Determining and Managing Contingency Reserve throughout the Lifecycle of Construction Projects

by

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Abstract

Managing risk events and uncertainties plays a key role in the successful delivery of construction projects. To cover the implementation cost of risk response actions as well as the effects of risks on project goals, contingency reserve must be calculated and considered in the project budget. Previous research on determining contingency reserve focused on the first steps in the risk management process, which are risk identification and assessment. However, incorporating risk response planning into risk identification and assessment can improve the accuracy of determining contingency reserve. The application of complex quantitative models such as optimization methods to select and rank risk response actions for large-scale construction projects can be a complex and costly process because of the effort and amount of data required. Moreover, these models account for only a limited number of criteria, which can lead to the selection of risk responses that are cost effective but unfeasible in terms of technology, environment, and achievability.

Previous research has also limitations on determining contingency reserve not only in the absence of sufficient quantitative historical data in construction projects but also in considering positive risks (opportunities). Fuzzy logic and fuzzy arithmetic can be employed to capture the subjective uncertainty and take linguistic evaluations into consideration when numerical project data fall short of the amount or quality requirements for successful modelling. However, previous research (i.e., both expert-driven and data-driven methods) has difficulty to determine the fuzzy membership function of linguistic terms used to assess the probability and impact of risk events. Previous research on risk assessment and contingency determination methods assume that the probability and impact of risk events and risk response actions are independent and static.

However, in practice, these values change over the course of project and depend on the occurrence and impact of other risk events.

To address the limitations of previous research on determining contingency reserve in construction projects, a hybrid fuzzy arithmetic-based contingency reserve method (HFACRM) was proposed which is the combination of four fuzzy models: (1) a fuzzy model consisting of fuzzy rule-based system (FRBS) along with fuzzy ranking methods to evaluate the effectiveness of risk response actions and rank them, (2) a hybrid fuzzy model to determine the MBFs of linguistic terms used to describe the probability and impact of risk events, the causality degree among project components, and the effectiveness of risk response actions, (3) an adaptive hybrid fuzzy model to determine the degree of causality and formulate soft causal relationships between risk events together and with risk response actions, (4) a hybrid fuzzy model to formulate hard relationships, stocks and flows of quantitative fuzzy system dynamics model.

The main contribution of this thesis is to propose a novel hybrid fuzzy method to determine the value of contingency reserve at different stages of construction projects in work package and project level. It identifies the most critical criteria to evaluate the effectiveness of risk response actions; it improves the accuracy and effectiveness of determining contingency reserve by modeling time dependent elements and cause-and-effect relationships between them; it addresses the problem of high reliance on quantitative data by using fuzzy arithmetic and capturing subjective uncertainty associated with linguistic evaluations; and it improves the process of determining memberships functions by considering the level of risk expertise of multiple experts and aggregating multiple experts' assessments.

Preface

This thesis is an original work by Seyed Hamed Fateminia. The research project, on which this dissertation is based on, received research ethics approval from the University of Alberta Research Ethics Board, Project Name “Risk Assessment of Power Projects’ Budgets Using Fuzzy Logic”, Study ID: Pro00044029, approved on October 16, 2018. This research was funded by the Natural Sciences and Engineering Research Council of Canada Industrial Research Chair in Strategic Construction Modeling and Delivery (NSERC IRCPJ 428226–15), which is held by Dr. Aminah Robinson Fayek.

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I was responsible for the data collection and analysis, as well as the composition of the manuscripts. Dr. Aminah Robinson Fayek was the supervisory author and was involved with concept formation and composition of the manuscripts.

Dedication

I dedicate this research to my wife Sama Sadat Parian, to my mother, Zahra Daneshvar, to my father, Seyed Hossein Fateminia, and to the baby who we are expecting.

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List of Abbreviations and Notations

Abbreviations

AACE	Association for the Advancement of Cost Engineering International
AC	Automation in Construction
AHP	Analytical hierarchical process
ANP	Analytic network process
ASCE	American Society of Civil Engineers
BBN	Bayesian belief network
CII	Construction Industry Institute
CLDs	Causal loop diagrams
COA	Center of area
DEMATEL	Decision making trial and evaluation laboratory
DTA	Decision tree analysis
FAHP	Fuzzy analytical hierarchical process
FCM	fuzzy cognitive maps
FMEA	Failure mode and effect analysis
FRA©	Fuzzy Risk Analyzer©
FRBS	Fuzzy rule-based systems
FSD	Fuzzy system dynamics
FTA	Fault tree analysis
H	High
IRM	Influence relation map
L	Low
LOM	Largest of maxima
M	Medium
MBF	Membership function
MCS	Monte Carlo simulation
MOM	Middle of maxima

MW	Megawatt
N/A	Not applicable
P–I	probability–impact
PMI	Project Management Institute
RBS	Risk breakdown structure
SD	System dynamics
SMAPE	Symmetric mean absolute percentage error
SOM	Smallest of maxima
VH	Very high
VL	Very low

Notations

A	The set of all risk response action (RRAs)
$CTWP_j$	Threat contingency reserve of *j*th work package
$COWP_j$	Opportunity contingency reserve of *j*th work package
CWP_j	Total contingency reserve of *j*th work package
CRT	Total contingency reserve
E	The set of all risk events (REs)
IT_i	Impact of *i*th threat before implementing risk response action
IT_i^k	Impact of *i*th threat after implementing *k*th risk response action (RRA_k)
IO_i	Impact of *i*th opportunity before implementing risk response action
IO_i^k	Impact of *i*th opportunity after implementing *k*th risk response action (RRA_k)
PT_i	Probability of *i*th threat before implementing risk response action
PT_i^k	Probability of *i*th threat after implementing *k*th risk response action (RRA_k)
PO_i	Probability of *i*th opportunity before implementing risk response action
PO_i^k	Probability of *i*th opportunity after implementing *k*th risk response action (RRA_k)
$RRAC_{ikr}$	Implementation cost of *k*th risk response action for *i*th risk in *r*th category of risks
RST_{rij}	Threat risk severity of *i*th threat in *r*th category of risk events for *j*th work package

RST_{rj} Threat risk severity of *i*th category of risk events for *j*th work package

RSO_{rij} Opportunity risk severity of *i*th opportunity in *r*th category of risks for *j*th WP

RSO_{rj} Opportunity risk severity of *r*th category of risk events for *j*th work package

RSN_{rj} Net risk severity of *r*th category of risk events for *j*th work package

WPC_j Cost of *j*th work package

$WPIC_{ij}$ Impacted cost of *j*th work package by the *i*th risk

$\ominus$ Fuzzy subtraction

$\oplus$ Fuzzy addition

$\otimes$ Fuzzy multiplication

Chapter 1: Introduction

1.1. Background

The construction industry contributes close to 7 percent of Canada's overall gross domestic product (GDP), and almost 10 percent of the Canadian workforce worked in the construction sector in 2019. Therefore, the successful delivery of construction projects is vital from both economical and social aspects. The uncertainty of construction projects has increased dramatically due to the recent COVID-19 pandemic, advancement in construction technologies, changes in supply chain paradigms, higher complexity of projects, and shortage of knowledge workers. Moreover, construction projects have high levels of uncertainty due to their dynamic and complex nature, multiple feedback processes, and non-linear relationships and interdependencies among project components (Ahmadi-Javid et al. 2020; Fateminia et al. 2021; Siraj & Fayek 2020). Therefore, managing risks and uncertainties is crucial for construction projects to successfully achieve project goals in terms of time, cost, and quality. Risk management is recognized as an essential contributor to project success, since it addresses uncertain events so as to control their impact and probability of occurrence (Ahmadi-Javid et al. 2020).

The Project Management Institute (PMI) (2017) defines a project risk as an uncertain event or condition that has a positive effect (opportunity) or negative effect (threat) on one or more project objectives, such as scope, schedule, cost, or quality. According to PMI, a risk management plan determines how to structure, fund, and perform risk management activities and should be developed in the first step of the risk management process. Then, qualitative and quantitative analysis techniques are employed to evaluate and prioritize identified uncertain events. Subsequently, in the risk response planning step, identified response strategies and actions are assessed, selected, and implemented considering project resource constraints. Finally, the overall effectiveness of a risk management process is evaluated and controlled (Fateminia et al. 2020b,a). To cover the implementation cost of risk response actions and the effects of risks on project goals, contingency reserve must be calculated and considered in the project budget. Contingency reserve is the money or time allocated in the cost or schedule baseline to decrease overruns of project objectives due to known risks (Ahmadi-Javid et al. 2020; Fateminia et al. 2020a; PMI 2017). Contingency reserve is a key tool for the decision makers of a project to respond to positive and negative risks, which are also referred to as opportunities and threats, respectively.

The first four steps in the risk management process (i.e., planning risk management, risk identification, qualitative assessment, and quantitative assessment) have been widely studied in the literature, resulting in various risk assessment tools and techniques. However, previous studies have not paid much attention to investigating risk response planning, which plays a vital role in managing project risks (Hillson 1999; Nasirzadeh et al. 2008). Incorporating risk response planning with risk identification and assessment can improve the accuracy of contingency reserve determination by considering 1) the effects of risks on project goals before and after implementing risk response actions (Ahmadi-Javid et al. 2020) and 2) the implementation cost of risk response actions in the total contingency reserve amount.

Researchers have used different techniques to determine the optimal contingency reserve. The issue of determining optimal values for a set of decision variables falls within the field of optimization. However, optimization techniques require many assumptions and simplifications (Onwubolu & Babu 2013). So, optimization models may oversimplify real-world problems (Barnett 2003). Moreover, they do not capture the time dependent variables and complex nature of systems, which makes these models inaccurate in modeling complex and uncertain systems (Ahmadi-Javid et al. 2020). On the other hand, simulation methods are used to dynamically analyze and evaluate the performance of systems as they change over time, in order to make future inferences. Simulation methods are more flexible than optimization models and do not generally require those assumptions made with the optimization models (Helal 2008). The goal of simulation is to determine which factors have the greatest effect on an output. Therefore, employing simulation methods can lead to more realistic modeling results.

The appropriate simulation technique must be selected to accurately mimic the complexity and uncertainty of construction projects (Helal 2008). Large-scale construction projects belong to the class of dynamic systems that are extremely complex and consist of multiple interdependent components. Moreover, construction projects are highly dynamic and involve multiple feedback processes and non-linear relationships. In discrete event simulation models, system performance can be evaluated for specific values of decision variables or control policies (Helal, 2008; Helal & Rabelo, 2017). However, determining the stability of the system in any region or neighborhood of those values or policies is not possible. This is critically important in dynamic and complex systems where performance may be driven by causal relationships that can be highly non-linear. In such systems, small deviations from the optimal decision point can cause disproportionately large changes in the system performance (Helal 2008). In agent-based modeling (ABM) simulation, which is a type of bottom–up computational simulation modeling, individual entities are represented by discrete agents and interactions among agents, and macro factors cannot be modeled (Ding et al. 2018). On the contrary, system dynamics (SD) is a well-elaborated technique for continuous simulation that can model dynamic behaviour of complex systems and is a feasible simulation method for modeling the complexity of construction projects (Fateminia et al. 2021). By employing SD, causal interactions among system variables, such as interdependencies among probability dependencies and impact dependencies among risk events, risk response actions, and secondary risks, can be modeled (Sterman, 2010).

Complex construction systems involve subjective variables that are qualitative in nature and are best expressed using linguistic terms. Since most construction projects suffer from lack of sufficient historical quantitative data, the development of probabilistic distributions for system variables can be challenging (Raoufi et al. 2016). Furthermore, casual relationships of systems cannot be clearly calculated by statistical methods and represented as numerical values owing to the lack of sets of similar data (Raoufi et al., 2016; Nasirzadeh et al., 2008). Therefore, to capture the subjective uncertainties of the subjective variables and relationships in the simulation model, SD must be integrated with fuzzy logic, resulting in fuzzy system dynamics (FSD) (Raoufi et al. 2016; Siraj & Fayek 2016). The FSD technique can capture the dynamism of construction uncertainties and the interactions among the components influencing contingency (Raoufi et al. 2016).

1.2. Problem Statement and Current Research Gaps

An extensive literature review of contingency reserve determination methods revealed that current conventional and hybrid risk and contingency analysis techniques have limitations to incorporate risk response planning into risk assessment while considering the complexity and dynamism of construction project components. This review of the risk-related literature indicates that current techniques of determining contingency reserve have not focused much on: 1) risk response actions, 2) cause-and-effect relationships between risk events together and with risk response actions, 3) opportunities, or positive risks, and 4) linguistic assessments of risk events, risk response actions, and causal relationships between risk events together and with risk response actions. The main objective of the proposed research is to develop a hybrid fuzzy method for determining and managing contingency reserve throughout the life cycle of project while addressing above mentioned gaps and taking all of the following into consideration.

