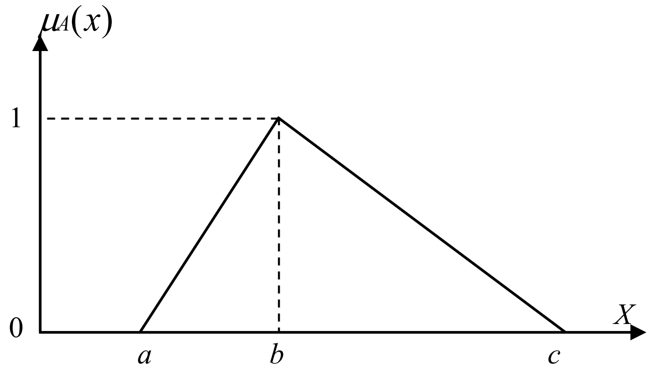

Figure 1: Triangular fuzzy membership function

3.3. Linguistic Variable

In 1973, Professor Lotfi L. Zadeh introduced the concept of linguistic variables in fuzzy logic. Qualitative risk assessment methods are still based on linguistic variables that are often obtained from expert's subjective judgment. Linguistic variable may be defined as a variable which can take words in natural languages as its value. For example, the occurrence probability of risk (i.e., RL) or RS can be expressed with five simple linguistic terms like "Very High", "High", "Medium" "Low", and "Very Low", etc. rather than a sharp numerical value. Here, each linguistic term represents a range of risk occurrence probability rather than crisp value. The value range of each linguistic term is usually defined by the risk assessment team at the beginning stage of fuzzy process.

3.4. Uncertainty in Risk assessment

Uncertainty may be defined as a situation which involves imperfect, imprecise and/or unknown information. Risk is fully concerned with uncertainty (e.g., the more uncertainty, the more involvement of risk). Therefore, uncertainty always exists in any risk assessment process that must be considered in risk analysis process.

In real world situation, uncertainty in risk analysis arises from several different sources that must be identified for controlling purpose. Halder and Mahadevan (2000) discussed that the uncertainties in a system may come from cognitive (qualitative) and non-cognitive (quantitative) sources. They further classified these non-cognitive or quantitative sources of uncertainty into three major groups. The first source is the inherent randomness in all physical observations. For example, same physical quantity produces different values for repeated measurements due to natural variation in the environment. Limited or insufficient data availability leads to the second source of uncertainly, known as statistical uncertainty. The third type of uncertainty is referred to as modeling uncertainty. System analysis models are only approximate or partial representations of real world situation. Some idealizations or assumptions are made to capture the essential characteristics of system behavior in any computational models. Qualitative or cognitive sources of uncertainty relate to the haziness of the problem arising from subjective judgments about reality. This uncertainty may depend on (*a*) the complexity level of the problem and (*b*) skills, knowledge, education and experience required to solve the problem. For the research purpose, these uncertainties may be classified into two broad types, namely *a*) uncertainty associated with randomness in phenomenon that is due to natural variability of the observed information, and *b*) uncertainty associated with imperfect models because of insufficient data (Choi and Mahadevan, 2008, Ang and Tang, 2006). These two types of uncertainty may be called aleatory and epistemic uncertainty, respectively. Aleatory uncertainty is irreducible where epistemic uncertainty may be reduced by gathering more precise or perfect information.

3.5. VIKOR method

The basic idea of VIKOR was initially developed by Serafim Opricovic in 1980 and became internationally known as VIKOR method later in 2004. The name VIKOR came from Serbian word "VIseKriterijumska Optimizacija I Kompromisno Resenje", which means multicriteria optimization and compromise solution. This method was originally designed to solve a discrete decision-making problem with non-commensurable and clashing criteria. However, over the years this method has been used by researchers who used it for ranking the alternatives in various MCDM problems with mild modifications. Sayadi et al., (2009) proposed an extended VIKOR method to solve the decision-making problem with interval data. Table 1 shows the decision matrix with interval numbers. It is seen that $A_1, A_2, \ldots, A_m$ are the possible alternatives which are to be ranked and $C_1, C_2, \ldots, C_n$ are the criteria with which alternative performances are to be measured. x_{ij}'s are the ratings of alternatives A_i with respect to criteria C_j.

Table 1: Decision matrix with interval data

	C_1	C_2	…	C_n
A_1	$[x_{11}^L, x_{11}^U]$	$[x_{12}^L, x_{12}^U]$	…	$[x_{1n}^L, x_{1n}^U]$
A_2	$[x_{21}^L, x_{21}^U]$	$[x_{22}^L, x_{22}^U]$	…	$[x_{2n}^L, x_{2n}^U]$
…	…	…	…	…
A_m	$[x_{m1}^L, x_{m1}^U]$	$[x_{m2}^L, x_{m2}^U]$		$[x_{mn}^L, x_{mn}^U]$

The necessary steps for ranking with the extended VIKOR method are given below:

Step 1: Determine the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS).

$$A^* = \{x_1^*, x_2^*, \dots x_n^*\} = \left\{\left(\max_i x_{ij}^U \mid j \in I\right) or \left(\min_i x_{ij}^L \mid j \in J\right)\right\}, j = 1,2,\dots.n \dots\dots\dots\dots\dots\dots (6a)$$

$$A^- = \{x_1^*, x_2^*, \dots x_n^*\} = \left\{\left(\min_i x_{ij}^L \mid j \in I\right) or \left(\max_i x_{ij}^U \mid j \in J\right)\right\}, j = 1,2,\dots.n \dots\dots\dots\dots\dots\dots (6b)$$

where, I denotes benefit criteria and J denotes cost criteria. $A^*$and $A^-$are PIS and NIS respectively.

Step 2: In this step, the $[S_i^L, S_i^U]$ and $[R_i^L, R_i^U]$intervals are calculated as below:

$$S_i^L = \sum_{j \in I} W_j \left(\frac{x_j^* - x_{ij}^U}{x_j^* - x_j^-}\right) + \sum_{j \in J} W_j \left(\frac{x_{ij}^L - x_j^*}{x_j^* - x_j^-}\right), \text{where}, i = 1,2\dots m \dots\dots\dots\dots\dots\dots (7a)$$

$$S_i^U = \sum_{j \in I} W_j \left(\frac{x_j^* - x_{ij}^L}{x_j^* - x_j^-}\right) + \sum_{j \in J} W_j \left(\frac{x_{ij}^U - x_j^*}{x_j^* - x_j^-}\right), \text{where}, i = 1,2\dots m \dots\dots\dots\dots\dots\dots (7b)$$

$$R_i^L = \max\left\{\left(W_j \left(\frac{x_j^* - x_{ij}^U}{x_j^* - x_j^-}\right) \middle| j \in I\right), \left(W_j \left(\frac{x_{ij}^L - x_j^*}{x_j^- - x_j^*}\right) \middle| j \in J\right)\right\}, \text{where}, i = 1,2,\dots.m \dots\dots\dots\dots (8a)$$

$$R_i^U = \max\left\{\left(W_j \left(\frac{x_j^* - x_{ij}^L}{x_j^* - x_j^-}\right) \middle| j \in I\right), \left(W_j \left(\frac{x_{ij}^U - x_j^*}{x_j^- - x_j^*}\right) \middle| j \in J\right)\right\}, \text{where}, i = 1,2,\dots.m \dots\dots\dots\dots (8b)$$

Step 3: Compute the interval Q_i=$[Q_i^L, Q_i^U]$; i = 1, 2… m, by the following equations:

$$Q_i^L = \nu \frac{(S_i^L - S^*)}{(S^- - S^*)} + (1-\nu) \frac{(R_i^L - R^*)}{(R^- - R^*)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (9a)$$

$$Q_i^U = v\frac{(S_i^U - S^*)}{(S^- - S^*)} + (1-v)\frac{(R_i^U - R^*)}{(R^- - R^*)} \quad \text{(9}b\text{)}$$

where,

$$S^* = \min_i S_i^L \text{, and } S^- = \max_i S_i^U \quad \text{(10}a\text{)}$$

$$R^* = \min_i R_i^L \text{, and } R^- = \max_i R_i^U \quad \text{(10}b\text{)}$$

where, v represents weight of the strategy of "the dominant part of criteria".

Step 4: Based on the VIKOR method, the alternative which has minimum Q_i is the best alternative and is chosen as compromise solution. However, here Qi, i =1, 2 ... m are interval numbers. To find the alternative with minimum interval number, pairwise comparisons are made. The following Step 5 shows the method for comparison of two interval numbers.

Step 5: Suppose that a minimum interval number have to be selected between two interval numbers like $[a^L, a^U]$ and $[b^L, b^U]$. Therefore, these two interval numbers may have four statuses:

(a) If there is no intersection between these two interval numbers, the minimum interval is that one which has lower values. In different words: if $a^U \leq b^L$, then interval $[a^L, a^U]$ is the minimum one.

(b) If two interval numbers are the same, then two have similar priority for us.

(c) In circumstances that $a^L \leq b^L < b^U \leq a^U$, the minimum interval number is computed as follows: if $\alpha(b^L - a^L) \geq (1-\alpha)(a^U - b^U)$, then $[a^L, a^U]$ is the minimum interval number, else $[b^L, b^U]$ is minimum interval number.

(d) In circumstances that $a^L < b^L < a^U < b^U$, and if $\alpha(b^L - a^L) \geq (1-\alpha)(b^U - a^U)$, then $[a^L, a^U]$ is the minimum interval number, else $[b^L, b^U]$ is minimum interval number.

Here, α is introduced as optimism level of the decision maker $(0 < \alpha \leq 1)$. The optimist decision maker has higher value of α than the pessimist decision maker. In this situation, the final ranking is obtained by the method of pairwise comparisons of interval numbers as discussed above.

Based on the theories described above, a risk assessment methodology for construction project under epistemic uncertainty is proposed in the next chapter.