1) Reviewing current studies (Ahmadi-Javid et al. 2020; Hillson & Simon 2020; Murray-Webster & Hillson 2021) showed that risk response planning plays a vital role in risk management by addressing identified risk events. Incorporating risk response planning into risk assessment can improve the accuracy of determining contingency reserve and the effectiveness of risk management. However, previous research on project risk management has mainly focused on risk identification and assessment, resulting in various risk analysis tools and techniques (Teller et al. 2014). Therefore, **the first gap** addressed in this research is the lack of a contingency determination model that incorporates risk response planning into risk analysis in order to determine contingency reserve in construction projects.

2) In construction, numerical project data frequently falls short of the amount or quality requirements for successful modelling or is not fully representative of new project environments. Moreover, subjective uncertainty exists in many decision-making processes in construction projects and stems from the use of approximate reasoning and expert knowledge, which are expressed linguistically. Fuzzy arithmetic can address the mentioned limitations by capturing subjective uncertainty and incorporate linguistic evaluations.

   To employ fuzzy arithmetic, membership functions (MBFs) of linguistic terms are required to be initially determined in order to assess probability and impact of risk events, causality degree among project components, and effectiveness of risk response actions. However, both expert-driven and data-driven methods have limitations in forming MBFs of linguistic terms. Therefore, **the second gap** addressed in this research is that both expert-driven and data-driven methods have limitations in determining the MBFs of linguistic terms used to assess the probability and impact of risk events, causality degrees of causal relationships, and the effectiveness of risk response actions while considering experts' risk expertise.

3) There are two types of risk: threats, which have negative impacts on objectives; and opportunities, which have positive impacts on objectives. Ignoring opportunities in risk management process can lead to inaccurate contingency reserve amounts and waste of project budget (Hillson 2002, 2003), because the monetary profits of opportunities can be added to the contingency reserve. The **third gap** addressed in this research is addressing the challenge to considering positive risks (opportunities) in the contingency reserve determination methods of most current research.

4) To select the most effective risk response actions on large-scale construction projects, the application of complex quantitative models such as optimization methods, can be a complex and costly process because of the effort and amount of data required (Fateminia et al. 2019a). Moreover, these models account for only a limited number of criteria, which can lead to the selection of risk responses that are cost effective but unfeasible in terms of technology, environment, and achievability. Optimization models have low transparency (i.e., they operate in such a way that it is not easy for others to see what actions are performed) during the process of selecting most effective risk response actions. Furthermore, current ranking and selection methods of risk response actions cannot consider linguistic assessments. Therefore, employing approaches with the capability to address the abovementioned limitations can result in more realistic, applicable, and feasible risk responses. Therefore, the **fourth gap** addressed in this research is the lack of research on criteria required to evaluate the effectiveness of risk response actions and rank them based on linguistic assessments of experts.

5) Current risk assessment and contingency determination methods consider risk events as independent and static variables. Thus, they do not capture the cause-and-effect interactions between risk events together and with risk response actions in the dynamic and complex environment of construction projects (Ahmadi-Javid et al. 2020). The FSD simulation approach, which focuses on the cause-and-effect relationships of model variables, is a feasible option to 1) model causal relationships between variables that affect contingency using SD simulation, 2) consider time-dependent variables whose values may vary during the lifecycle of project, and 3) consider linguistic evaluations represented linguistic terms, such as "Very Low" or "High." Therefore, there is a lack of research in developing a hybrid FSD model for determining and managing contingency reserve value throughout the life cycle of construction projects to address the aforementioned issues. The development of a hybrid FSD model comprises qualitative and quantitative phases. The qualitative phase of FSD modeling has been widely studied, and different techniques and tools have been proposed. However, in the quantitative phase of FSD modeling, there is a lack of research for a fuzzy arithmetic-based risk analysis model to formulate variables, stocks, flows, and causal relationships among variables. Consequently, to develop the required fuzzy arithmetic-based risk analysis model, the following issues must be addressed initially.

   a) Subjective variables of FSD models such as linguistic assessments of probability and impact of risk events are fuzzy numbers represented by fuzzy MBFs, rather than deterministic or probabilistic values. Therefore, the **fifth gap** addressed in this research is developing a fuzzy arithmetic-based risk analysis model that uses fuzzy arithmetic is required to formulate stocks and flows in quantitative FSD modeling.

b) The two types of causal relationships among model variables in FSD models are soft and hard relationships. Regular or fuzzy arithmetic can be applied for hard causal relationships, depending on the objectivity or subjectivity of variables. The literature reveals a lack of structured and systematic methods for formulating hard causal relationships among the elements of a quantitative FSD model. Therefore, the **sixth gap** addressed in this research is the lack of research in formulating hard causal relationships in FSD modeling of construction risk management problems.

c) Soft causal relationships are fuzzy numbers expressed in linguistic terms. The literature reveals a lack of structured and systematic fuzzy arithmetic–based methods to calculate the degree of causality for soft causal relationships between risk events together with risk response actions. Therefore, the **seventh gap** addressed in this research is the limitations of current methods to calculate crisp values of causality degrees of soft causal relationships in FSD modeling of construction risk management projects. In this respect, an equation comprising the values of impacted and caused variables along with the crisp values of soft causal relationships can be determined.

Table 0.1 Current state of research, gaps and proposed methodological approach

State of prior research efforts	Identified Gaps	Methodological approach
Both deterministic and probabilistic techniques have limitations to incorporate risk response planning into risk identification and risk analysis to determine contingency reserve in construction projects	lack of a contingency determination model that incorporates risk response planning into risk analysis in order to determine contingency reserve in construction projects	Contingency determination fuzzy procedure
Previous studies (i.e., both expert driven, and data driven methods) had limitations in their ability to form MBFs of linguistic terms. For example, to form the MBF of probability by using an expert-driven method such as analytical hierarchy process (AHP), almost 4,900 pair-wise comparisons among risk events must be performed by each expert for a project with 100 risk events, and the results are not necessarily linear	The expert-driven method may become broad in nature and may not even be necessarily reflective of the experimental data used to generate these fuzzy sets using data-driven methods may result in semantically meaningless fuzzy sets data-driven methods inefficient and time consuming	Standard fuzzy arithmetic Interval type-2 fuzzy sets Principle of justifiable granularity
Previous studies focused on the limited criteria which can lead to the selection of risk responses that are cost effective but unfeasible in terms of technology, environment, and achievability The previous studies focused on employing complex quantitative models such as optimization methods to select and rank risk response actions for large-scale construction projects can be a complex and costly process because of the effort and amount of data required. Moreover, these models accounted for only a limited number of criteria, which can lead to the selection of risk responses that are cost effective but unfeasible in terms of technology, environment, and achievability. Optimization models have low transparency	lack of research on criteria and techniques required to evaluate the effectiveness of risk response actions and rank them based on linguistic assessments of experts.	An extensive literature review A fuzzy rule-based system (FRBS) and multiple fuzzy ranking methods to evaluate the effectiveness of risk response actions and rank them

Reviewing the literature showed a lack of research in FSD quantitative model development for contingency determination in construction projects. Subjective variables of FSD models are fuzzy numbers represented by fuzzy MBFs rather than deterministic or probabilistic values. Therefore, a fuzzy arithmetic-based model was required to formulate stocks, flows, and hard relationships of quantitative FSD model as well as analyze risk events and risk response actions to determine construction project contingency reserve	Lack of a fuzzy arithmetic-based risk analysis model that uses fuzzy arithmetic is required to formulate stocks, flows, and hard relationships in quantitative FSD modeling	Contingency determination fuzzy procedure
The literature review revealed a lack of structured and systematic methods for constructing and analyzing soft causal relationships among the elements of an FSD model. Since most construction projects suffer from lack of sufficient historical quantitative data, the casual relationships of systems cannot be clearly calculated by statistical methods and represented as numerical values owing to the lack of sets of similar data. Consequently, to capture the subjective uncertainties of the subjective variables and relationships in the simulation model, soft causal relationships must be expressed in linguistic terms	lack of a systematic method to calculate crisp values of causality degrees of soft causal relationships in FSD modeling of construction projects	Fuzzy AHP Interval type-2 fuzzy sets Weighted principle of justifiable granularity Fuzzy ordered weighted average
Considering positive risks (opportunities) as well as negative risks and their respective risk response actions in determining contingency reserve	Ignoring opportunities in risk management process can lead to inaccurate contingency reserve amounts and waste of project budget	Contingency determination fuzzy procedure

1.3. Research Objectives

The objectives of the research are to address the gaps and limitations outlined in section 1.2. They are as follows:

1) The main objective of the proposed research is to determine and manage value of contingency reserve throughout the life cycle of construction projects in project and work package levels to address the gaps with current methods. The developed method addresses the gap of ignoring

risk response actions in determining contingency reserve. The proposed method considers time-dependent nature of risk events, cause-and-effect relationships, linguistic assessments of risk events and risk response actions, and linguistic assessments of causal relationships. Therefore, a hybrid fuzzy arithmetic-based contingency reserve model (HFACRM) is developed to determine contingency reserves throughout the lifecycle of construction projects, which is fulfilled in Chapter 4. The following sub-objectives are accomplished in order for HFACRM development to proceed:

a) A novel fuzzy arithmetic based contingency determination procedure is developed to address the lack of systematic method to formulate stocks, flows, and hard relationships between subjective and objective variables which is fulfilled in Chapter 4.

b) An adaptive hybrid model is proposed to fill the gap by determining the degree of causality and formulate soft causal relationships between risk events together and with risk response actions. The proposed model employs FAHP and fuzzy aggregation operators. This objective is fulfilled in Chapter 4.

c) To address the problem of determining the MBFs of linguistic terms used to describe and evaluate the probability and impact of risk events, the causality degree among project components, and the effectiveness of risk response actions, a Fuzzy hybrid model is proposed which is fulfilled in Chapter 3. The proposed method addresses the gaps with the both expert-driven and data-driven methods.

d) To address the gap with the current techniques of evaluating the effectiveness of risk response actions described in section 1.2, a fuzzy model consisting of fuzzy rule-based system (FRBS) along with fuzzy ranking methods is developed, which is fulfilled in Chapter 3.

e) The other objective is to implement the proposed method in an actual wind farm construction project to validate the proposed HFACRM. This objective is fulfilled in Chapter 5.

1.4. Expected Contributions

The proposed research will contribute to current risk management techniques and modeling by developing a hybrid fuzzy simulation method for determining and managing contingency reserve throughout the life cycle of construction projects. The expected contributions of the proposed research are outlined below in terms of advancing current fuzzy hybrid modeling techniques and risk modeling techniques.

1.4.1. Expected academic contributions

The expected academic contributions of this research are listed below.

1) Developing a methodology for evaluating the effectiveness of identified risk responses by:

    a) employing an FRBS to determine the effectiveness of risk responses, and

    b) employing a fuzzy ranking method for selecting the most effective risk responses.

2) Developing a hybrid fuzzy model which contributes the advancement of the state of the art in forming fuzzy MBFs by:

    a) considering the opinions of several subject matter experts to develop the MBFs of linguistic terms,

    b) reducing the effect of outlier opinions in developing the MBFs of linguistic terms, and

    c) enabling the aggregation of non-linear MBFs into trapezoidal MBFs.

3) Proposing an adaptive hybrid fuzzy model to improve efficiency and effectiveness of developing FSD quantitative modeling by:

    a) optimizing MBFs for linguistic terms representing the causality degree of soft relationships, and

    b) calculating the crisp value for the causality degree of soft relationships between different variables in FSD models.

4) Developing a hybrid fuzzy model to formulate stocks, flows, and hard relationships of quantitative FSD model for determining contingency reserve in construction projects.

1.4.2. Expected industrial contributions

The expected industrial contributions of this research are listed below.

1) Incorporating risk response planning into risk identification and assessment to determine and manage contingency reserve all over the life cycle of construction projects.

2) Identifying the most critical criteria to evaluate the effectiveness of risk response actions.

3) Capturing the soft and hard causal relationships and interactions between risk events together and with risk response actions.

4) Considering positive risks (opportunities) as well as negative risks and their respective risk response actions in determining contingency reserve.

5) Providing construction industry organizations with:

    a) with an integrated risk assessment and risk response planning model to determine and manage the value of contingency reserve in construction projects with better transparency and visibility to understand the effects of causal interactions,

    b) with a validated risk assessment and risk response planning model to assist practitioners in modeling project uncertainties,

c) a method for determining the value of contingency reserve at different stages of a project and throughout the life cycle of a construction project from project initiation to the end, and

d) a method for increasing the accuracy of managing contingency reserve in construction projects significantly.

6) Applying an expert driven FRBS and fuzzy ranking method can help automate the evaluation of risk response actions. This technique also delivers an expert-level risk management tool to a non-expert in the field.

1.5. Research Methodology

The objectives of this research (see Section 1.3) are achieved in the four stages as illustrated in Figure 1.1 and described below.