CHAPTER 4

PROPOSED RISK ASSESSMENT MODEL

A typical risk management process consists of four steps: risk identification, risk assessment, risk response, and risk monitoring and controlling. It should cover all aspects of risks in construction project and demonstrate risks with potential causes, effects and their corrective actions. All the previously proposed fuzzy based risk assessment methodologies have three common steps as follows:

Step 1: *definition and fuzzification*- all the fundamental parameters are defined basically with vague data or linguistic terms and then these parameters are converted into suitable fuzzy numbers.

Step 2: *fuzzy inference system*- the relation between inputs and output parameters are defined by the appropriated fuzzy mathematical operations or *if-then* rules.

Step 3: *defuzzification*- the output result in the form of fuzzy number is converted into appropriate numerical value that can adequately represent it.

This thesis proposes a risk assessment model under epistemic uncertainty based on fuzzy concept as shown in Figure 2. In this risk assessment framework, the algorithm of risk model consists of four phases: preliminary phase, data collection phase, risk measurement phase, and uncertainty measurement phase. In brief, the risk assessment team must go through these four phases to implement the proposed construction project risk assessment model. The following four phases are basically concerned with the following tasks:

Phase 1: The review of risks data, definition of fuzzy linguistic variables and selection of their corresponding fuzzy membership function. Here, in this thesis, TFN is used to map the membership values to take the advantage of its simplicity and familiarity.

Phase 2: Identification of risks sources and gathering risk related information (e.g., RL or RS) from diversified sources to reduce biasness.

Phase 3: Application of the appropriate fuzzy operations for aggregation of data obtained from multiple sources and computation of risk value through FIS.

Phase 4: Determination of uncertainty range of each risk event by selecting appropriate fuzzy membership curves and prioritization of risk events based on their uncertainty ranges.

The details of the risk assessment methodology are described in the following sections of this chapter.

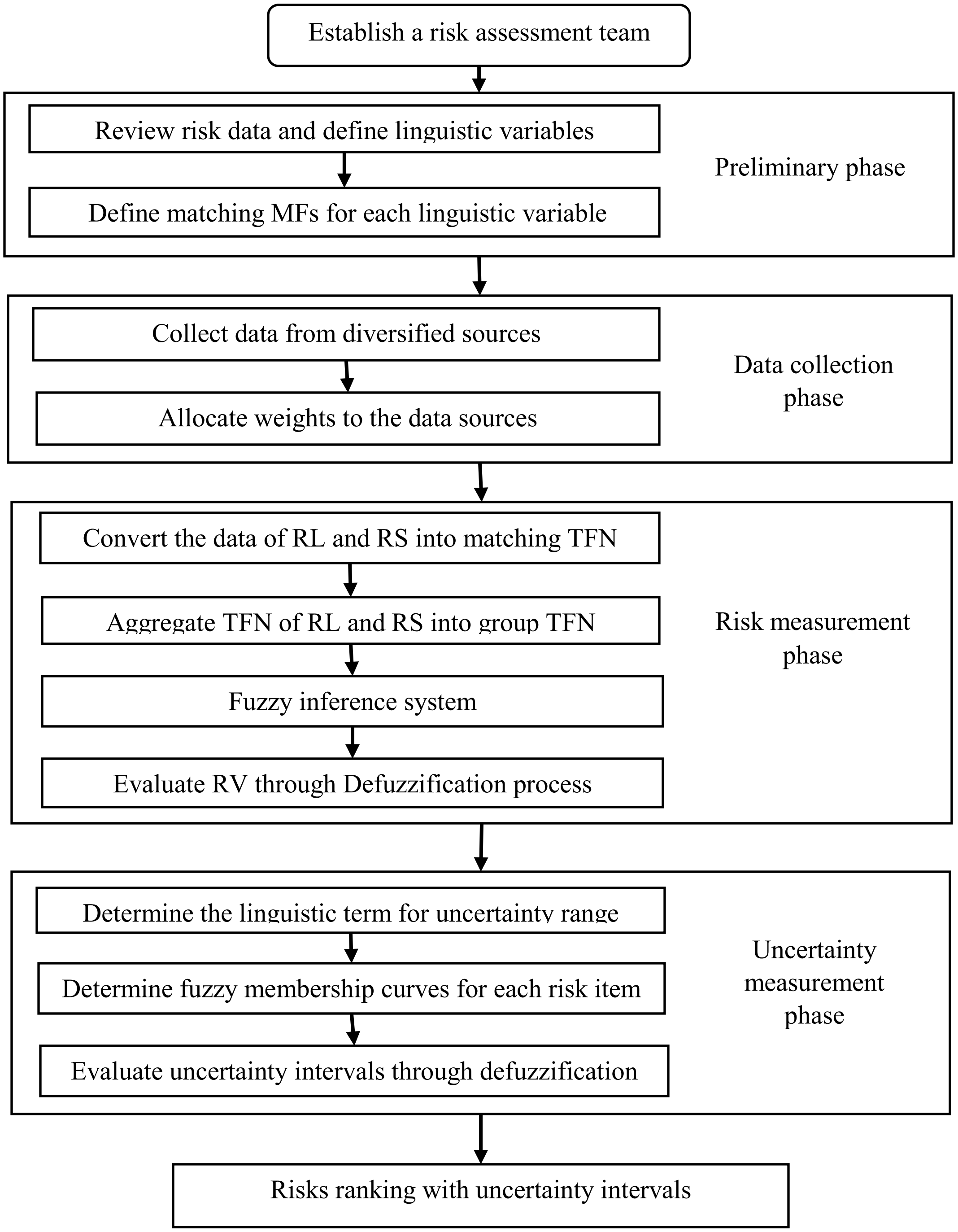

Figure 2: A fuzzy based risk assessment model

4.1. Preliminary Phase

4.1.1. Establish a risk assessment team

Risk assessment process is basically a team work and its success mainly depend on how well the risk assessment team is formed. Therefore, selection of members in the risk assessment team is very crucial and needs great attention of senior management. The team should be formed with the experts from different background and discipline and having a high degree of knowledge and previous experience of working in similar construction projects. This team may include the following experts: project managers, site engineers, construction managers, project team members, subject specialists, etc. The size of the team is also important; too big can create many opinions which often lead to lack of coordination and too small may lead to biasness due to incomplete viewpoints. The author claims that the perfect team size may vary from approximately 3 to 7 members depending on the project's type, size and length. The risk assessment team will undertake the review of risk data and information, identification of risk sources and determination of risk parameters.

4.1.2. Review risk data and define linguistic variables

All the members of risk assessment team are required to review the risk related information and should be clarified by themselves if they have any doubts about the risk assessment procedures. All the risk parameters such as RL, RS and associated linguistic variables should be defined by the risk assessment team at the very beginning of the risk assessment process. It is extremely difficult to quantify the construction project risks with an exact numerical value due to the involvement of greater uncertainties. If the risk assessment group has imprecise, imperfect or lack of information about risks associated with a project, then the assessment of risk cannot be exact but approximate. In these situations, the judgments of the risk assessment group members are expressed by means of linguistic terms instead of numerical values or real numbers. The variable which can take words in natural languages as its value is called linguistic variable. For example, the occurrence probability of a risk event can be expressed with simple linguistic terms such as "High", "Low", "Very Low", and "Very High", etc. instead of exact numerical values such as 2/10, 4/100, etc. For evaluating the risk parameters with this risk assessment model, RL and RS are defined by five linguistics terms: "Very low", "Low", "Medium", "High" and "Very high'.

4.1.3. Define matching MFs for each linguistic variable

The linguistics terms must be converted into a matching fuzzy number by using appropriate conversion scale for numerical quantification of risks. The linguistics variables are characterized by fuzzy membership functions defined in the universe of discourse in which the variable is defined. Various types of fuzzy membership functions are available, such as triangular, trapezoidal, Gaussian and S-shaped MFs. However, triangular and trapezoidal MFs are the most frequently used MFs in construction project risk analysis in practice because of its simplicity. Figure 3 shows the TFN for the associated linguistic variables of RS and RL. It is seen that the TFN for linguistic term “Very low” is (0, 0, 0.25), for “Low”, it is (0, 0.25, 0.5) and so on.

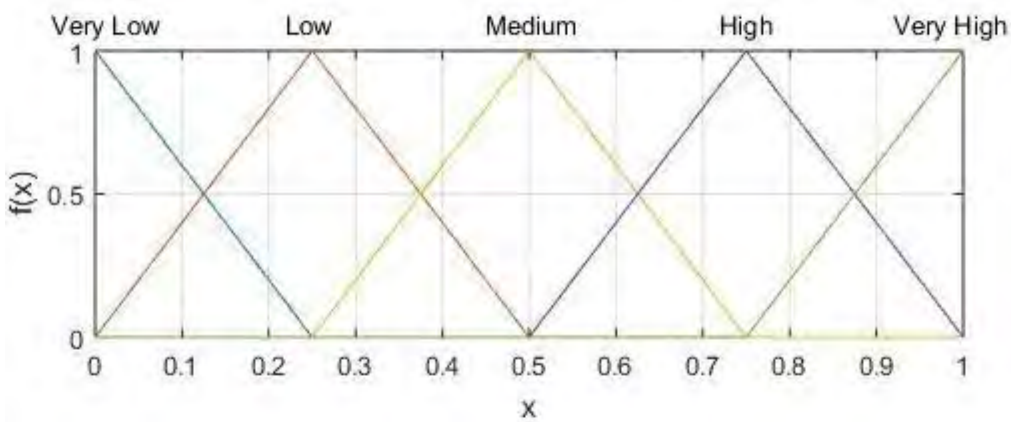

Figure 3: TFN for linguistic variables

4.2. Data collection Phase

4.2.1. Collect data from diversified sources

In construction project risk analysis, sufficient amount of historical or statistical data is often hard to obtain. Therefore, most of the existing models use only data from expert’s judgments. However, these insufficient statistical data along with expert’s judgments can be used in risk evaluation process for better performance. Although, the projects are characterized as unique, one-time endeavor, there are some common risk events that exist for all types of projects and some are specific for particular project. Therefore, risk data are available for these common risk events in the historical sources. This thesis evaluates risks considering both data from historical source (i.e., insufficient statistical data) and subjective judgments from many experts. If data are collected from m number of experts, then total number of data source will be $n = m+1$, because data from statistical source should be considered as one source. It is important to note that data should be collected from as diversified and multiple sources as possible to reduce biasness, because different experts will see the problems from their own viewpoints. Here, the term diversified is used to mean the experts from different backgrounds and sectors.