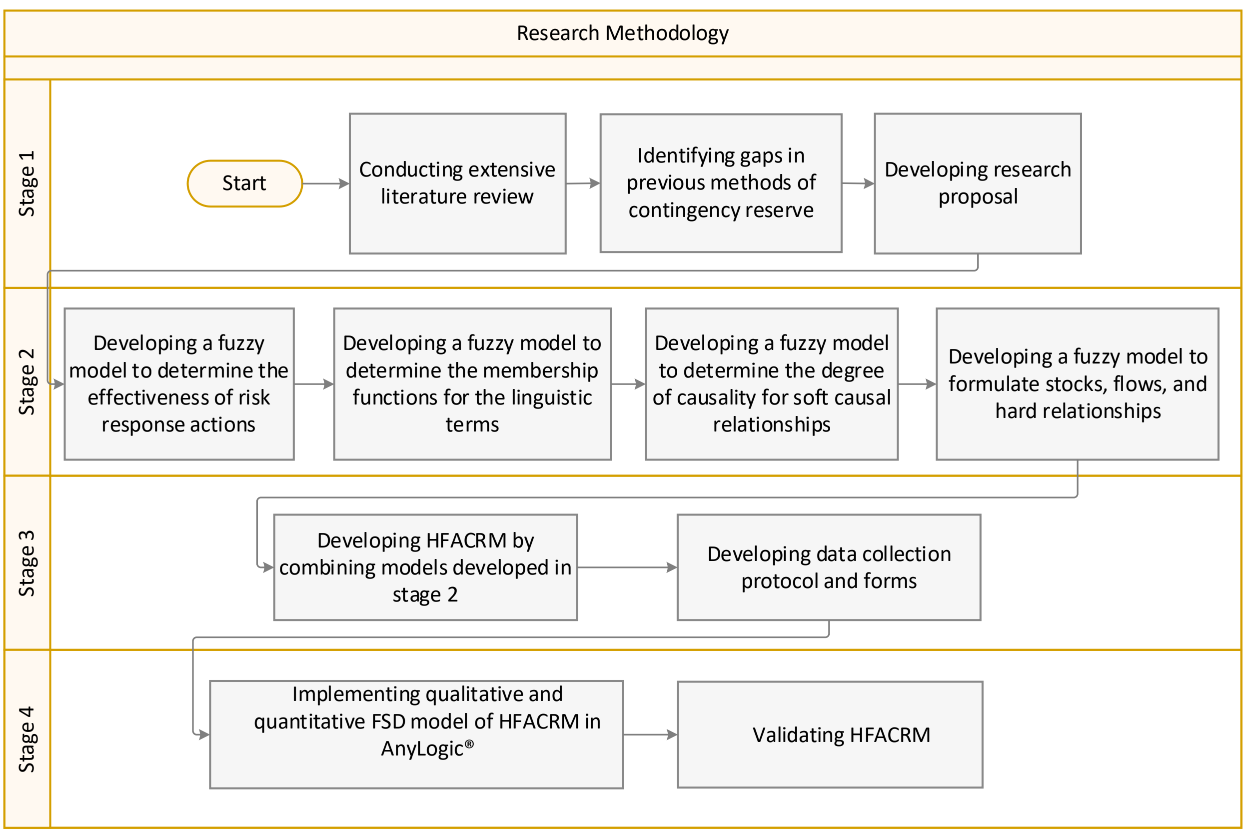

Figure 01.1 Research methodology.

1.5.1. The first stage

An extensive literature review was conducted on the relevant topics. The first topic is risk response planning processes in construction projects. This review showed that a gap exists in the research on this topic, since current contingency determination methods have limitations on their ability to consider risk response actions. Next, previous research on application of SD and FSD techniques and their advantages in construction risk management was reviewed, followed by a literature review of current contingency reserve determination methods. Two gaps were identified, 1) one regarding research on the integration of the FSD technique with other methods to define the soft relationships of FSD models, and 2) one regarding research on formulating quantitative FSD modeling in construction risk management. Finally, the advantages of employing fuzzy hybrid models in determining contingency reserve of construction projects were reviewed. This review showed that a gap exists in the research on this topic, since current fuzzy hybrid models have limitations on determining MBFs of linguistic terms used to assess the probability and impact of risk events.

1.5.2. The second stage

All fuzzy models are proposed in the second stage based on the research objectives to address the gaps with the current methods. A list of the most critical criteria to evaluate the effectiveness of risk response actions was developed. Next, an FRBS was developed based on the identified criteria as well as fuzzy ranking methods to evaluate the effectiveness of risk response actions and rank them based on their effectiveness. Then, a hybrid fuzzy model was developed to integrate, optimize, and construct MBFs of linguistic terms used to evaluate the probability and impact of risk events and the identified criteria of assessing risk response actions using interval type 2 fuzzy sets and principle of weighted justifiable granularity (WPJG). Next, a hybrid fuzzy model was developed to calculate the crisp value for the causality degree of soft relationships between different variables in quantitative FSD models. Finally, a fuzzy model was developed to formulate stocks, flows, and hard relationships.

1.5.3. The third stage

In the third stage, a hybrid fuzzy arithmetic-based contingency reserve method (HFACRM) was developed to determine contingency reserve throughout the lifecycle of construction projects by combining the proposed fuzzy models in the second stage. HFACRM employs FSD to 1) model the dynamic behavior of time-dependent components such as probability and impact of risk events and 2) capture the interactions, relationships, and mutual impact of risk events together and with risk response actions over the course of project. The qualitative FSD model of HFACRM was developed using the list of risk events and risk response actions. The qualitative FSD model of contingency reserve determination has two components: the cause-and-effect diagram and the stock and flow diagram. The cause-and-effect diagram is developed to capture causal relationships between system variables. The stock and flow diagram is developed to show the contingency determination process. Then, causal relationships and logical interactions among the model variables are determined. Finally, the corresponding causal loop diagrams (CLDs) of identified variables and their interrelationships is constructed by determining feedback loops and stock and flow structures. The quantitative FSD model is developed in four steps and begins with determining the value of subjective and objective variables. The causal relationships between variables identified in the qualitative phase are formulated in the second and third steps. Finally, all stocks and flows are formulated using both crisp and fuzzy arithmetic.

1.5.4. The fourth stage

The proposed models of the study were validated using a case study of a wind farm construction project in Alberta. To accomplish this, a data collection protocol and detailed data collection forms were developed. Next, the qualitative and quantitative FSD models were validated by conducting structural and behavioral validations. Structural validation (i.e., structural verification, parameter verification, and dimensional consistency) was performed on the CLDs, flow and stock diagrams, and mathematical equations. For behavioral validation, the performances of the FSD model (i.e., the defuzzified net project contingency values calculated by the FSD model) were compared to the outcomes of Mont Carlo simulation (MCS), the actual amount of project contingency reserve, and the defuzzified contingency values derived by using Fuzzy Risk Analyzer© (FRA©), a fuzzy arithmetic-based risk analysis software developed at the University of Alberta. FRA© was selected because it employs linguistic terms represented by triangular and trapezoidal fuzzy numbers to assess the probability and impact of risk events as well as fuzzy arithmetic techniques based on the α-cut method to generate work package and project contingencies. The symmetric mean absolute percentage error (SMAPE) was utilized to quantify the error and measure the level of agreement between results.

The proposed models were implemented in AnyLogic® simulation software. MATLAB was linked to AnyLogic® to perform fuzzy arithmetic operations using the α-cut method as well as determining contingency values using defuzzification methods in the model through Matlabcontrol, which is a Java API that allows for calling MATLAB from AnyLogic®. At each timestep, fuzzy arithmetic equations containing fuzzy variables were calculated, and the appropriate output fuzzy numbers or defuzzified values were produced.

1.6. Thesis Organization

Chapter 1 presents a brief background on risk response planning and contingency determination in construction projects. Then, it identifies the gaps in the research on risk response planning and contingency determination and FSD techniques. This chapter also presents the research objectives, expected academic and industrial contributions, and research methodology of the thesis.

Chapter 2 provides a review of current literature on risk response planning. Following the performed literature review, this chapter identifies the most critical criteria to evaluate risk response actions. The identified critical criteria and fuzzy ranking methods are then used in an FRBS model to calculate the effectiveness of risk response actions and rank them based on their effectiveness.

Chapter 3 presents the proposed hybrid fuzzy model to determine the MBFs of linguistic terms used to describe the probability and impact of risk events, and the effectiveness of risk response actions.

Chapter 4 presents a proposed hybrid fuzzy model to calculate the crisp value of causality degree for soft causal relationships between the probability and impact of risk events together and with risk response actions.

Chapter 5 presents a hybrid fuzzy arithmetic-based contingency reserve model (HFACRM) to determine contingency reserves throughout the lifecycle of construction projects. This chapter presents the application of the proposed models for calculating the contingency reserve values of a selected case study in a wind farm construction project. The work package and project cost contingency results of the dynamic simulation of the proposed model based on α-cut method are presented and discussed. The structural and behavioral validation tests used for validating the FSD models are also presented in this chapter.

Chapter 6 presents the conclusions, contributions, and the limitations of this research as well as the recommendations for future research.

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Chapter 2: Evaluating Risk Response Strategies on Construction Projects Using a Fuzzy Rule-Based System[1]

2.1. Introduction

Risk management is vital for achieving business objectives on construction industry projects. Current trends in the construction industry are towards bigger and more complex projects, which can result in a greater number of risks and uncertainties (Abdelgawad & Fayek 2010). These risks can cause failures in terms of cost overruns, schedule delays, environmental damages, and fatal injuries. In general, risk management processes include identification, qualitative analysis, quantitative analysis, risk response planning, and monitoring and control (PMI 2017). First, risk events need to be identified and documented. These risk events should be analyzed by qualitative methods so they can be prioritized based on probability and impact. Next, quantitative risk analysis must be performed to model the combined effects of randomly occurring risk events and to develop a synthesized view of the overall effects of risk events on the project. Then, risk responses should be identified, evaluated, and implemented to mitigate occurrence probability and/or the negative impacts of risk events. Finally, the overall effectiveness of the risk management process needs to be monitored, reviewed, and controlled on a regular basis. The effectiveness of the risk response is the extent to which the risk events' probabilities and/or impacts are reduced as a result of implementing the risk responses.

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A large amount of the research on risk management acknowledges the importance of risk response planning (Ben-David & Raz 2001). Hillson (2004) argues that identifying and analyzing risks and uncertainties is clearly vital for the risk management process, as it is not possible to address risks that are not identified or that are poorly analyzed. Risk response planning is considered an important step for effective risk management; it is a process that is complementary to risk identification and analysis; and without risk response planning, only limited benefits can be had from the risk management process (Hillson 1999). Risk response strategies need to be developed and implemented as follows: first, all possible risk response strategies for each given risk event of the project are identified. Next, each risk response strategy is evaluated to determine its effectiveness. Then, for each risk event, the optimal risk response strategy is identified and implemented. Finally, the risk events and the response strategies are consistently monitored.

Although some researchers have developed optimization-based methods for selecting an optimal set of risk responses (Fan et al. 2008), the application of these methods on real projects can be a complex and costly process due to the effort and amount of data that are required. Moreover, these models account for only a limited number of criteria, namely time, cost, and quality, which can lead to the selection of risk responses that are cost effective but unfeasible in terms of technology, environment, and achievability. Optimization-based approaches have low transparency (i.e., they operate in such a way that it is not easy for others to see what actions are performed) during the process of selecting the optimal set of risk responses. Employing approaches with the ability to address the abovementioned weak points can result in more realistic, applicable, and feasible risk responses—a fuzzy ruled-based system (FRBS) is just such an approach. The existing literature confirms that there is a lack of research on evaluation criteria for risk response strategies, making it difficult to determine their effectiveness. The objectives of this chapter are to (1) identify appropriate criteria for evaluating risk responses; (2) develop an FRBS to determine the effectiveness of risk responses; and (3) develop a fuzzy ranking method for selecting the most effective risk responses.

This chapter is organized as follows. First, a brief literature review of risk management and risk response planning in construction projects is presented, followed by a discussion about the application of fuzzy logic methods in the risk management process. Second, evaluation criteria for risk responses are identified and an FRBS is developed for determining the effectiveness of risk responses; a fuzzy ranking method is then applied to rank the risk responses based on their effectiveness (determined by the FRBS) on construction projects. Third, a hypothetical example is provided to illustrate the proposed framework. Finally, conclusions are presented, and future extensions of the current research are discussed.

2.2. Overview of Risk Response Evaluation and Selection Approaches

Risk response planning involves reducing the negative impact and probability of occurrence of risk events to ensure project success. Identified risk responses need to be evaluated, and the optimal risk response needs to be implemented for each risk event. Several researchers have developed decision support systems for evaluating and selecting risk responses using different approaches, including the trade-off approach (Hillson 2004; Kujawski 2002; Qazi et al. 2016) , the zonal-based approach (Datta & Mukherjee 2001), mathematical modeling and optimization (Ben-David & Raz 2001; Fan et al. 2008; KAYIS et al. 2007; Wu et al. 2018; Zhang & Fan 2014), and a combination of these approaches and fuzzy logic (Nik et al. 2011).