4.2.2. Allocate weights to the data sources

As different sources of data have different impacts on the final decision, weights are introduced into the project risk analysis model. Weights (Ws) will be allocated to experts on the basis of experience, knowledge and expertise and to the statistical source on the basis of data quality, quantity and credibility. If data are collected from n number of sources, then the kth data source S_k is assigned a weight factor W_k, where $W_k \in [0, 1]$, and $W_1 + W_2 + \ldots\ldots + W_n = 1$.

4.3. Risk Measurement Phase

4.3.1. Convert the data of RL and RS into matching TFN

In this step, all the risk data related to RL and RS obtained from expert's opinions and historical source should be converted into appropriate fuzzy number. In this risk assessment model, TFN is used for its simplicity and popularity. Expert's judgments in the form of linguistic variables are needed to convert into matching TFN as defined earlier by the risk assessment team. For example, an expert might say that the occurrence probability for the k^{th} risk events is "High", then according to the definition, the matching TFN is (0.5, 0.75, 1.0). Experts are also allowed to give any intermediate values of TFN about RL and RS directly without any help of linguistic variables. Suppose, it is possible to put (0.3 0.4 0.5) directly as TFN for both RL and RS. In case of statistical data source, single numerical values are obtained about RL and RS from probabilistic analysis such as frequency analysis, Monte Carlo simulation, Bayesian approach, etc. Data obtained from probabilistic analysis also need to be converted into TFN to take advantages of merging with TFN obtained from other sources in the aggregation process. If "a" be the measured value of RS or RL by probabilistic analysis, then TFN is converted as (a, a, a). For example, if the occurrence probability of a risk event is found as 0.3, then TFN will be (0.3, 0.3, 0.3).

4.3.2. Aggregate individual TFN of RL and RS into group TFN

The aim of this step is to apply appropriate operator to aggregate the individual TFN of RL and RS obtained from various sources into group TFN. The aggregation of TFN scores is performed by applying the fuzzy weighted triangular averaging operator, which is defined by

$$A_k^* = \left(A_{i1}^* \otimes W_1 \oplus A_{i2}^* \otimes W_2 \oplus \ldots\ldots. \oplus A_{in}^* \otimes W_k\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

where, A_k^* is the fuzzy aggregated TFN score and A_{ik}^* (for $k = 1, 2 \ldots . m + 1$) are the measured TFN of m numbers of experts from diversified field and one from statistical source. Here, $\otimes$ and $\oplus$ denote the fuzzy multiplication and fuzzy addition operators, respectively. W_1, W_2,… ,W_{m+1} are the weights allocated to experts, E_1, E_2,…,E_m and $W_1 + W_2 + \ldots\ldots + W_{m+1} = 1$.

4.3.3. Fuzzy Inference system

Fuzzy Inference System (FIS) is the process of transferring from a given input mapping to an output mapping using fuzzy logic. In the fuzzy inference phase, the aggregated TFNs of RL and RS are converted into matching fuzzy sets of RV. Therefore, this fuzzy inference system has two inputs RL and RS and one output variable RV. Here, the value of the output RV depends on both values of RL and RS. Therefore, according to fuzzy set theory, the logical operation between RL and RS is “fuzzy intersection" or “AND”. In other words, according to *truth table* of standard Boolean logic, RV is “truth” when both RL and RS are “truth”. The classical fuzzy operator for this function is: *min,* but the fuzzy *T-norm* operator (i.e., triangular norm) enables us to customize the AND operator. The intersection of two fuzzy sets *A* and *B* is defined in general by a binary mapping *T*, which aggregates two membership functions as follows:

$$\mu_{A \cap B}(x) = T(\mu_A(x), \mu_B(x)) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

where, binary operator T represents the *product* of $\mu_A(x)$ and $\mu_B(x)$.

The classical method of fuzzy intersection (i.e., “*min*”) considers only the minimum value of the two input variables. This implies that the value of RV is equal to the minimum value between them that may come from either RL or RS value ignoring the maximum value. However, there is great impact of both inputs RL and RS to the output RV. In this respect, *prod* operator considers the effects of both inputs to the output RV, which is desirable.

4.3.4. Evaluate RV through Defuzzification

Defuzzification of fuzzy numbers is the process of producing non-fuzzy number that is needed for decision making in a fuzzy environment. There are many defuzzification methods available; any one of which can be selected according to the requirements for reflecting the real situation and viewpoints of the decision maker. Centroid, bisector, middle of maximum, largest of maximum, smallest of maximum, and α-cut are the very popular defuzzification methods. In this phase, the centroid method is selected as it is relatively easy to apply, which can be mathematically defined as:

$$RV = \frac{\int_0^1 xf(x)dx}{\int_0^1 f(x)dx} \qquad (13)$$

where, *f(x)* denotes the membership function of RV.

4.4. Uncertainty measurement Phase

4.4.1. Determine the linguistic variables for uncertainty range.

This risk assessment model uses both expert's judgments and insufficient historical data in risk analysis. Therefore, uncertainties are involved in both processes: probabilistic analysis and subjective judgments. The uncertainties involved in probabilistic estimations of RV and RS are basically due to (*i*) unreliable/ insufficient data or (*ii*) approximation in statistical analysis methods. On the other hand, the factors influencing the uncertainties in subjective judgments are: (*iii*) the complexity of work/conditions and (*iv*) the level of education and experience of the experts. Based on these four factors, a linguistic variable of "Close to ~" type is determined to consider the degree of uncertainties involved in each risk event as shown in Table 2. It is seen that five linguistic variables such as "Very very close to", "Very close to", "Close to", "Fairly close to" and "Fairly fairly close to" are used to evaluate a proper uncertainty range. Here, this "Close to ~" type linguistic variables are basically used to mean how close the determined risk value to the actual value (i.e., the RV with zero degree of uncertainty). In general, four possible grades of uncertainties such as "Very Small", "Small", "Normal" and "Large" are assumed in these four uncertainty factors. Table 2 shows the classification of linguistics variables that represent the degree of uncertainties according to different combinations of the four possible uncertainty grades.

Table 2: Factors for determining uncertainty range of RV (proposed by Choi et al., 2008)

Subjective judgments		Probabilistic parameter estimations		Determined uncertainty range
Complexity of work	Level of education, experience & confidence	Unreliable/ Insufficient data	Approximation in statistical analysis	
Very small	Very small	Very small	Very small	Very very close
Very small	Small	Very small	Small	Very close
Small	Very small	Small	Very small	
Very small	Normal	Very small	Normal	
Normal	Very small	Normal	Very small	
Small	Small	Small	Small	Close
Small	Normal	Small	Normal	
Normal	Small	Normal	Small	
Very small	Large	Very small	Large	Fairly close
Large	Very small	Large	Very small	
Normal	Normal	Normal	Normal	
Small	Large	Small	Large	
Large	Small	Large	Small	
Normal	Large	Normal	Large	Fairly fairly close
Large	Large	Large	Large	

4.4.2. Determine fuzzy membership curve for each risk item

In this step, after determination of appropriate linguistic variables for the degree of uncertainties involved in each risk event, a fuzzy membership curve is drawn based on the determined linguistic variables. The fuzzy membership functions of “Close to ~” type have been developed earlier by Choi et al. (2008) to represent the uncertainty range involved in probability of occurrence. Here, in this thesis, these membership functions are used to compute the uncertainty interval involved in individual risk event. Figure 4 shows the sample membership curves for a risk event with RV of 0.5 which are drawn for all the five defined linguistic variables as described in the previous section. If x be the RV of a risk event, then the fuzzy memberships curve is defined for “Close to x” type as below:

$$f(x') = \begin{cases} \left\{ \left[\left(2x'^{1/y} \right)^{y} \right]^{p} \right\}, \text{for } 0.0^{y} \leq x' \leq 0.5^{y} \\ \left\{ \left[\left(2-2x'^{1/y} \right)^{y} \right]^{p} \right\}, \text{for } 0.5^{y} \leq x' \leq 1.0^{y} \end{cases} \quad \text{...(14)}$$

where, x' is the transformed axis such that estimated or determined value of each risk event is located at the midpoint (0.5) of x-axis. Thus $x^y = x'$; where y is calculated by using the value of the fuzzy number at the midpoint, so that $0.5^y = x'$. Here, y is the midpoint transfer function and p is the coefficient of power according to linguistic variables.

For example, assume that the risk value (RV) of a risk event A is determined as 0.204 through fuzzy inference system, then the corresponding value of midpoint transfer function y will be 2.293 as shown below:

$0.5^y = 0.204$ or $y = 2.293$

Table 3 shows the equations which are associated with the five linguistic variables.