The trade-off approach makes trade-offs between parameters—such as cost, time, and quality—that are either risk event related, or risk response related in order to evaluate a set of risks. Kujawski (2002) makes trade-offs that account for a project's objective requirements and project stakeholders' subjective preferences. Risk responses are selected based on the cost of implementing each risk response compared with the probability of project success when the risk response is implemented. Hillson (2004) argues that the effectiveness of proposed risk responses must be assessed based on appropriateness (i.e., the correct level of risk response according to the severity of the risk event, ranging from a crisis response to a "do nothing" response), affordability (i.e., the cost effectiveness of the risk response), achievability (i.e., how realistically achievable or feasible the risk response is, either technically or in terms of a respondent's capability and authority), agreement (i.e., the consensus and commitment of stakeholders), and allocation (i.e., the responsibility of and accountability for implementing the risk response). Qazi et al. (2016) develop a model for selecting a set of optimal risk responses by measuring the impacts of different combinations of risk responses on the objective function of a project. In zonal-based approaches, two-dimensional diagrams are applied to assess the regions of the risk responses using one of two common assessment tools: (1) a matrix that features different factors in a two-dimensional diagram and (2) a two-axis graph that maps risk responses based on the values of the two dimensions.

Using an optimization-based approach, Fan et al. (2008) suggest a model for assessing the effectiveness of risk responses based on three criteria: risk event controllability, risk response costs, and project characteristics. Kayis et al. (Kayis et al. 2007) employ five heuristic algorithms to minimize the cost of implementation within the constraints of the implementation budget and acceptable risk effects for new product development. Zhang and Fan (2014) maximize the sum of estimated risk response effects (i.e., they reduce the expected loss of the risk event) after risk response strategy implementation using a method for selecting risk responses with an integer linear programming (ILP) model. Zhang (2016) uses an ILP model that accounts for the cost of implementation and the determined budget for risk responses. Wu et al. (2018) propose a multiobjective decision-making model for the selection of risk responses that minimize total expected losses, total expected schedule delays, and total expected quality reduction. An optimization model is used to minimize expected time loss, expected cost loss, and expected quality loss. To calculate the coefficients of the objective function, a fuzzy analytic hierarchy process (FAHP) is employed as a technique to guide the risk analysts (Nik et al. 2011).

2.3. Developing the Risk Response Evaluation and Selection Approach

In order to develop the proposed FRBS for the evaluation of risk responses, appropriate evaluation criteria are identified, which are the inputs of the FRBS. The output of the FRBS is the effectiveness of the risk responses. Based on the output of the FRBS, the risk responses are then ranked using a fuzzy ranking method that allows the model to mimic the three human attitudes towards risk: risk averse, neutral, and risk taking.

2.3.1. Evaluating risk responses: Identifying inputs and outputs

This study uses three criteria to evaluate risk responses: affordability of the risk response, achievability of the risk response, and controllability of risk events. These criteria make up the three inputs of the FRBS, and its output is the effectiveness of the risk response strategy. There is a positive correlation between the controllability of a risk event and the effectiveness of its risk response. For example, even if you implement a risk response with high affordability and high achievability, the risk response will not be effective in addressing a risk event with low controllability. Therefore, the FRBS developed for the evaluation of risk responses needs to evaluate both risk events and their identified risk responses in order to identify the most effective risk responses. Subjective system variables (evaluation criteria) are represented by triangular fuzzy membership functions, which are commonly used in engineering applications.

Affordability refers to the cost-effectiveness of risk responses, where the amount of time, effort, and money spent on addressing a risk should not exceed the available resources for implementing risk responses. One way to measure the cost-effectiveness of risk responses is to use the risk reduction leverage (RRL) factor, which can be calculated by converting the impact of the risk event into a monetary value (for example, the cost of delay and/or the cost of negative impacts on quality) (Hillson 2004). RRL represents the ratio of the increase in risk event exposure to the cost of risk response implementation. RRL can be calculated by dividing the difference between the risk responses' cost impacts before and after implementation by the implementation cost (see Equation (1)) (Hillson 2004).

$$RRL = \frac{(\text{Cost Impact})_{\substack{before \\ response}} - (\text{Cost Impact})_{\substack{after \\ response}}}{\text{Cost of response}} \tag{1}$$

Hillson (1999) proposes that responses with high effectiveness in terms of affordability should have RRL values above 20. Responses with medium effectiveness have RRL values ranging from 1 to 20, and RRL values of less than 1 can be labelled as having low effectiveness (i.e., they are ineffective) because their implementation cost is more than what they might save later. Thus, the fuzzy membership functions for affordability are defined as low (less than 1), medium (between 1 and 20), and high (more than 20).

Achievability refers to the feasibility of a risk response in terms of three considerations: the technical complexity of the proposed risk response, the capability of the respondent, and the authority of respondent (Hillson 2004). According to Fan et al. (2008), the complexity of a risk response may stem from technical obstacles, political obstacles, limited access to information, or conflict resolution obstacles. Three fuzzy membership functions of achievability can be defined, namely low, medium, and high achievability.

Miller and Lessard (2001) define controllability as the likelihood that the probability of occurrence of a risk event can be changed. This criterion describes the nature of the risk situation. Risk events with a low degree of controllability include occurrences such as natural disasters, while risk events with a high degree of controllability are caused by scheduling and budget problems. The latter can be addressed more effectively than the former by implementing an identified risk response (Fan et al. 2008). Although the controllability value of a risk event is the same for all of its related risk responses, this criterion can be used to ascertain whether risk responses meet the threshold for effectiveness, which can be determined by risk decision makers. As with affordability and achievability, controllability can be categorized into three fuzzy membership functions, namely low, medium, and high.

2.3.2. Evaluating risk responses using an FRBS

An FRBS is a methodology for modeling human logical thinking and decision-making. These systems use membership functions and fuzzy rules to make a decision (Fayek & Lourenzutti 2018). An FRBS can be developed with either data or expert judgments using one of the few approaches proposed in the literature. Fuzzy c-means (FCM) clustering can be employed when there is access to historical data (Bezdek 2013). Expert judgments can be applied to develop an FRBS when historical data is unavailable (Gerami Seresht & Fayek 2018; Khanzadi et al. 2012). In this chapter, the FRBS for the evaluation of risk responses is developed using expert judgments. The membership functions of three inputs and one output are determined based on documented literature using MATLAB® R2018b.

In this chapter, a Mamdani fuzzy inference system is used to develop an FRBS for the evaluation of risk responses; by delivering fuzzy outputs, the Mamdani inference system facilitates the use of different defuzzification methods for fuzzy ranking. The membership functions of affordability are determined by RRL values between 0 and 20 as recommended by Hillson (2004). Figure 2.1 shows the membership functions of affordability.

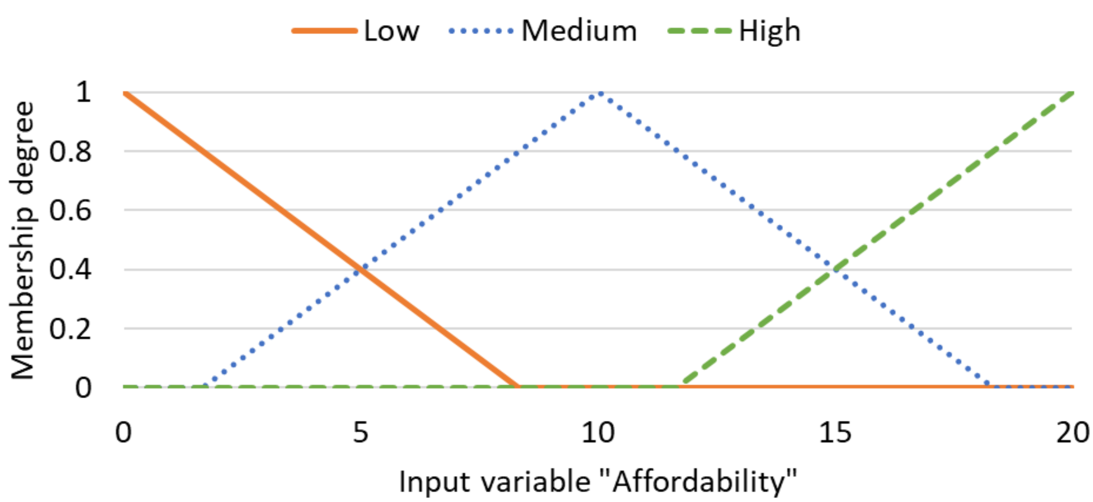

Figure 20.1 Membership functions of affordability.

For the achievability and controllability membership functions, the three linguistic terms low, medium, and high are used, as illustrated in Figure 2.2 and Figure 2.3, respectively.

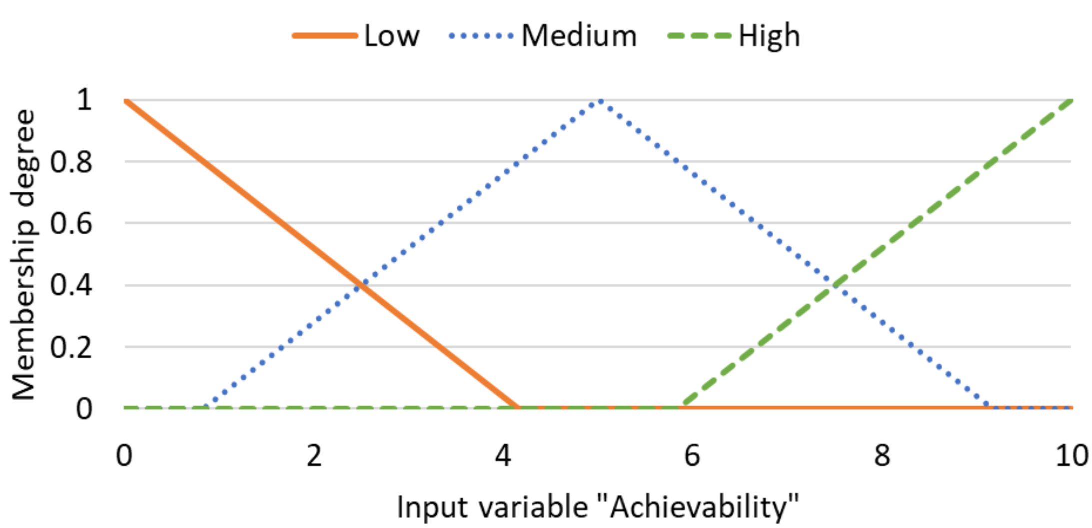

Figure 2.2 Membership functions of achievability.

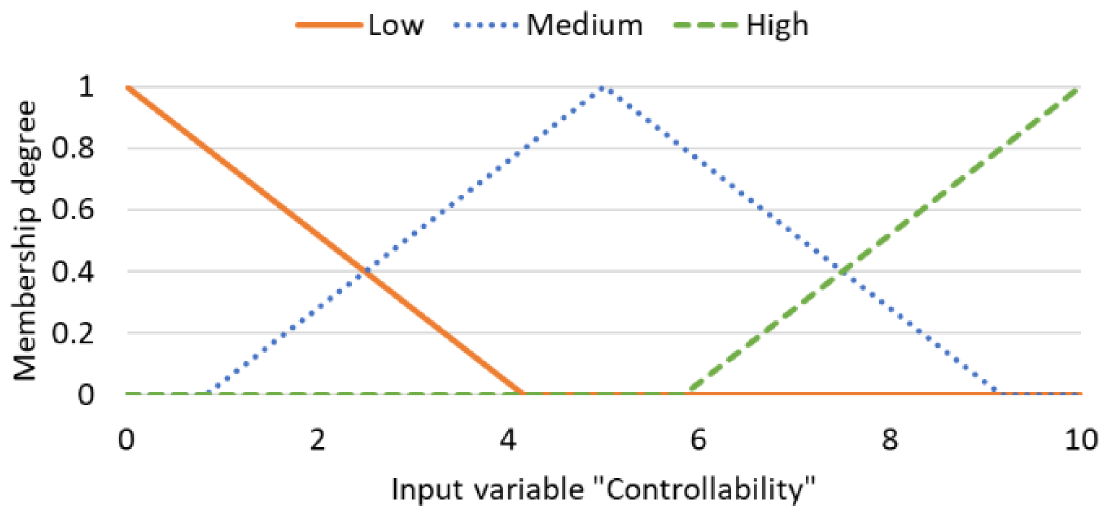

Figure 2.3 Membership functions of controllability.

The membership function of the FRBS output (effectiveness) is also between 0 and 1, as shown in Figure 2.4.

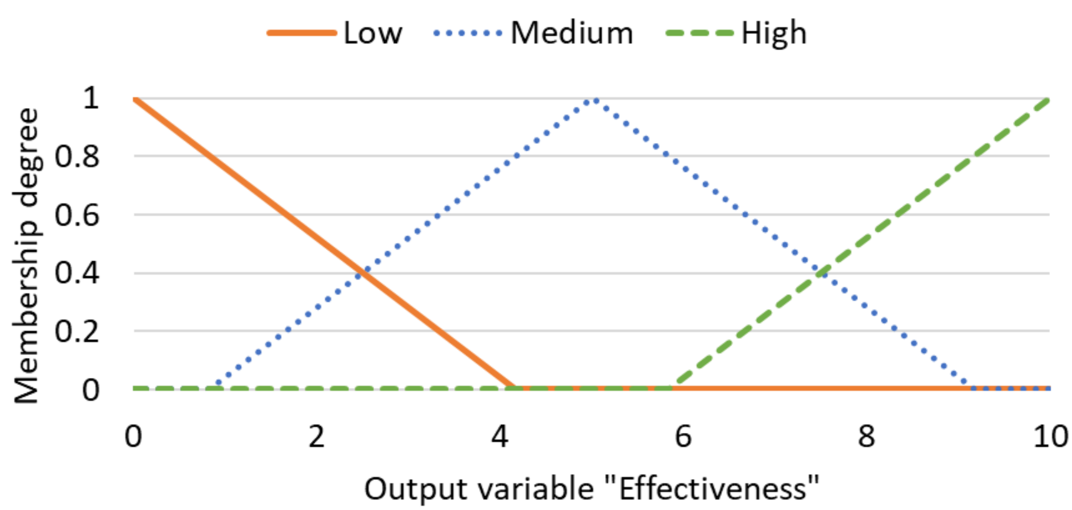

Figure 2.4 Membership functions of effectiveness.

Fuzzy rules are defined as “if-then” rules. In this system, 27 if-then fuzzy rules are defined. Some of these rules are presented in Table 2.1.

Table 2.1 Fuzzy rules used in the FRBS

Rule	If			Then
	Affordability	Achievability	Controllability	Effectiveness
1	Low	Low	Low	Low
2	Low	Low	Medium	Low
3	Medium	Medium	Medium	Medium
4	Low	Medium	Medium	Medium
5	High	High	High	High
6	Medium	High	High	High

Figure 2.5 shows the three-dimensional curve that represents the mapping from inputs to output and the dependency of effectiveness on controllability and affordability.

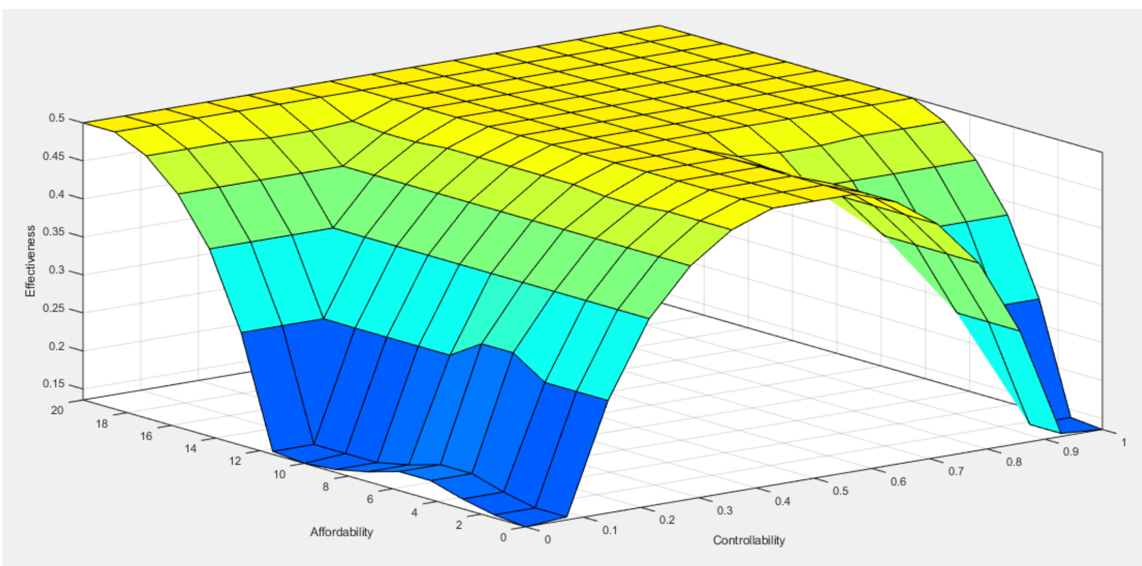

Figure 2.5 Three-dimensional representation of the proposed FRBS.

2.3.3. Selecting effective risk responses using the fuzzy ranking method

In the next step, the risk responses need to be ranked based on their effectiveness, so that the most effective risk response can be selected for each risk event. In order to solve decision-making problems, fuzzy ranking methods are commonly used, wherein the evaluation scores (i.e., effectiveness) of decision alternatives (i.e., risk responses) are represented by fuzzy membership functions (Chen & Wang 2009a; Sadeghi et al. 2016). There are various fuzzy ranking methods discussed in the literature, the majority of which can be grouped into three categories based on the approaches they use to rank fuzzy numbers. The first category of fuzzy ranking methods includes those methods that rank fuzzy numbers based on their α-cuts at a pre-specified level of α (Chen & Wang 2009b) ; thus, these methods change the fuzzy ranking problem into an interval ranking problem. The second category of fuzzy ranking methods includes those methods that use fuzzy distance measures to rank fuzzy numbers (Cheng 1998). The third category of fuzzy ranking methods includes those that rank the fuzzy numbers based on their defuzzified values (Chen & Wang 2009b); these methods change the fuzzy ranking problem into a simple problem of ranking crisp numbers. The first two categories of fuzzy ranking methods (i.e., α-cut-based methods and fuzzy distance-based methods) usually require that fuzzy numbers be regularly shaped (e.g., triangular or trapezoidal fuzzy numbers)(Chen & Wang 2009b). However, in this chapter, the output of the FRBS (i.e., the effectiveness of the risk responses) is an irregularly shaped fuzzy membership function. Therefore, in this chapter, the third category of fuzzy ranking methods (i.e., ranking methods based on the defuzzified value) is used to rank risk responses based on their effectiveness. To do this, the results of the FRBS need to be defuzzified. There are various defuzzification methods proposed in the literature; the smallest of maximum (SOM), largest of maximum (LOM), and center of area (COA) methods are commonly used in different engineering applications of fuzzy logic. Figure 2.6 presents the three aforementioned defuzzification methods implemented on a hypothetical example of risk response effectiveness. Moreover, Figure 2.6 also shows how different defuzzification methods can result in different defuzzified values for risk response effectiveness.

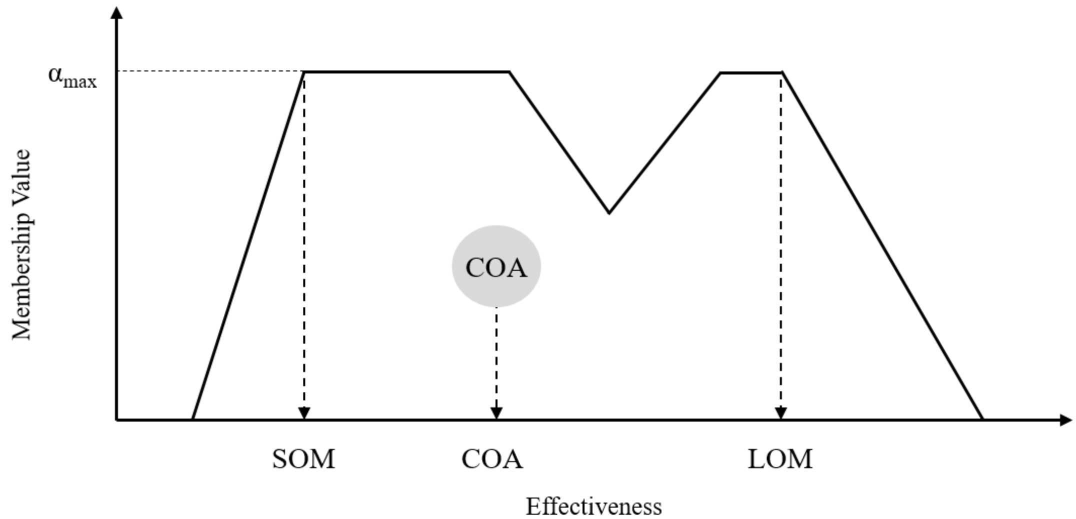

Figure 2.6 COA, SOM, and LOM defuzzification methods.

When ranking risk responses based on the defuzzified value of their effectiveness, the use of different defuzzification methods can mimic different human attitudes towards risk. Ranking risk responses based on the results of the SOM method means that the decision maker considers the smallest maximum value of effectiveness for each risk response and ignores all other possible values for the effectiveness of the risk response (see Figure 2.6). Thus, ranking risk responses based on the results of the SOM method mimics a risk-averse attitude. In contrast, ranking the risk responses based on the results of the LOM method means that the decision maker considers the largest maximum value of effectiveness for each risk response and ignores all other possible values for the effectiveness of the risk response (see Figure 2.6). Thus, ranking the risk responses based on the results of the LOM method mimics a risk-taking attitude. The COA, on the other hand, determines the defuzzified value of effectiveness by taking into consideration all possible values of effectiveness for each risk response. Accordingly, ranking risk responses based on the results of the COA method mimics a neutral human attitude towards risk. In this chapter, the three defuzzification methods (i.e., SOM, LOM, and COA) are used to rank risk responses based on their effectiveness so that all three human attitudes towards risk can be mimicked in the selection of the most effective risk responses.

2.4. Hypothetical Example

In this section, a hypothetical example is presented to demonstrate how to use the proposed approach to evaluate the effectiveness of risk responses and select the most effective. Assume two risk events: (1) incomplete design and (2) operation interruption due to adverse weather conditions. The first risk event can be addressed by two possible risk responses: (1-1) outsourcing design to subcontractors or (1-2) employing professional design teams. To mitigate the second risk event, two risk responses are possible: (2-1) schedule compression using extra resources or (2-2) considering alternative construction methods, such as using precast materials. A number between 0 and 10 represents achievability (where 10 is high) and another number between 0 and 10 represents controllability (again, 10 is high); these numbers are determined for each risk response by expert judgment. The values for each criterion can be found in Table 2.2.

Table 2.2 The input values of each risk response and its related risk event.

Risk Event	Risk Response	Affordability (RRL)	Achievability	Controllability
1	1-1	7.00	9.00	6.00
	1-2	12.00	5.00	6.00
2	2-1	7.00	6.00	2.00
	2-2	5.00	3.00	2.00

Table 2.3 shows the effectiveness values, which are based on the information in Table 2.2. The inputs are imported to the FRBS to evaluate the effectiveness of the risk responses. Crisp numbers representing the effectiveness of the risk responses are then predicted by the FRBS using three defuzzification methods (i.e., SOM, LOM, and COA) as discussed in Section 3.3 and the risk

responses are ranked accordingly. Table 2.3 presents the effectiveness of the risk responses and their rankings for the two risk events.

Table 2.3 The effectiveness values of each risk response and its related risk event

Risk Response	Effectiveness					
	(SOM)	Rank	(LOM)	Rank	(COA)	Rank
1-1	8.50	1	10.00	1	6.95	1
1-2	4.10	2	6.00	2	5.00	2
2-1	0.00	-	2.00	2	3.74	2
2-2	0.00	-	2.50	1	3.92	1

Table 2.3 presents the most effective risk response for each of the two risk events as determined by three different defuzzification methods. The effectiveness value determined using the SOM defuzzification method mimics a risk-averse attitude; the LOM defuzzification method mimics a risk-taking attitude; and the COA defuzzification method mimics a neutral attitude towards risk. Although in this case study the rankings of the risk responses are similar for each of the three defuzzification methods, on real construction projects with numerous risk responses, rankings can be different for different defuzzification methods. Since higher effectiveness of risk responses is favorable, in the hypothetical example, risk responses 1-1 and 2-2 should be selected for risk events 1 and 2, respectively. As shown in Table 2.3, the values of effectiveness for risk responses 2-1 and 2-2 are equal to zero, which indicates neither of these two risk responses should be applied to risk event 2 if the risk response strategy is based on a risk-averse attitude. Moreover, as discussed in Section 3.1, risk responses can be rejected if their effectiveness is less than a threshold value that is determined by the decision maker. For instance, assuming an effectiveness value of 5 as the

threshold for the risk responses' effectiveness, both risk responses for the second risk event (i.e., 2-1 and 2-2) are not acceptable in this case study (refer to Table 2.3). In this situation, new risk responses should be identified for the second risk event or its adverse effects on the project should be accepted.

2.5. Chapter Summary

This chapter presents a methodology for evaluating the effectiveness of identified risk responses by applying an FRBS that has three inputs as evaluation criteria and that produces the effectiveness of risk responses as an output. The three inputs are the affordability of each risk response, the achievability of each risk response, and the controllability of related risk events. The FRBS uses the estimated crisp values of affordability, achievability, and controllability to evaluate the effectiveness of risk responses according to the rules developed based on experts' opinions. The output, which is a fuzzy set, is used as an input for three different fuzzy ranking methods, one based on SOM, one based on LOM, and one based on COG (COA), to determine the most effective risk response in terms of affordability, achievability, and controllability. Applying an expert-driven FRBS and fuzzy ranking methods can help automate the evaluation of risk response strategies, and this technique delivers an expert-level risk management tool to a non-expert in the field.