Table 3: Membership functions to capture uncertainty ranges (Cho et al., 2002)

Linguistic variable	Values (f(x′))	Limit
Very very close (VVC)	$\left[\left(2x'^{1/y}\right)^{y}\right]^{4}$	$0.0^{y} \leq x' \leq 0.5^{y}$
	$\left[\left(2-2x'^{1/y}\right)^{y}\right]^{4}$	$0.5^{y} \leq x' \leq 1.0^{y}$
Very close (VC)	$\left[\left(2x'^{1/y}\right)^{y}\right]^{2}$	$0.0^{y} \leq x' \leq 0.5^{y}$
	$\left[\left(2-2x'^{1/y}\right)^{y}\right]^{2}$	$0.5^{y} \leq x' \leq 1.0^{y}$
Close (C)	$\left(2x'^{1/y}\right)^{y}$	$0.0^{y} \leq x' \leq 0.5^{y}$
	$\left(2-2x'^{1/y}\right)^{y}$	$0.5^{y} \leq x' \leq 1.0^{y}$
Fairly close (FC)	$\left[\left(2x'^{1/y}\right)^{y}\right]^{1/2}$	$0.0^{y} \leq x' \leq 0.5^{y}$
	$\left[\left(2-2x'^{1/y}\right)^{y}\right]^{1/2}$	$0.5^{y} \leq x' \leq 1.0^{y}$
Fairly fairly close (FFC)	$\left[\left(2x'^{1/y}\right)^{y}\right]^{1/4}$	$0.0^{y} \leq x' \leq 0.5^{y}$
	$\left[\left(2-2x'^{1/y}\right)^{y}\right]^{1/4}$	$0.5^{y} \leq x' \leq 1.0^{y}$

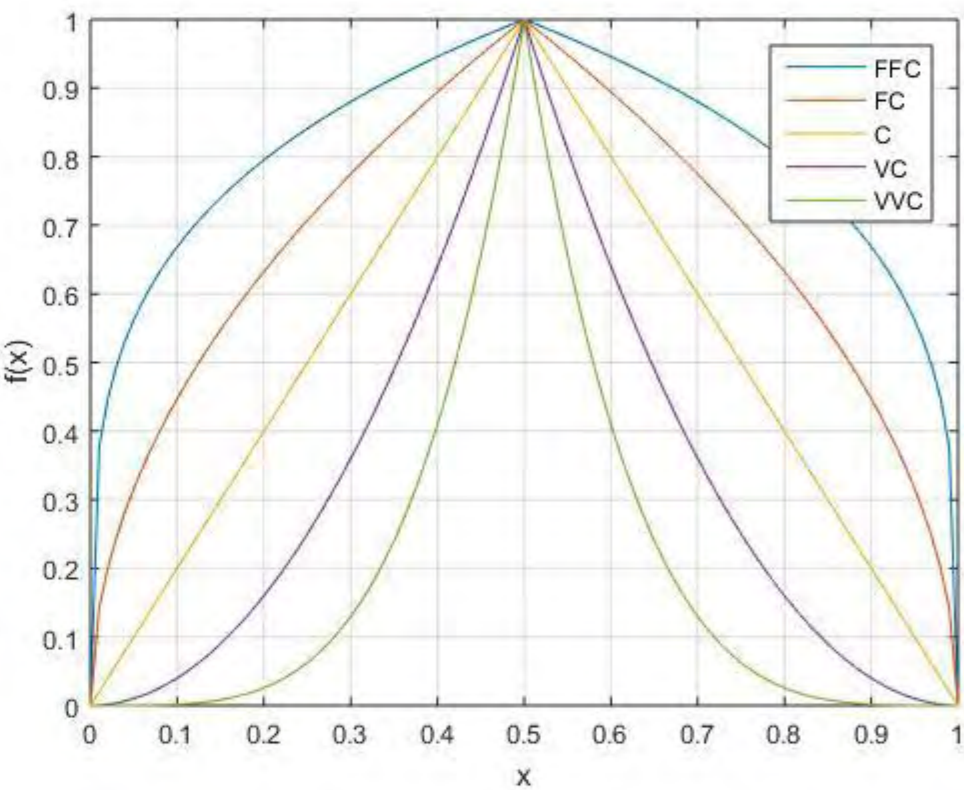

Figure 4. Membership curves with different degrees of uncertainty

4.4.3. Evaluate uncertainty intervals through defuzzification

The uncertainty ranges of these linguistic expressions of each risk event are evaluated quantitatively by using α-cut defuzzification method. Although there exists numerous defuzzification methods, especially for this defuzzification step, α-cut method is recommended due to its capability to produce interval data from membership functions. Here, α represents the degree of membership functions or belief functions. The optimistic decision makers will have higher values of α than the pessimistic decision makers.

4.5. Risks ranking with uncertainty intervals

In this section, risks are ranked based on uncertainty range by applying extended VIKOR method (Sayadi et al., 2009) described in the previous chapter. In the proposed methodology, a minor modification is needed because the method was proposed for general purpose of solving MCDM problem. However, in this risk analysis model, the problem is more specific and ranking or prioritizing of risks is based on only uncertainty interval of each risk event. Therefore, a minor modification is made in order to simplify the model for ranking risks with the help of uncertainty intervals. The modified extended VIKOR method consists of the following steps:

Step 1: Determine the positive ideal solution (PIS) and negative ideal solution (NIS).

$$A^* = \{x_1^*, x_2^* \ldots x_n^*\} = \left(\min_i x_{ij}^L \middle| j \in J\right) \text{for}, j = 1,2,\ldots n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15a)$$

$$A^- = \{x_1^*, x_2^* \ldots x_n^*\} = \left(\max_i x_{ij}^U \middle| j \in J\right) \text{for}, j = 1,2,\ldots n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15b)$$

where, $A^*$and $A^-$are the PIS and NIS, respectively and J denotes uncertainty range as cost criterion

Step 2: The original extended VIKOR method (Sayadi et al., 2009) has been developed aiming to solve problems with conflicting multi-criteria in which different criteria represent different dimensions of the alternatives. In this case, the risk ranking based on uncertainty interval is a single dimensional problem (minimization problem). Since uncertainty range is the only criterion and there is no benefit criteria in ranking the construction project risks by using this modified VIKOR method, the values of the intervals $[S_i^L, S_i^U]$, $[R_i^L, R_i^U]$ and $[Q_i^L, Q_i^U]$ will be same. Therefore, the equations for computation of these intervals can be simplified as follows:

$$S_i^L = R_i^L = Q_i^L = \sum_{j \in J} W_j \left(\frac{x_{ij}^L - x_j^*}{x_j^* - x_j^-}\right), \text{where}, i = 1,2 \ldots m \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (16a)$$

$$S_i^U = R_i^U = Q_i^U = \sum_{j \in J} W_j \left(\frac{x_{ij}^U - x_j^*}{x_j^* - x_j^-}\right), \text{where}, i = 1,2 \ldots m \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (16b)$$

$$Q_i = \left[Q_i^L, Q_i^U\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (17)$$

Step 3: According to the VIKOR method, the alternative which has minimum Q_i is the best alternative and it is chosen as compromise solution. However, here in risk analysis model, Q_i intervals are being used to rank the risks. The risks with higher values of Q_i will get higher priority in the ranking order as opposed to the VIKOR method. To rank all construction risks with Q_i interval numbers, pairwise comparisons among all risks are made. The next step shows the method for comparison of two interval numbers.

Step 4: Suppose that $[a^L, a^U]$ and $[b^L, b^U]$ are two interval numbers and the maximum interval number has to be chosen from them. Therefore, these two interval numbers may have four possible states:

(a) If there is no intersection between these two interval numbers, the maximum interval is that one which has higher values. In different words: if $a^u \leq b^L$, then interval $[b^L, b^U]$ is the maximum one.

(b) If two interval numbers are the same, then two have similar priority.

(c) In circumstances that $a^L \leq b^L < b^U \leq a^U$, the maximum interval number is computed as follows: if $\alpha(b^L - a^L) \geq (1-\alpha)(a^U - b^U)$, then $[b^L, b^U]$ is the maximum interval number, else $[a^L, a^U]$ is maximum interval number.

(d) In circumstances that $a^L < b^L < a^U < b^U$, and if $\alpha(b^L - a^L) \geq (1-\alpha)(b^U - a^U)$, then $[b^L, b^U]$ is the maximum interval number, else$[a^L, a^U]$ is maximum interval number.

Here α is introduced as optimism level of the decision maker $(0 < \alpha \leq 1)$. The optimistic decision maker will use higher value of α than the pessimistic decision maker. In this situation, the final ranking is obtained by the proposed modified VIKOR method with pairwise comparisons of interval numbers.

Therefore, once the ranking of the construction project risk is obtained by the method described above, risk response strategies are taken against only for the higher order risks due to the limitation of time and cost. In the following Chapter, an example problem (a real engineering problem) has been illustrated to demonstrate the applicability of the proposed risk assessment methodology.

CHAPTER 5

NUMERICAL EXAMPLE

5.1 A Case Study on Building Construction Project

In this chapter, a case study of risk assessment on the building construction project is presented to illustrate the applicability of the proposed risk assessment methodology. As the construction project is associated with a large numbers of risk events, nevertheless a very few common risk events are considered in this building construction project's risk assessment case study as shown in Figure 5. After a critical review of these risks data, all the possible risks events that involved in a construction project can be categorized into some major groups such as technical risks, operational risks, managerial risks, political risks, etc. For example, the risk events, *design mistakes* and *design changes* can be grouped into the technical risk, whereas *delays*, *injuries/accidents*, *construction mistakes* are the operational type risk. To demonstrate the proposed model and to simplify the calculations, only the technical and operational risks are assessed in this case study. Rest of the risk groups can also be assessed in the similar way.

Project Risks	Technical Risks:	-Design mistakes -Design Changes
	Operational Risks:	-Delays -Injuries/Accidents -Construction mistakes
	Management Risks:	-Inexperience team members -Lack of adequate process -Lack of resource
	Financial Risks:	-Cost overrun
	Logistics:	-Raw materials supply delay
	Political:	-Political instability
	Natural:	-Flood -Heavy rainfall etc.

Figure 5. Risks on building construction project

The step by step risk assessment procedures of the proposed model are discussed in the following subsections.

5.2. Preliminary Phase

5.2.1. Establish a risk assessment team

A risk assessment team of three members are formed for undertaking risk assessment of the building construction project by using the proposed methodology. Details about the team members are given in Table 4. A team leader is selected among the members based on their knowledge, experiences and qualifications who were the overall in-charge. This team has carried out the whole risk assessment process from data collection to the final risk ranking. All the members of the risk assessment team are allowed to give their own judgments about risks along with the data obtained from other sources.

5.2.2. Review risk data and define the linguistic variables

First, the risk data of similar previous projects are critically reviewed by the risk assessment team and the potential risks with their sources are identified. Before data collections, all the linguistic variables related to RL and RS are defined by the risk assessment team. These linguistic variables help the team in collecting data from experts in the form of defined linguistic terms. In this case study, five simple linguistic variables such as “Very High”, “High”, “Medium” “Low”, and “Very Low” are defined for both RL and risk RS with different meanings. For clarification, in case of RL, linguistic variable “Low” means “unlikely to occur” while for the case of RS it means “involved small impact”. The details with their corresponding interpretations are shown in Table 4.