On construction projects, risk events are often dependent on one another; for example, the risk of precipitation is linked to the risk of excessive soil moisture in earthmoving operations. In order to develop a comprehensive risk response planning tool, interdependencies between different risk events need to be taken into consideration. In future research, the FRBS developed in this chapter will be extended to capture these interdependencies and determine the most effective risk responses for each risk event, accounting for all risk events that affect a project throughout its life cycle.

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Chapter 3: An Interval Type-2 Fuzzy Risk Analysis Model for Determining Construction Project Contingency Reserve[2]

3.1. Introduction

Dealing with uncertainties is an unavoidable challenge of every project. The effect of uncertainties on project objectives, which may be positive or negative, can be controlled by implementing a risk management process. Risk management starts with developing the risk management plan, which determines how risk management activities will be structured, funded, and performed. Subsequently, the risk events must be identified and documented. Then, these events must be analyzed qualitatively and quantitatively in order to be prioritized based on their probability and impact, and to determine the contingency reserve. Response strategies must be identified, assessed, and implemented in order to control the probability of occurrence and/or the impacts of the events. Finally, the effectiveness of the risk management process throughout the project must be evaluated and controlled. In this chapter, to highlight the importance of uncertainties with positive effects, "risk event" and "opportunity event" are defined as uncertain events or conditions that can negatively or positively affect the project objectives, respectively.

To deal with uncertain events, there are two types of reserves in a project, namely management and contingency reserves, that must be calculated and considered in the project budget. Contingency reserve is defined as the money or time allocated in the cost or schedule baseline to

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reduce the overruns of project objectives due to known risks and opportunities (Fateminia et al. 2020a; PMI 2017) . The management reserve is an amount of project budget that is reserved to handle unforeseen events (PMI 2017). The project budget is the summation of the cost baseline and management reserve. The cost baseline is made up by adding the cost estimates of all work packages with contingency reserve (PMI 2017). Ahmadi-Javid et al. (Ahmadi-Javid et al. 2020) categorized uncertain events into two main groups: (1) unknown unknowns that must be addressed with management reserve, and (2) known unknowns that must be addressed proactively (i.e., by employing avoiding, mitigating, and transferring strategies for risks and also exploiting, enhancing, and sharing strategies for opportunities) or reactively (i.e., by employing active and passive accepting strategies). Those events that are addressed by applying proactive response strategies or active acceptance response strategies are dealt with using contingency reserve. Risk and opportunity events addressed with passive acceptance response strategies are dealt with using management reserve (Fateminia et al. 2019a, 2020a). Contingency reserve is a key tool for the decision makers of a project for controlling and responding to risks and opportunities.

Allocating too little or too much for the contingency reserve amounts required for a project may result in significant losses and inefficient resource management (Salah & Moselhi 2015). The accurate estimation of contingency leads to achieving project objectives (e.g., schedule and cost objectives) (Bakhshi & Touran 2014; Salah & Moselhi 2015). Moreover, different uncertainties need to be considered in calculating contingency reserve. Helton (Helton 1997) first defined the dual nature of uncertainty by categorizing it into “objective uncertainty” and “subjective uncertainty.” Objective uncertainty refers to the variability that comes from the stochastic characteristic of an environment and its concepts rooted in probability theory. Subjective uncertainty stems from employing approximate reasoning and linguistically expressed expert knowledge. Fayek and Lourenzutti (2018) break down subjective uncertainty into vagueness, ambiguity, and subjectivity. Vagueness results from the lack of sharpness of relevant distinctions. Ambiguity stems from the lack of certain distinctions characterizing an object, from conflicting distinctions, or from both. Subjectivity results from the influence of personal beliefs or feelings rather than facts (Klir 2006). Classic techniques of calculating the contingency reserve have serious drawbacks and fail to consider vagueness, ambiguity, and subjectivity uncertainties. On the one hand, deterministic approaches, which are based on the intuition and experience of experts, have difficulty calculating the exposure of risk events and determining the appropriate contingency applying to a single crisp value (Iranmanesh et al. 2009). Moreover, deterministic techniques fail to consider opportunities. On the other hand, in the probabilistic approaches, the value of contingency reserve can be affected by the lack of quality and quantity in historical data, since these techniques significantly rely on historical data (Salah & Moselhi 2015). Additionally, probabilistic techniques assume that cost variations are inherently random. Many find it difficult to perform an accurate and precise risk assessment, since the data are either scarce or of low quality (Hao et al. 2019).

Fuzzy logic, which is based on the fuzzy set theory developed by Zadeh (1965, 1999), fills the gap for classic techniques as it handles such uncertainties. Applying fuzzy logic, experts are able to assess the probability and impact of events with linguistic terms such as very low, medium, and high, which can be represented by fuzzy numbers (Zadeh 1975). Fuzzy numbers are a special type of fuzzy sets employed to represent the values of real-world parameters when the exact amounts cannot be measured due to a lack of information or knowledge (Abdelgawad & Fayek 2010). Reviewing the literature shows that fuzzy logic alone or as integrated with other techniques can be employed to address the limitations associated with classic contingency reserve determination tools and techniques. A hybrid method that integrates the fuzzy set theory with the Monte Carlo simulation, proposed by Iranmanesh et al. (2009), can handle both random and subjective uncertainties. However, this suggested method fails to determine the individual effect of each risk event, and instead calculates the range estimation of the combined effect of risk events. Another method proposed by Nieto-Morote and Ruz-Vila (Nieto-Morote & Ruz-Vila 2011) combines the analytic hierarchy process (AHP) with fuzzy set theory to prioritize different risk factors in a building project. However, this proposed fuzzy AHP method (Nieto-Morote & Ruz-Vila 2011) fails to deal with definite scales and has a high potential of encountering inconsistencies during pairwise comparison. In another study (Abdelgawad & Fayek 2011), fault tree analysis (FTA) and fuzzy set theory are integrated for the quantitative assessment of risk events; however, this hybrid approach is unable to handle the drawbacks of the FTA method, which does not model large systems and is inflexible for incorporating later changes. Failure mode and effect analysis (FMEA), AHP, and fuzzy set theory are combined by Abdelgawad and Fayek (2010) to assess risks and determine contingency; however, establishing clearly defined terms for its input and output variables requires a significant effort. To capture the interdependencies among different risk events and variables, a fuzzy system dynamic model (Nasirzadeh et al. 2008) has been proposed; however, it has difficulty establishing the feedback loops and the mathematical equations. Fateminia et al. (2020a) proposed using fuzzy arithmetic-based risk analysis method (FRAM) to fill the gap by addressing the imprecision in measurement and the subjective uncertainty inherent in experts' estimations. FRAM applies a fuzzy arithmetic procedure that solves the problem of substantial reliance on historical data in probabilistic methods. The fuzzy arithmetic procedure employs expert judgment, linguistic scales, and fuzzy numbers resulting in the flexibility of FRAM. Moreover, experts are able to customize linguistic scales and fuzzy numbers for different types of projects and phases. FRAM also considers risk attitude in terms of its contingency calculation and output determination methods. Compared to fuzzy FMEA (Abdelgawad & Fayek 2010), FRAM does not rely on complicated failure cause-and-effect scenarios in its computation procedures. Moreover, FRAM does not depend on feedback loops with complex mathematical equations when several variables are considered in the fuzzy system dynamics model (Nasirzadeh et al. 2008). Moreover, FRAM addresses the measurement imprecision and the subjective uncertainty of experts' opinions when assessing the probability and impact of risks and opportunities. Finally, FRAM enables risk analysts to estimate contingency at different levels of confidence.

FRAM has limitation despite all the mentioned advantages. To implement FRAM in practice, it is necessary to determine the membership functions of linguistic terms pertaining to risk probability, risk impact, opportunity probability, and opportunity impact. FRAM does not propose a systematic method for determining the membership functions of linguistic terms for probability and impact, which are the foundations of its risk analysis process. Moreover, FRAM fails to aggregate the opinions of different subject matter experts (SMEs) about the membership functions of the aforementioned linguistic terms. The membership functions of linguistic terms can vary depending on how the characteristics of each project affect experts' judgements based on their risk attitude, knowledge, experience, and so on. In general, the two main categories of estimating membership functions are expert-driven and data-driven approaches (Pedrycz & Wang 2015). In expert-driven approaches, the elicitation of membership functions is considered as a process of knowledge acquisition via eligible experts. The most common method in expert-driven approaches is the AHP (Saaty 1987), which enables experts to perform pairwise evaluations of alternatives in order to determine their membership function. Membership functions in data-driven approaches, however, are elicited based on the organization (structuring) of data, such as in fuzzy clustering (Pedrycz

2005). There are some limitations to eliciting membership functions through the aforementioned approaches. For example, AHP, as the most common expert-driven method, is not applicable in forming the membership functions of risk analysis linguistic terms in FRAM. To employ AHP, all risks and opportunities must be considered as alternatives for pairwise comparison, which can be impossible or very time-consuming. Moreover, the aggregation of different opinions of SMEs is impossible through AHP. Besides, according to Pedrycz and Wang (2015), there are no explicit performance indexes invoked by the AHP approach. However, since industries suffer from accessing qualified data about risk management, data-driven approaches are not applicable in most cases. Moreover, they may cause fuzzy sets that are not semantically meaningful, which means that fuzzy clustering could result in some "crowded" fuzzy sets with unclear meaning and they would need to be optimized (Pedrycz & Wang 2015). These further adjustments during the optimization process could hinder the interpretability aspect. Various optimization methods are employed to adjust fuzzy sets including the simulated annealing algorithm (Cheng & Chen 1997), genetic algorithm (Arslan & Kaya 2001; Lee & Takagi 1993), and tabu search (Bağiş 2003).

To address these gaps, the objective of this chapter is to propose an interval type-2 fuzzy risk analysis model (IT2FRAM) that extends FRAM (Fateminia et al. 2020a) for determining contingency reserve. The proposed method employs interval type-2 fuzzy sets (introduced by Zadeh (1975)) in order to provide a broader knowledge representation and approximate reasoning for computing with words. Because "words mean different things to different people" (Mendel 2001, 2007), wider knowledge representation in terms of a spread in membership values through type-2 fuzzy sets is more useful as compared to the standard fuzzy sets(Liu & Mendel 2008; Mendel 2007; Mendel & Wu 2006, 2007, 2008). IT2FRAM aggregates the opinion of SMEs using optimized interval type-2 fuzzy sets. The principle of justifiable granularity (Pedrycz 2021) is employed for determining the optimized interval type-2 membership functions of risk analysis concepts (i.e., linguistic variables including probability and impact). This principle provides an alternative to clustering methods in constructing information granules based on the criteria of coverage and specificity of data (Pedrycz & Homenda 2013). However, fuzzy arithmetic using type-2 membership functions versus type-1 membership functions is computationally more demanding (Pedrycz 2005). Thus, type-2 membership functions are type-reduced to type-1 or a standard membership function to perform the fuzzy arithmetic and the calculate crisp output values. The statistical representation of the optimized interval type-2 membership function is used to form a standard membership function, consequently enabling it to be used in a software tool such as the Fuzzy Risk Analyzer© (FRA©). A hypothetical case study is presented to illustrate the application of IT2FRAM in FRA©.

The rest of this chapter is organized as follows. First, the basic definitions of required fuzzy arithmetic operations, type-2 fuzzy sets, and the principle of justifiable granularity are discussed and are necessary to model. Second, the use of IT2FRAM to determine the contingency reserve of projects is described. This model is developed to determine the optimized membership values of linguistic terms of probability and impact for risk and opportunity events. Then, a hypothetical case study was used to show how IT2FRAM can be implemented in practice using FRA©. Finally, the contributions and results of this research are presented, and potential future extensions are discussed.

3.2. Preliminaries Required in IT2FRAM

Fuzzy arithmetic operations, type-2 fuzzy set concepts, and the principle of justifiable granularity are applied in IT2FRAM. Fuzzy arithmetic enables IT2FRAM to employ natural language to assess risk and opportunity events and in turn, determine project contingency reserve by employing fuzzy numbers, which represent linguistic scales. The initial membership functions of linguistic terms are formed using interval type-2 fuzzy set concepts. The intervals of type-2 fuzzy sets are optimized applying the principle of justifiable granularity. Then, the optimized interval type-2 fuzzy sets are converted into standard fuzzy sets.