5.2.3. Define matching MFs for each linguistic variable

In this step, a matching TFN are defined for each linguistic term to evaluate the risks of building construction project. The matching TFN for each linguistic variable of both factors RL and RS are shown in the last column of Table 4. It is seen that the matching TFNs are defined for the linguistic terms “Very High” as (0.75, 1, 1), whereas for the linguistic term “High”, it is (0.5, 0.75, 1) and so on for the rest. Experts are allowed to give their judgments about RL and RS with these defined linguistic terms as well as with TFN directly. For instance, it is possible to put any intermediate value of TFN for both RL and RS, if any expert wishes to do that. Therefore, (0.20, 0.3, 0.45) is also possible to take as TFN for RL or RS. In Table 5, it is seen that expert E_2 gives his judgments about RL and RS with his own defined TFN such as (0.25, 0.35, 0.50) for RL and (0.50, 0.70, 0.90) for RS, respectively.

Table 4: Descriptions of WDS, RL, RS and RV

Weights of the Data Source (WDS)	Descriptions	Weight (W_i)
Expert 1 ($E1$)	Project manager	W_1= 0.23
Expert 2 ($E2$)	Construction Manager	W_2= 0.20
Expert 3 ($E3$)	Chief Engineer	W_3= 0.30
Statistical Data (SD)	Data from previous project	W_4= 0.27
Total		$\sum W_i = 1.0$
Risk Likelihood (RL)	Descriptions	Fuzzy Number
Very Low	Very rarely to occur	(0.0, 0.0, 0.25)
Low	Unlikely to occur	(0.0, 0.25, 0.5)
Medium	Occurrence is usual	(0.25, 0.5, 0.75)
High	Very likely to occur	(0.5, 0.75, 1.0)
Very High	Occurrence is almost inevitable	(0.75, 1.0, 1.0)

Risk Severity (RS)	Descriptions	Fuzzy Number
Very Low	Impact is quite negligible	(0.0, 0.0, 0.25)
Low	Involved small impact	(0.0, 0.25, 0.5)
Medium	Moderate impact is involved	(0.25, 0.5, 0.75)
High	Involved highly impact	(0.5, 0.75, 1.0)
Very High	Very high impact is involved	(0.75, 1.0, 1.0)

5.3. Data collection Phase

5.3.1. Collect data from diversified sources

For the purpose of risk assessment of the illustrated building construction project, data are collected from three experts who are working in diversified working area to reduce biasness. The first expert is a project manager with 12 years of experiences, second expert is a construction manager with 10 years of experiences and third expert is chief engineer with 15 years of experience. All the collected data are shown in Table 5, in the form of TFN system. Here, E_1, E_2, and E_3 represent the first, second and third experts, respectively. The data from historical source of previously completed similar projects are also taken in risk analysis. The simple frequency analysis or Monte Carlo simulation methods are employed to analysis the Statistical Data (SD). A crisp or single numerical value about RL and RS for each risk event is obtained from statistical source by probabilistic analysis. However, this value is also converted into TFN to make ease in calculation with the data from subjective judgment. For example, in Table 5, RL value for design mistakes is found 0.20 by statistical analysis, then converted to the corresponding TFN value as (0.20, 0.20, 0.20).

5.3.2. Allocate weights to the data sources

Weights (W_s) are allocated to three experts on the basis of their experience, knowledge and expertise and to the statistical data on the basis of quality, quantity and credibility. These weights are allocated by risk assessment team. Here, for four data sources such as E_1, E_2, E_3 and SD, the weights are determined as W_1, W_2, W_3, and W_4 respectively. Table 4 shows the weights for four data sources as W_1= 0.23, W_2 = 0.20, W_3 = 0.30 and W_4= 0.27, respectively.

5.4. Risk Measurement Phase

5.4.1. Convert the data of RL and RS into matching TFN

The risk data of RL and RS are found in different forms from different sources. For example, data from experts-some are found in the linguistic forms, some are found as TFNs directly and data from statistical source are found as point data by probabilistic analysis. Therefore, in this step, all the collected data from different sources in different forms are converted into matching TFN as defined in the previous chapter. Table 5 shows the summary of data from four sources about RL and RS in the converted TFN forms.

Table 5: Measure of RL and RS parameters and aggregation.

Risks	Data Sources	Measure of RL	Measure of RS
Design mistakes	E_1	(0.25, 0.50, 0.75)	(0.50, 0.75, 1)
	E_2	(0.25, 0.35, 0.50)	(0.50, 0.70, 0.90)
	E_3	(0.20, 0.30, 0.40)	(0.25, 0.40, 0.60)
	SD	(0.30, 0.30, 0.30)	(0.35, 0.35, 0.35)
	Ag.	(0.258, 0.356, 0.474)	(0.384, 0.527, 0.686)
Changes in design	E_1	(0.30, 0.50, 0.75)	(0.40, 0.70, 0.90)
	E_2	(0.30, 0.45, 0.65)	(0.50, 0.70, 0.90)
	E_3	(0.20, 0.35, 0.50)	(0.25, 0.40, 0.60)
	SD	(0.32, 0.32, 0.32)	(0.29, 0.29, 0.29)
	Ag.	(0.275, 0.396, 0.539)	(0.345, 0.498, 0.645)
Delays	E_1	(0.50, 0.75, 1.0)	(0.25, 0.50, 0.75)
	E_2	(0.50, 0.75, 1.0)	(0.50, 0.75, 1.0)
	E_3	(0.50, 0.75, 1.0)	(0.25, 0.50, 0.75)
	SD	(0.63, 0.63, 0.63)	(0.30, 0.30, 0.30)
	Ag.	(0.585, 0.768, 0.9)	(0.314, 0.496, 0.678)
Injuries/Accidents	E_1	(0.0, 0.25, 0.50)	(0.0, 0.25, 0.50)
	E_2	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)
	E_3	(0.0, 0.25, 0.50)	(0.25, 0.50, 0.75)
	SD	(0.26, 0.26, 0.26)	(0.28, 0.28, 0.28)
	Ag.	(0.12, 0.303, 0.485)	(0.201, 0.383, 0.565)
Construction mistakes	E_1	(0.0, 0.25, 0.50)	(0.0, 0.25, 0.50)
	E_2	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)
	E_3	(0.20, 0.40, 0.60)	(0.15, 0.25, 0.45)
	SD	(0.10, 0.10, 0.10)	(0.25, 0.25, 0.25)
	Ag.	(0.137, 0.305, 0.472)	(0.163, 0.3, 0.467)

5.4.2. Aggregate TFN of RL and RS into group TFN

In this step, the collected risk data of RL and RS from four individual sources are aggregated into group TFN. The aggregation of TFN scores is performed by applying fuzzy weighted triangular averaging operator which is defined with the equation (11) as illustrated in Chapter 4. This aggregated TFN scores of RL and RS are used as inputs in the next fuzzy inferences phase to evaluate output RV. The aggregated TFNs of RV are shown in Table 5.

5.4.3. Fuzzy inference phase

In the fuzzy inference process, there are two input variables RL and RS and one output variable RV. The aggregated TFNs of RL and RS are converted into TFN of RV through the fuzzy inference system where fuzzy intersection operator is employed. Using Eq. (12), described in Chapter 4, the input TFNs of RL and RS are converted into output TFN of RV. The RV values in TFN forms are shown in the fourth column of Table 6.

5.4.4. Evaluate RV through defuzzification

Since the output RV of fuzzy inference system is a fuzzy number, an appropriate defuzzification method is employed to convert it into matching numerical value. Center of area or centroid method (Eq. (13)) is applied as defuzzification method to convert the triangular fuzzy number into matching numerical value of RV. The defuzzied RV are shown in the last column of the Table 6.

Table 6: Evaluation of RV through defuzzification

Risks	RL	RS	TFN of RV	RV
Design mistakes	(0.258, 0.356, 0.474)	(0.384, 0.527, 0.686)	(0.096, 0.188, 0.324)	0.204
Change in design	(0.275, 0.396, 0.539)	(0.345, 0.498, 0.645)	(0.095, 0.198, 0.348)	0.214
Delays	(0.585, 0.768, 0.9)	(0.314, 0.496, 0.678)	(0.183, 0.381, 0.611)	0.392
Injuries/Accidents	(0.12, 0.303, 0.485)	(0.201, 0.383, 0.565)	(0.024, 0.116, 0.274)	0.138
Construction mistakes	(0.137, 0.305, 0.472)	(0.163, 0.3, 0.467)	(0.022, 0.091, 0.221)	0.111

5.5. Uncertainty measurement phase

5.5.1. Determine the linguistic variable for each risk event

The linguistic variables that represent the degree of uncertainties involved in each risk event are selected based on four factors as described in the previous chapter. Table 7 shows the determined linguistic variables for five risk events that are selected subjectively considering the four uncertainty factors as described in Chapter 4. For instance, the linguistic variable "Fairly close" is selected for the risk event "Design mistakes". It means that the calculated RV is fairly close to the actual RV indicating that a high level of uncertainty is involved.

Table 7: Degree of uncertainties involved in each risk event

Risks	Subjective judgements		Probabilistic parameter estimations		Determined linguistic variable
	Complexity of work	Level of education & experience	Unreliable/ Insufficient data	Approximation in statistical analysis	
Design mistakes	Small	Large	Small	Large	Fairly Close
Change in design	Very small	Normal	Very small	Normal	Very close
Delays	Very small	Large	Very small	Large	close
Injuries/Accidents	Very small	Small	Very small	Small	Very very close
Construction mistakes	Normal	Large	Normal	Large	Fairly fairly close

5.5.2. Determine the fuzzy membership curve for each risk event

Fuzzy membership function for each risk event is selected based on linguistic variables as described in the previous chapter. The fuzzy membership curves for the representation of the degrees of uncertainty for the risk events are shown in Figures 6-10.

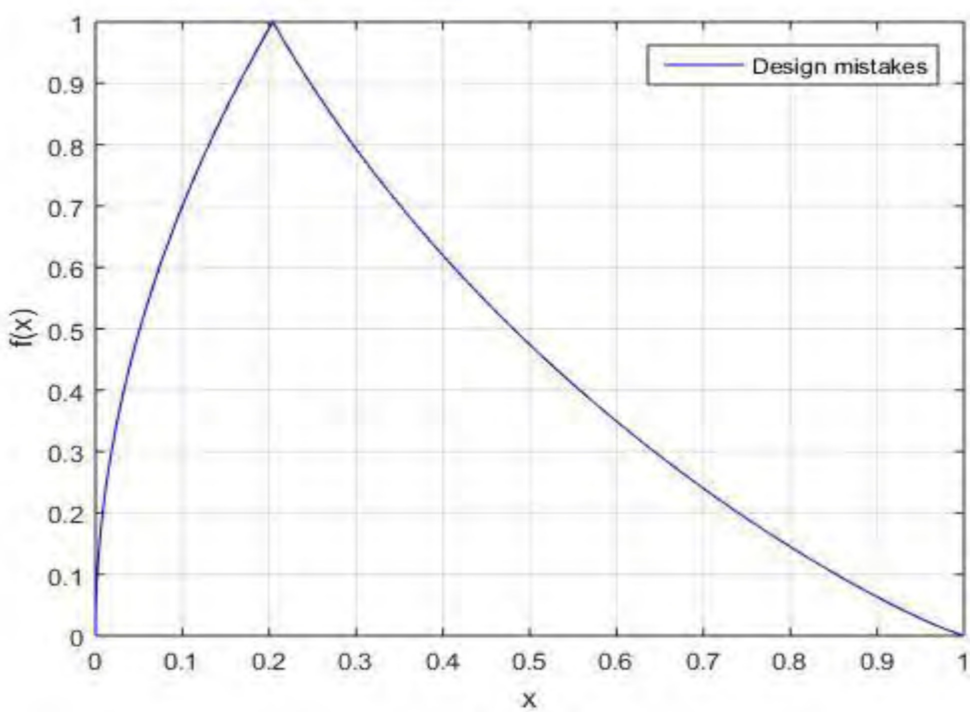

Figure 6: Membership curve for “design mistakes”

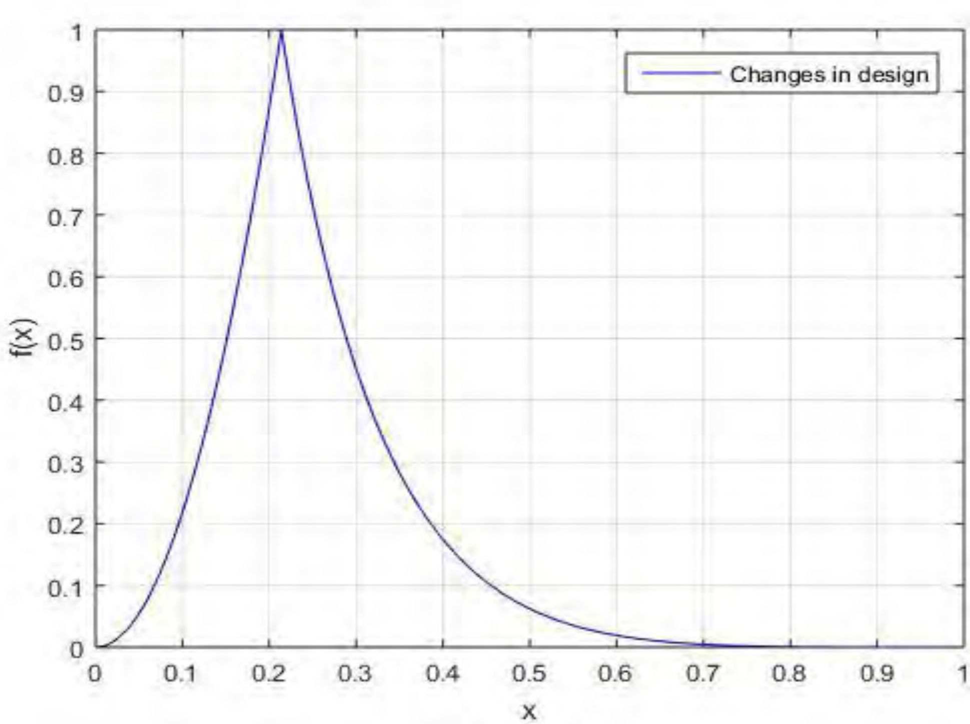

Figure 7: Membership curve for “Change in design”

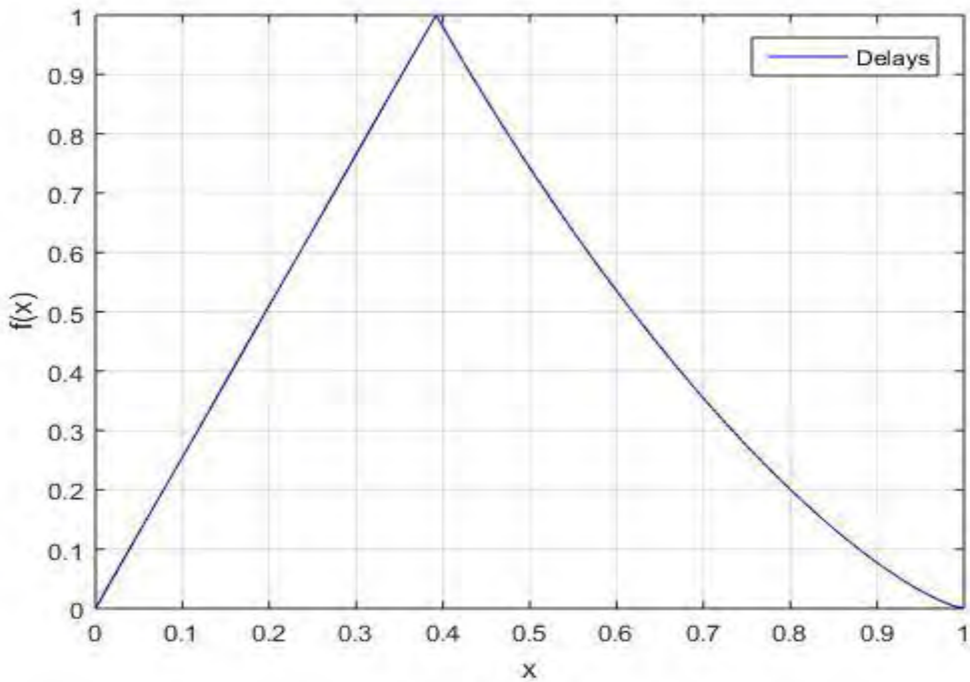

Figure 8: Membership curve for “delays”

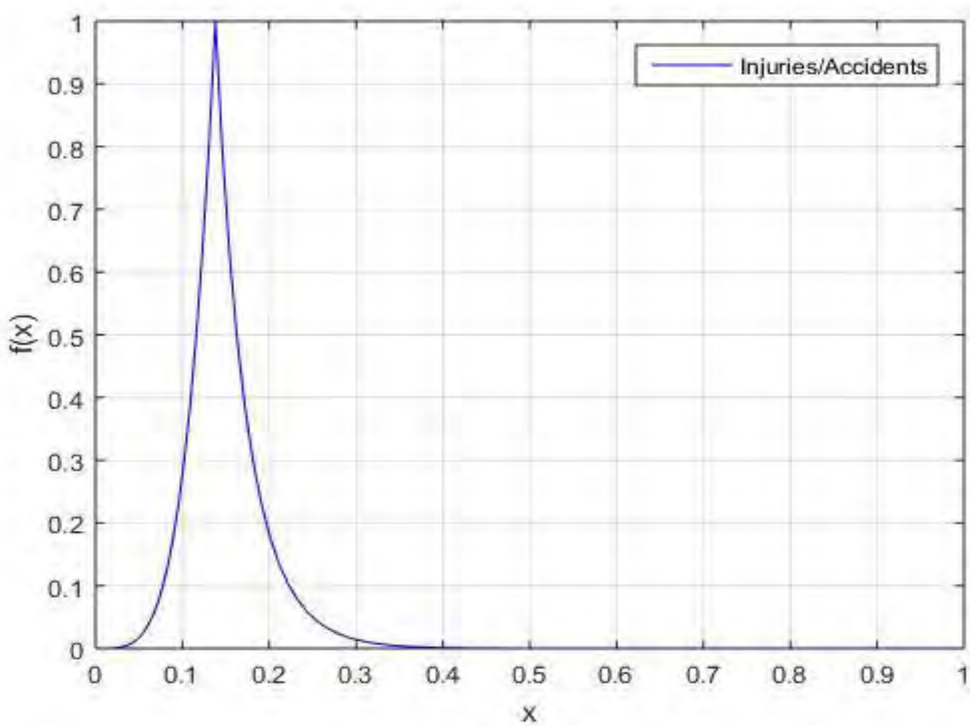

Figure 9: Membership curve for “injuries/accidents”