3.2.1. Fuzzy arithmetic operations in IT2FRAM

A fuzzy set is defined as a set of elements with a degree of membership varying between 0 and 1. The elements of crisp sets, however, have membership degrees of either 1 (fully belong in the set) or 0 (do not belong in the set) (Bezdek 2013; Zadeh 1965). IT2FRAM uses either the α-cut technique (standard fuzzy arithmetic) or the extension principle based on different t-norms (extended fuzzy arithmetic) to perform fuzzy arithmetic operations. The standard fuzzy arithmetic is based on interval analysis and discretizes the input fuzzy numbers into several α-cuts. Then, the α-cut of the output is achieved by interval calculations on each α-level cut of the inputs. Subsequently, the union of the α-cuts is applied to gain the final fuzzy set based on the representation theorem. The mathematical representation of standard fuzzy arithmetic is illustrated in the following:

$$C(z) = A(x) \circledast B(y) = sup_{\alpha \in [0,1]}\, \alpha\big((A_\alpha * B_\alpha)(z)\big) \tag{3.1}$$

where *A(x)* and *B(y)* are input fuzzy numbers and *C(z)* is an output fuzzy number. The α-cuts of the input fuzzy numbers are represented by $A\alpha$ and $B\alpha$, and $\circledast$ represents the basic arithmetic operations. The accumulation of fuzziness results in the overestimation of uncertainty in a standard fuzzy arithmetic method (Pedrycz & Gomide 1998). Extended fuzzy arithmetic is preferred in recent applications because of its capability to reduce uncertainty overestimation problems using any t-norm other than min t-norm (Chang et al. 2006; Lin et al. 2011b,a). Extended fuzzy arithmetic, developed by Zadeh (1965, 1975, 1999), extends the domain of a function on fuzzy sets. It generalizes a common point-to-point mapping of a function to a mapping between fuzzy sets. As presented, in extended fuzzy arithmetic, the membership degree of each output is calculated by taking the supremum of the t-norms of the membership degrees of the inputs:

$$C(z) = A(x) \circledast B(\mathrm{y}) = sup_{z=x*y}\left(t(A(x), B(y))\right) \tag{3.2}$$

where *t* can be one of the common four t-norm operators on fuzzy sets, fuzzy number *C(z)* is the output, and fuzzy numbers *A(x)* and *B(y)* are the inputs. The t-norm *t* is a binary operation, $T: [0,1] \times [0,1] \rightarrow [0,1]$, which is commutative, associative, and non-decreasing in each argument, and $t(x, 1) = x$ for each $x \in (0,1)$. The strength and continuity of common fuzzy t-norms (minimum, algebraic product, Lukasiewicz, and drastic product) are different. In terms of strength, the minimum t-norm is the highest and the drastic product t-norm is the lowest (Pedrycz & Gomide 1998). Furthermore, the changes in output fuzzy numbers result in continuous t-norms, which are less sensitive to the changes in input fuzzy numbers compared to non-continuous t-norms.

Various defuzzification methods are suggested in the literature. As illustrated in Figure 3.1, the single value (defuzzification) methods include the smallest of maximum (SOM), middle of maximum (MOM), largest of maximum (LOM), and the center of area (COA). The best representation of the shape of the output fuzzy number is the COA.

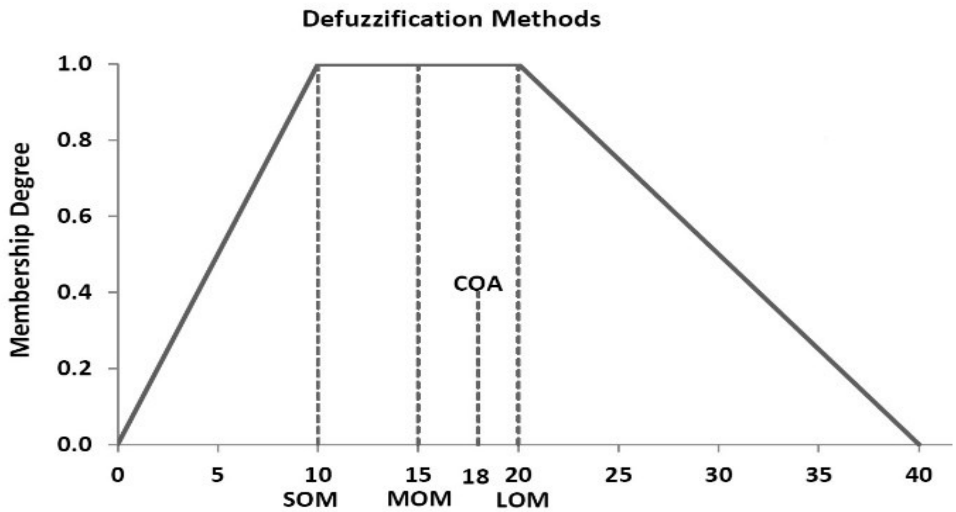


Figure 3.1 Defuzzification: smallest of maximum (SOM), middle of maximum (MOM), largest of maximum (LOM), and COA.

The level of confidence associated with the range of output fuzzy number, represented by the confidence level, can be determined from the corresponding α-cut level (or possibility degree) and ranges between 0 and 1. The possibility degree is the difference between 1 and the confidence level (1—confidence level).

3.2.2. Associated concepts of Type-2 fuzzy set

In IT2FRAM, the interval type-2 fuzzy sets are employed to represent the different opinions of a group of decision makers, or SMEs. This section presents brief introductions to the basic definitions, equations, and theorems associated with type-2 fuzzy sets, and the detailed theoretical background can be found in Mendel (2001), Liu and Mendel (2008) , and Mendel et al. (2006).

Definition 1. *A type-2 fuzzy set, denoted by* $\tilde{A}$ *and represented by a type-2 fuzzy set membership function* $\mu_{\tilde{A}}(x,u)$ *where* $x \in X$ *and* $u \in J_x \subseteq [0,1]$, *is defined as*

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)) | \quad \forall u \in J_x \subseteq [0,1]\}, \tag{1.3}$$

in which $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$. $\tilde{A}$ *can be expressed as*

$$\tilde{A} = \int_{x\in X}\int_{u\in J_x} \mu_{\tilde{A}}(x,u)\,/(x,u)\,. \qquad J_x \subseteq [0,1] \tag{3.2}$$

where $\int \quad \int$ *denotes union over all admissible* x *and* u*.*

Definition 2. *If* $\mu_{\tilde{A}}(x,u) = 1, \tilde{A}$ *is called an interval type-2 fuzzy set. Thus:*

$$\tilde{A} = \int_{x\in X}\int_{u\in J_x} 1\,/(x,u) \qquad J_x \subseteq [0,1] \tag{3.3}$$

Interval type-2 fuzzy sets are a special case of general type-2 fuzzy set. Interval type-2 fuzzy sets can be defined based on vertical slice representation as

$$\tilde{A} = \int_{x\in X} \mu_{\tilde{A}}(x)\,/x = \int_{x\in X}\left[\int_{u\in J_x} 1\,/u\right]/x \qquad J_x \subseteq [0,1]. \tag{3.4}$$

Definition 3. *Primary membership of* x *is the domain of a secondary membership function. Thus, in Equation (3.6), the primary membership of* x *is* J_x*,* $J_x \subseteq [0,1]\ \forall x \in X$*. The secondary grade is the amplitude of secondary membership function. For an interval type-2 fuzzy set, all secondary grades are equal to 1.*

Definition 4. *Footprint of uncertainty (FOU) of* $\tilde{A}$ *is the bounded region depicting the uncertainty in the primary membership function. It can be represented as the union of all the primary membership functions:*

$$FOU(\tilde{A}) = \bigcup_{x\in X} J_x \tag{3.5}$$

This is vertical slice representation of FOU.

In the case of an interval type-2 fuzzy set, FOU conveys all the necessary information; the secondary grades do not convey any new information. Knowledge of FOU is highly useful, because it highlights the inherent uncertainties of the type-2 fuzzy set membership functions whose shape indicates the nature of uncertainties. Furthermore, it helps in choosing appropriate type-2 fuzzy set membership functions. Some of the commonly used FOUs are shown in Figure 3.2.

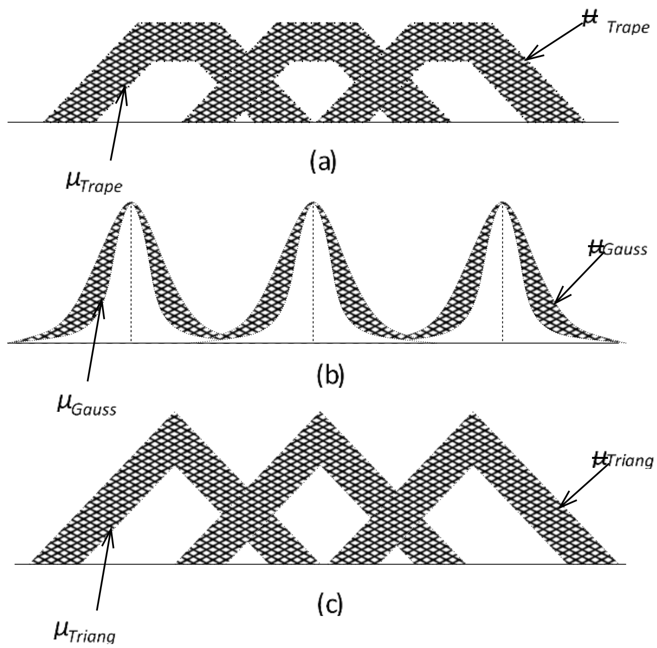


Figure 3.2 Some commonly used footprints of uncertainty (FOUs) for type-2 fuzzy sets with primary membership functions: (a) trapezoidal, (b) Gaussian, and (c) triangular.

3.2.3. Interval Type-2 fuzzy set modeling using uncertainty degree

There are two methods of constructing interval type-2 fuzzy set models from data. One is the interval approach (Liu & Mendel 2008; Wu et al. 2011) and the other is the fuzzistics approach (Mendel 2007; Mendel & Wu 2006, 2007). The former method involves the use of statistics to realize the interval type-2 fuzzy set modeling, whereas the latter uses a kind of uncertainty measure (mostly centroid) of interval type-2 fuzzy sets in order to ensure that an identified interval type-2 fuzzy set model captures the uncertainty of the collected data. In addition to the well-studied centroid of interval type-2 fuzzy sets (Mendel 2007; Mendel & Wu 2006, 2007), other uncertainty measures exist in the literature (Li et al. 2013). In Li et al. (2013), the uncertainty measure is called the "uncertainty degree of interval type-2 fuzzy sets" and it is based on the lower and upper α-cuts of interval type-2 fuzzy sets. This method provides a type-1 fuzzy set if all the uncertainties in the interval end points data vanish. This method is applied in modeling the interval type-2 fuzzy sets from the data collected from surveys. The brief description of uncertainty degree method in modeling interval type-2 fuzzy sets, as adapted from Li et al. (2013), is described below.

Suppose *p* words need to be modeled using interval type-2 fuzzy sets. To model these, data need to be collected from a group of SMEs. Let us assume *n* subjects are surveyed. Thus, for each word we get *n* intervals $\left[x_i^l, x_i^r\right]$. The sample mean x_m^l for left end points, mean x_m^r for right end points, and the standard deviation s^l for the left end points, s^r for right end points are given as follows:

$$x_m^l = \frac{\sum_{i=1}^{n} x_i^l}{n} \tag{3.6}$$

$$x_m^r = \frac{\sum_{i=1}^{n} x_i^r}{n} \tag{3.7}$$

$$s^l = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i^l - x_m^l\right)^2}{n}} \tag{3.8}$$

$$s^r = \sqrt{\frac{\sum_{i=1}^{n}(x_i^r - x_m^r)^2}{n}} \tag{3.9}$$

Statistically, the word should be contained within the $[x_m^l, x_m^r]$ data. For some subjects, the word should be contained in the data $[x_m^l - \Delta x, x_m^l] \cup [x_m^r, x_m^r + \Delta x]$. The following equation was used to determine the end points' uncertainty degree (Li et al. 2013):

$$\rho x = \frac{2\Delta x}{x_m^r - x_m^l + 2\Delta x} \tag{3.10}$$

Li et al. (2013) have shown that in the case of $\Delta x = 0$, the interval type-2 fuzzy set reduces to a type-1 fuzzy set.

3.2.4. Principle of justifiable granularity

The principle of justifiable granularity is used in IT2FRAM to determine the optimum value of upper and lower bounds of intervals in interval type-2 fuzzy sets. One of the fundamentals of granular computing is the principle of justifiable granularity, which is about constructing information granules based on the available experimental evidence resulting in a form of a collection of one-dimensional numeric data, D = {x1, x2, ..., xN} where xk ∈ R. A given information granule Ω must satisfy two requirements of high specificity and appropriate experimental evidence (coverage). *High specificity* refers to the required level of abstraction of information granules and implies their tangible semantic of them. Higher specificity represents more specific (less abstract) information granules. Moreover, an "experimentally justified information granule" means that an information granule should be supported by the available experimental evidence. The following definitions and equations are adapted from Pedrycz (2005) , Pedrycz and Homenda (2013), and Pedrycz (2018).