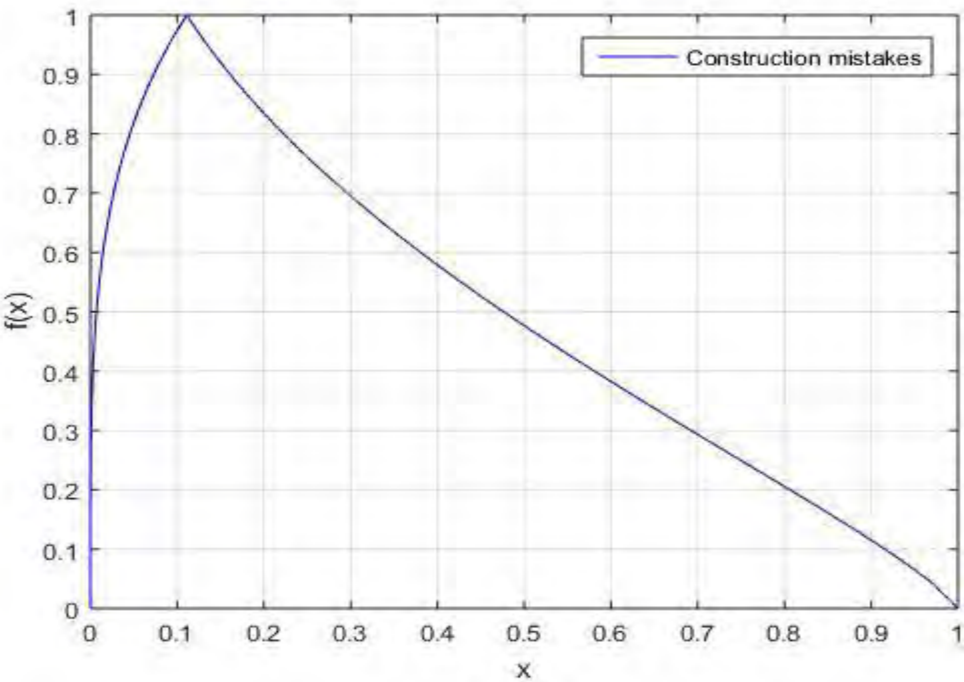

Figure 10: Membership curve for “construction mistakes”

5.5.3. Evaluate uncertainty intervals through defuzzification

The uncertainty ranges for each risk event are evaluated quantitatively through the application of appropriate defuzzification process. In this step, α-cut defuzzification method is employed because of its pertinence. Here, α represents the degree of belief or membership function that is represented by y axis of the fuzzy membership curve. At $\alpha = 0.8$, uncertainty range for the risk event “Delays” is obtained as 0.31 – 0.48, from the membership curve shown in Figure 8. The ranges of uncertainties of all technical and operational risks at $\alpha = 0.8$ are shown in Table 8.

Table 8. Calculated uncertainty interval for each risk event

Risks	RV	Degree of uncertainty	Uncertainty range
Design mistakes	0.204	Fairly Close	0.13 - 0.298
Changes in design	0.214	Very close	0.185 – 0.243
Delays	0.392	close	0.31 – 0.48
Injuries/Accidents	0.138	Very very close	0.13 – 0.146
Construction mistakes	0.111	Fairly fairly close	0.046 – 0.22

5.6. Risks ranking with uncertainty intervals

In this section, the proposed modified VIKOR method is used to rank the risks with their uncertainty intervals. In order to solve the example problem by modified VIKOR method, risk assessment team must go through the following steps:

(1) PIS and NIS are computed by Eqs. (15a) and (15b), respectively as shown in Table 9.

(2) The Q_i intervals are computed by using Eqs. (16a) and (16b). The results are presented in Table 10.

(3) Using step 4, described in Section 4.5 and taking optimism level α = 0.8, final ranking of technical and operational risks is obtained by pairwise comparison as follows:

$$\text{Pairwise comparisons}\begin{cases}\text{Design mistakes} > \text{Changes in design}\\ \text{Design mistakes} < \text{Delays}\\ \text{Design mistakes} > \text{Injuries/Accidents}\\ \text{Design mistakes} > \text{Construction mistakes}\\ \text{Changes in design} < \text{Delays}\\ \text{Changes in design} > \text{Injuries/Accidents}\\ \text{Changes in design} > \text{Construction mistakes}\\ \text{Delays} > \text{Injuries/Accidents}\\ \text{Delays} > \text{Construction mistakes}\\ \text{Injuries/Accidents} > \text{Construction mistakes}\end{cases}$$

The final ranking is:

→ Delays > Design mistakes > Changes in design > Construction mistakes > Injuries/Accidents

Table 9: Interval decision matrix and PIS and NIS

Risks	Uncertainty range	PIS and NIS
Design mistakes	0.13 - 0.298	
Changes in design	0.185 – 0.243	
Delays	0.31 – 0.48	$\begin{cases} A^* = x^* = 0.046 \\ A^- = x^- = 0.48 \end{cases}$
Injuries/Accidents	0.13 – 0.146	
Construction mistakes	0.046 – 0.22	

Table 10: $Q_i$interval numbers

Risks	$[Q_i^L, Q_i^U]$
Design mistakes	[0.194, 0.581]
Change in design	[0.320, 0.454]
Delays	[0.608, 1.000]
Injuries/Accidents	[0.194, 0.230]
Construction mistakes	[0.000, 0.401]

5.7. Results and discussion

Table 11 shows the ranking of operational and technical risks of the studied building construction project based on both RV and uncertainty intervals. It is seen that ranking based on uncertainty intervals is slightly different from the ranking based on RV. In both cases, the risk "Delays" comes first in the ranking, but the ranking of the rest of the risks have been changed. The consideration of the degree of uncertainty involved in the individual risk event has brought this change into the results. For example, the risk "Design mistakes" comes up with position 2 in the ranking based on uncertainty interval, where it was at position 3 in the ranking based on RV. This change is basically due to the involvement of higher degree of uncertainty than that of the risk "Change in design". Therefore, the results indicate that there is a great impact of the degree of uncertainty that involved in individual risk in case of risks ranking or prioritization. Since the preventive actions are taken against only higher order risks, a logical question arises that which ranking should be followed for better performances.

Table 11: Risks ranking based on RV and uncertainty interval.

Risks	Ranking based on RV	Ranking based on uncertainty interval
Design mistakes	3	2
Changes in design	2	3
Delays	1	1
Injuries/Accidents	4	5
Construction mistakes	5	4

The application of the proposed risk assessment methodology to the case on the building construction project in Bangladesh leads to the following conclusions. In real-life problems, the involvement of uncertainty level varies from one risk event to another due to the existence of variations in the data availability, data quality and complexity level. Therefore, its quantification is quite logical and effective in case of risk ranking. Note that the change in α value may leads to change in risks ranking. However, in comparison with conventional method, the result using the proposed method is found reliable and reasonable. This result provides valuable information to the risk assessment team in making risk response strategies.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1. Conclusions

The construction projects are becoming more complex and dynamic in nature day by day. Additionally, the sources of uncertainties are also increasing with the involvement of too many stakeholders. Therefore, project risk management is an essential and crucial task for the project team to avoid project losses. This thesis proposes a fuzzy-based risk assessment methodology for construction project incorporating epistemic uncertainties into conventional risk assessment framework. Because of the fact that determining the sharp or exact value of the risk is difficult or even impossible, it is more appropriate to consider them as interval numbers. This thesis presents the risks values as interval numbers and ranks them by using modified VIKOR method with their associated interval numbers. Basically, risks are assessed at the earlier stage for taking preventive measures against only the identified top order risks which have tremendous impact on project failure or loss. It is not always possible and will not even be a wise decision to take actions against too many risk events because of the limitations in time, cost and budget. Also, impacts of all risks to the project objectives are not severe and considerable.

Based on the results from the case study, it may be stated that the proposed risk assessment and uncertainty representation methodology is capable of solving any construction risk assessment problem effectively and efficiently. In conclusions, the proposed methodology could be very much useful for risk assessment problem especially where epistemic uncertainty exists. The proposed methodology is quite general and it may be expected that it could be successfully applied to any kind of project risk assessment with only minor modifications.

6.2. Future work

There are many factors that are responsible for the uncertainty involvement. These factors have not always been dealt with adequately, often resulting in poor performance with increasing costs and delays. In this thesis, four major factors are considered in uncertainty evaluation process. Therefore, this research can be expanded with the consideration of more uncertainty factors. In additions, other types of fuzzy membership functions like Gaussian, trapezoidal and *S*-shaped membership functions also can be applied to estimate the uncertainties in risk assessment process. Many methods for ranking with interval numbers are available such as extended TOPSIS, fuzzy intuitionistic approach, etc., which could also be applied in this situation.

REFERENCES:

[1] Morote, A. N., and Vila, F. R., “A fuzzy approach to construction project risk assessment”, *International journal of project management*, vol. 29, pp. 220-231, 2011.

[2] Choi, H. H., Cho, H. N., and Seo, J. W., “Risk assessment methodology for underground construction projects”, *Journal of construction engineering and management*, vol. 130, pp. 258–272, 2004.

[3] Choi, H. H., and Mahadevan, S., “Construction project risk assessment using existing database and project-specific information”, *Journal of construction engineering and management*, vol. 11, pp. 894-903, 2008.

[4] Zeng, J., An, M., and Smith, N. J., “Application of a fuzzy based decision-making methodology to construction project risk assessment”, *International journal of project management*, vol. 25, pp. 589-600, 2007.

[5] Tian, J., and Yan, Z. F., “Fuzzy analytic hierarchy process for risk assessment to general assembling of satellite”, *Journal of applied research and technology*, vol. 11, pp. 568-577, 2013.

[6] Taroun, A., and Yang, J.B., “Dempster-Shafer theory of evidence: potential usage for decision making and risk analysis in construction project management.” *The built & human environment review*, vol. 7, pp. 155-166, 2011.

[7] Dikmen, I., Birgonul, M. T., and Han, S., “Using fuzzy risk assessment to rate cost overrun risk in international construction projects”, *International journal of project management*, vol. 25, pp. 494–505, 2007.

[8] Cho, H. N., Choi, H. H., and Kim, Y. B., “A risk assessment methodology for incorporating uncertainties using fuzzy concepts”, *Reliability engineering and system safety*, vol. 78, pp. 173–183, 2002.

[9] Dutta, P., “Uncertainty modelling in risk assessment based on Dempster-Shafer theory of evidence with generalized fuzzy focal elements”, *Fuzzy information and engineering*, vol. 7, pp. 15-30, 2015.

[10] Acedes, F., Pajares, J., Galan, J. M., and Paredes, A. L., “Exploring the influence of seasonal uncertainty in project risk management”, *Procedia - social and behavioural sciences*, vol. 119, pp. 329 – 338, 2014.

[11] Baldwin, J. F., and Pilsworth, B. W., “Fuzzy truth definition of possibility measure for decision classification.” *International journal of man-machine studies*, vol. 2, pp. 447–463, 1979.

[12] Sadiq, R. and Husain, T., “A fuzzy-based methodology for an aggregative environmental risk assessment: a case study of drilling waste.” *Environmental modelling & software*, vol. 20, pp. 33-46, 2005.

[13] Carr, V., and Tah, J. H. M., “A fuzzy approach to construction project risk assessment and analysis: Construction project risk management system.” *Advances in engineering software*, vol. 32(10–11), pp. 847–857, 2001.

[14] Jha, K. N. and Devaya, M. N., “Modelling the risks faced by Indian construction companies assessing international projects.” *Construction management and economics*, vol. 26(4), pp. 337-348, 2008.

[15] Baloi, D. and Price, A. D. F., “Modelling global risk factors affecting construction cost performance.” *International journal of project management*, vol. 21, pp. 261-269, 2003.

[16] Chapman, C. B. and Ward, S. C., “Project risk management: processes, techniques and insights.” *Wiley*, 1997.

[17] Hertz, D. B. and Thomas, H., “Risk analysis and its applications.” *John wiley & son*, Detroit, 1994.

[18] Brown C. B., “The merging of fuzzy and crisp information.” *Journal of engineering mechanical division, American society of civil engineering*, vol. 106(EM1), pp. 123–33, 1980.

[19] Cui W., Blockley D. I., “Interval probability theory for evidential support.” *International journal of intelligent systems*, vol. 5, pp. 183– 92, 1990.

[20] Hadipriono F. C., Lim C. L., Wong K. H., “Event tree analysis to prevent failures in temporary structures.” *Journal of construction engineering and management*, vol. 112(4), pp. 500 –13, 1986.

[21] Olsson, R., "In search of opportunity management: Is the risk management process enough?" *International journal of project management*, vol. 25(8), pp. 745-752, 2007.

[22] Tohidi, H., "The role of risk management in IT systems of organizations." *Procedia - computer science journal*, Vol. 3, pp. 881-887, 2011.

[23] Goh, C. S., Rahaman, H. A., and Samad, Z. A., "Applying risk management workshop for public construction projects: case study." *Journal of construction engineering and management*, vol. 139, pp. 572-580, 2013.

[24] Wang, S. Q., Dulaimi, M. F., & Aguria, M. Y., "Risk management framework for construction projects in developing countries." *Construction management and economics*, vol. 22(3), pp. 237–252, 2011.

[25] Andi, "The importance and allocation of risks in Indonesian construction projects." *Construction management and economics*, vol. 24(1), pp. 69-80, 2006.

[26] Dada, J. O. and Jagboro, G., "An evaluation of the impact of risk on project cost overrun in the Nigerian construction industry." *Journal of financial management of property and construction*, vol. 12(1), pp. 37–44, 2007.

[27] Deng, T. and Zhou, X., "Risk correlation analysis for China's construction projects based on stakeholder theory." *International journal of management science and engineering management*, vol. 5(4), pp. 285–292, 2010.

[28] Kululanga, G. and Kuotcha, W., "Measuring project risk management process for construction contractors with statement indicators linked to numerical scores." *Engineering, construction, and architectural management*, vol. 17(4), pp. 336–351, 2010.

[29] Manelele, I. and Muya, M., "Risk identification on community-based construction projects in Zambia." *Journal of engineering design and technology*, vol. 6(2), pp. 145–161, 2008.

[30] Zou, P. X. and Zhang, G., "Managing risks in construction projects: Life cycle and stakeholder perspectives." *International journal of construction management*, vol. 9(1), pp. 61–77, 2009.

[31] Ang, A. H. S., and Tang, W. H., "Probability concept in engineering: Emphasis on applications to civil and environmental engineering, 2nd Ed., *Wiley*, New York, 2006.

[32] Xiang, K., Zhou, J., Zhou, X. and Ye, K., “Construction project risk management based on the view of asymmetric information.” *Journal of construction engineering and management,* vol. 138 (11), pp. 1303-1311, 2012.

[33] Zhao, X., Hwang, B., and Phng, W., “Construction project risk management in Singapore: resources, effectiveness, impact, and understanding.” *Korean society of civil engineers journal of civil engineering*, vol. 18(1), pp. 27-36, 2014.

[34] Tamosaitiene, J., Zavadskas, E. K. and Turskis, Z., “Multi-criteria risk assessment of a construction project.” *Procedia computer science*, vol. 17, pp. 129 –133, 2013.

[35] Lipke, W., Zwikael, O., Henderson, K. and Anbari, F., “Prediction of project outcome: the application of statistical methods to earned value management and earned schedule performance indexes.” *International journal of project management*, vol. 27, pp. 400–407, 2009.

[36] Gladysz, B., Skorupka, D., Kuchta, D. andDuchaczek, A., “Project risk time management – a proposed model and a case study in the construction industry.” *Procedia computer science*, vol. 64, pp. 24-31, 2015.

[37] Zhi-qiang, H. and Ya-mei, Z., “Research on risk assessment technology of the major hazard in harbor engineering.” *Procedia engineering*, vol. 137, pp. 843-848, 2016.

[38] Lin, Z. and Jianping, Y., “Risk assessment based on fuzzy network (F-ANP) in new campus construction project.” *Systems engineering procedia,* vol. 1, pp. 162–168, 2011.

[39] Sohrabinejad, A. and Rahimi, M., “Risk determination, prioritization and classifying in construction project case study: gharb tehran commercial-administrative complex.” *Journal of construction engineering,* vol. 2015, pp. 1-10, 2015.

[40] Kuo, Y. and Lu, S., “Using fuzzy multiple criteria decision making approach to enhance risk assessment for metropolitan construction projects.” *International journal of project management*, vol. 31, pp. 602–614, 2013.

[41] Masce, J. W. S. and Choi, H. H., “Risk-based safety impact assessment methodology for underground construction projects in korea.” *Journal of construction engineering and management,* vol. 134, pp. 72-81, 2008.

[42] Yildiz, A. E., Dikmen, I. and Birgonal, M. T., “Using expert opinion for risk assessment: a case study of a construction project utilizing a risk mapping tool.” *Procedia-social and behavioral sciences*, vol. 119, pp. 519-528, 2014.

[43] Tesfaye, E., Berhan, E. and Kitaw, D., “A comprehensive literature review on construction project risk analysis.” *International journal of risk and contingency management,* vol. 5(4), pp. 1-15, 2016.

[44] Thaheem, M. J., Marco, A. D. and Barlish, K., “A review of quantitative analysis techniques for construction project risk management.” *Creative construction conference*, June 30-July 3, Budapest, Hungary, 2012.

[45] Haghshenas, S. S., Neshaei, M. A. L., Pourkazem, P. and Haghshenas, S. S., “The risk assessment of dam construction projects using fuzzy topsis (case study: alavian earth dam).” *Civil engineering journal*, vol. 2(4), pp.158-167, 2016.

[46] Asan, U., Soyer, A. and Bozdag, E., “An interval type-2 fuzzy prioritization approach to project risk assessment.” *Journal of multiple-valued logic and soft computing*, vol. 26 pp. 541-577, 2016.

[47] Ghaleb, T. A., Alsri, A. A., Shabaneh, L. and Niazi, M., “A survey of project risks assessment and estimation models.” *Proceedings of the world congress on engineering,* vol. I, July 2 - 4, London, U.K., 2014.

[48] Zadeh, L. A., "Fuzzy sets". *Information and Control*. Vol. **8** (3), pp. 338-353, 1965.

[49] Zadeh, L.A., “Outline of a new approach to the analysis of complex systems and decision processes,” *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 3(1), pp. 28-44, 1973.

[5] Zaman, K., Mcdonald, M. and Mahadevan, S., “Probabilistic framework for uncertainty propagation with both probabilistic and interval variables.” *Journal of mechanical design*, vol. 133(2), pp. 0210101-02101014, 2011.

[51] Halder, A. and Mahadevan, S., “Probability, reliability and statistical methods in engineering design.” *John wiley & sons, Inc.,* Newyork, 2000.

[52] Nikolaidis, E., Chen, S., Cudney, H., Hafta, R.T. and Rosca, R., “Comparison of probability & possibility for design against catastrophic failure under uncertainty.” *American society of mechanical engineering*. Vol. 126, pp. 386-394, 2004.

[53] Baccarini, D. and Archer, R., “The risk ranking of projects: a methodology.” *International journal of project management,* vol. 19, pp. 139-145, 2001.

[54] Opricovic S. and Tzeng G. H., "The Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS", *European Journal of Operational Research*, vol. 156(2), pp. 445-455, 2004.

[55] Sayadi, M. K., Heydari, M. and Shahanaghi, K., “Extention of VIKOR method for decition making problem with interval numbers”, *Applied mathematical modelling*, vol. 33, pp. 2257-2262, 2009.

[56] Song, P., Liang, J. and Qian, Y., “A two-grade approach to ranking interval data”, *Knowledge-based systems*, vol. 27, pp. 234-244, 2012.

[57] Sivaraman, G., Nayagam, V. L. G. and Ponalagusamy, R., “A complete ranking of incomplete interval information” *Expert systems with applications*, vol. 41(4), pp. 1947-1954, 2014.

[58] Chen, T., Wang, H. and Lu, Y., “A multicriteria group decision-making approach based on interval-valued intuitionistic fuzzy sets: A comparative perspective”, *Expert systems with applications*, vol. 38(6), pp. 7647-7658, 2014.

[59] Nayagam, V. L. G. and Sivaraman, G., “Ranking of interval-valued intuitionistic fuzzy sets”, *Applied soft computing*, vol. 11(4), pp. 3368-3372, 2011.

[60] Jahanshaloo, G. R., Lotfi, F. H., Balf, F. R. and Rezai, H. Z., “Using Monte Carlo method for ranking interval data”, *Applied mathematics and computation*, vol. 210(1), pp. 613-620, 2008.

[61] Jahanshaloo, G. R., Lotfi, F. H. and Davoodi, A., “Extension of TOPSIS for decision making problems with interval data: Interval efficiency”, *Mathematical and computer modelling*, vo. 49(5), pp. 1137-1172, 2009.