Definition 5. The numeric evidence accumulated within the bounds of information granule Ω (coverage) must be as high as possible. Therefore, the existence of the information granule Ω is justified as it reflects the existing experimental data D. For instance, if the information granule Ω is a set of numeric data, then the more data contained within the bounds of Ω, the better, and the set is more legitimate. Coverage is related to the ability of information granules to represent numeric data. Coverage is expressed as the cardinality (count) of the data X included in the interval [m,b], assuming m in the numeric representative of a data set, such as a median.

$$\mathrm{cov} = \mathrm{card}\ \{xk\ |xk \in [m, b]\} \tag{3.11}$$

Definition 6. The information granule Ω must be specific, which means that the resulting information granule must be semantically meaningful. This implies that the smaller the information granule Ω is, the better. In general, specificity is a measure of how detailed the formed information granule is. Some substantial requirements are: (1) specificity is the highest when there is only one element in the information granule, (i.e., sp({x}) = 1); (2) if two information granules have the relationship $A \subset B$, then sp(A) > sp(B); and (3) specificity is the lowest when the information granule Ω is constructed as an entire universe of discourse. We can view specificity as a decreasing function of the size of information granules. In the case of an interval, we can relate specificity directly with the length of the interval and define any decreasing function of the length that is |m−b| or |m−a|. For instance, we can express the specificity of A = [m,b] in the following detailed form:

$$\mathrm{sp}(A) = \exp(-|m - b|) \tag{3.12}$$

or exp(−|m − a|) for the lower bound of the interval. Alternatively, we can satisfy the formulation of the specificity measure with the relative length of all the possible values assumed by numeric data (the length). The specificity then is as follows:

$$sp = 1 - \frac{b - m}{x_{max} - m} \tag{3.13}$$

Note that both Equations (3.14) and (3.15) result in the highest specificity amount when b = m, however Equation (3.15) is equal to the zero value of specificity for $b = x_{max}$.

Definition 7. Coverage and specificity measures are conflicting by nature, which means that increasing coverage decreases specificity and vice versa, and constructing the information granules is a result of tradeoff between them. Therefore, there is an optimization problem with a multiplicative form of the objective function:

$$V(b) = \text{coverage} \times \text{specificity} \tag{3.14}$$

Equation (3.16) can be realized independently for the lower and upper bound of the interval as follows:

$$V(b) = \mathrm{f1}(\mathrm{card}\{xkD|med(D) < xk \leq b\}) * \mathrm{f2}(|med(D) - b|) \quad (3.15)$$

$$V(a) = \mathrm{f1}(\mathrm{card}\{xk \in D|a \leq xk < med(D)\}) * \mathrm{f2}(|med(D) - a|) \quad (3.16)$$

By maximizing V(b), we achieve an optimal value of b, i.e.,

$$b_{opt} = \arg\ \max b\ V(b). \quad (3.17)$$

3.3. Interval Type-2 Fuzzy Risk Analysis Model (IT2FRAM)

IT2FRAM is a multi-step model employing fuzzy arithmetic to analyze risk and opportunity events to determine contingency reserve for construction projects. Figure 3.3 presents the five steps of IT2FRAM and their outputs. In steps 1 and 2, the work, cost, and risk breakdown structures (WBS, CBS, and RBS) are determined. In step 3, the membership functions of the linguistic terms for risks and opportunities are determined using interval type-2 fuzzy sets and the principle of justifiable granularity as explained in Sections 2.2–2.4. Then, in step 4, the identified risks and opportunities are assessed by SMEs using linguistic terms and their related fuzzy numbers. Finally, the contingency reserve can be calculated in step 5 using fuzzy arithmetic as explained in Section 3.2.1.

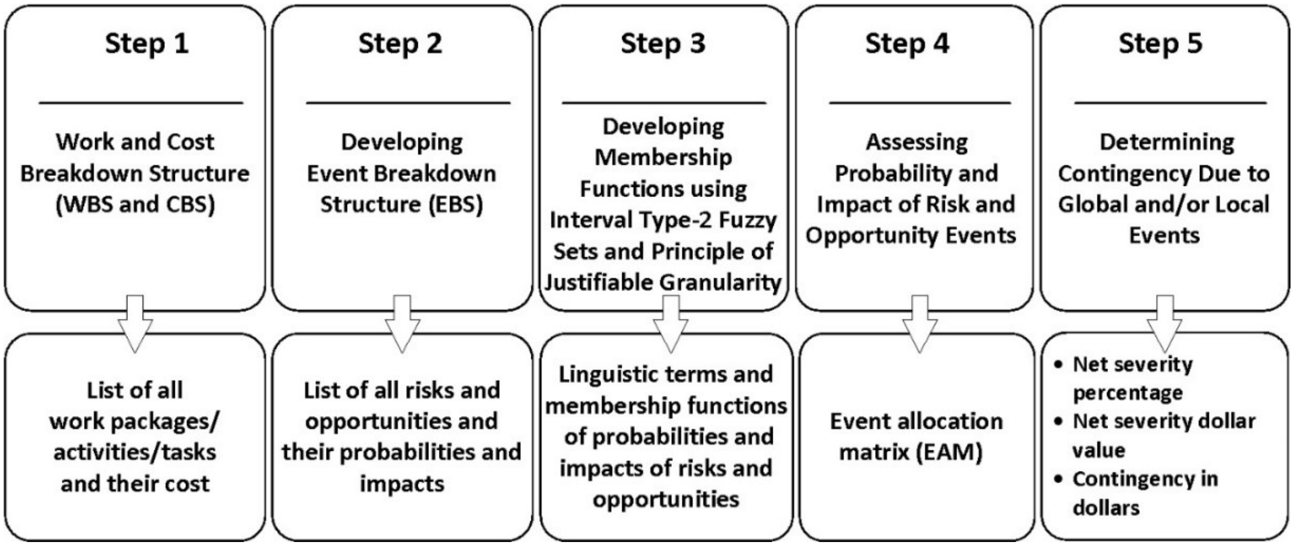


Figure 3.3 Steps of IT2FRAM (modified from Fateminia et al., 2020).

In step 1, the WBS and CBS are developed. The WBS is the foundation of IT2FRAM assuming that each project contains up to a three-level WBS, namely work package, activity, and task. As an example, Figure 3.4 shows a three-level WBS of a wind farm project illustrated in FRA©. The CBS must be developed after establishing the WBS to determine the cost of the work packages, activities, and tasks. Developing the event breakdown structure (EBS) and the identification of potential risk and opportunity events are step 2 in IT2FRAM. Since there is no consensus on the standard categorization of risk and opportunity events (Nieto-Morote & Ruz-Vila 2011), different combinations of risk and opportunity identification methods can be employed, ranging from information-gathering methods to analysis-based techniques. Siraj and Fayek (2019) conducted a systematic review and content analysis of 130 papers from journals with high impact factors in the construction engineering and management area published between 1990 and 2017. They propose eleven categories of risk and opportunity events, which are considered as the default template of IT2FRAM. These event categories are depicted in Figure 3.5: resource-related, management, technical, construction, site conditions, contractual and legal, economic, financial, environmental, social, political, and health and safety.

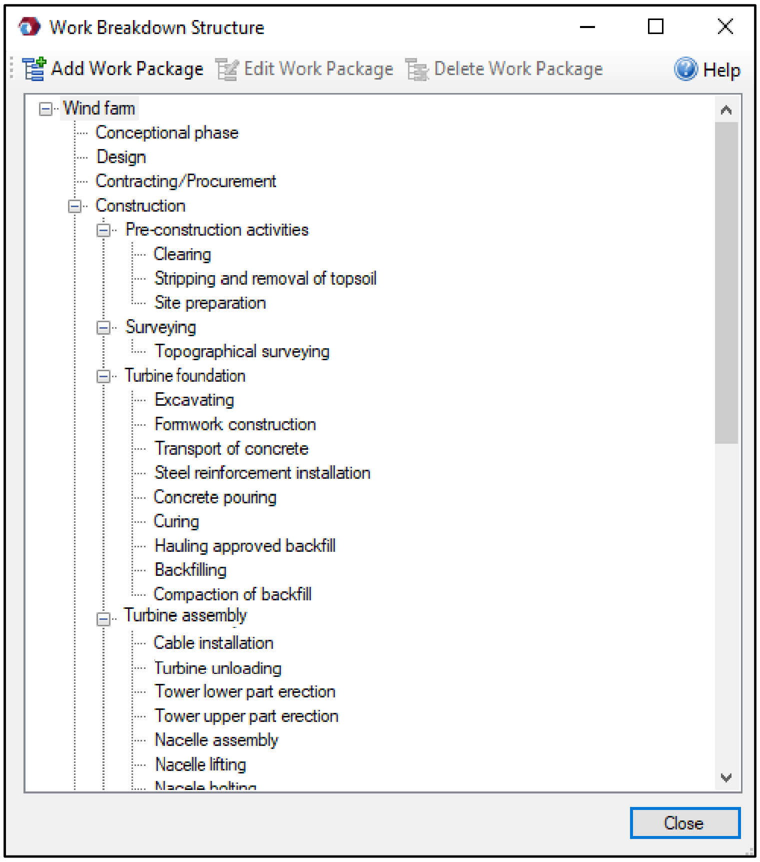


Figure 3.4 Three-level work breakdown structure (WBS) comprising work packages, activities, and tasks in FRA©.

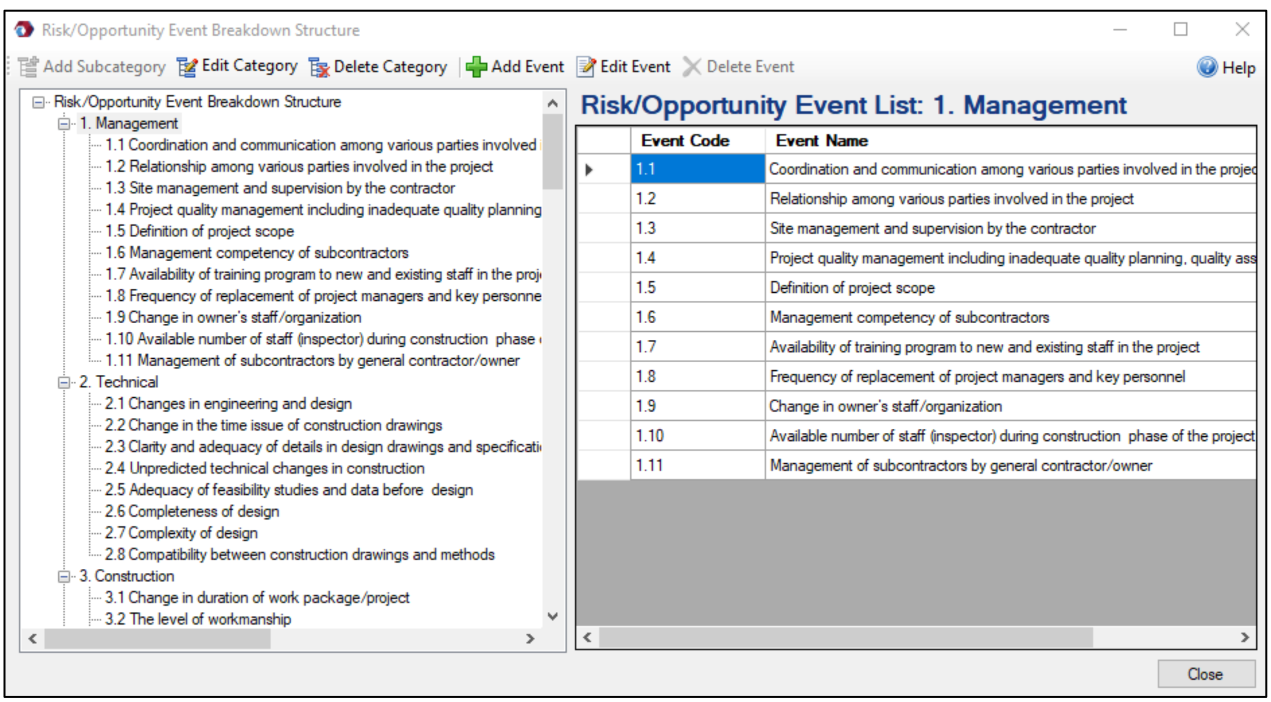


Figure 3.5 Two-level event breakdown structure (EBS) in FRA©.

In step 3, the linguistic terms and scales must be established and optimized to assess the probability and impact of the events. Triangular or trapezoidal fuzzy numbers represent linguistic terms. According to Fayek and Lourenzutti (2018)Click or tap here to enter text., Pedrycz (1994), and Proske (2008), triangular and trapezoidal shapes are the most common shapes for fuzzy numbers that have supports with the open intervals of real numbers. Triangular fuzzy numbers are a special case of trapezoidal fuzzy numbers. In IT2FRAM and according to Hall (1998), the probability and impact of events are commonly determined by five linguistic terms namely, *very low*, *low*, *medium*, *high*, and *very high*. A sample of triangular membership functions for risk and opportunity probability with respective linguistic terms is presented in Figure 3.6.

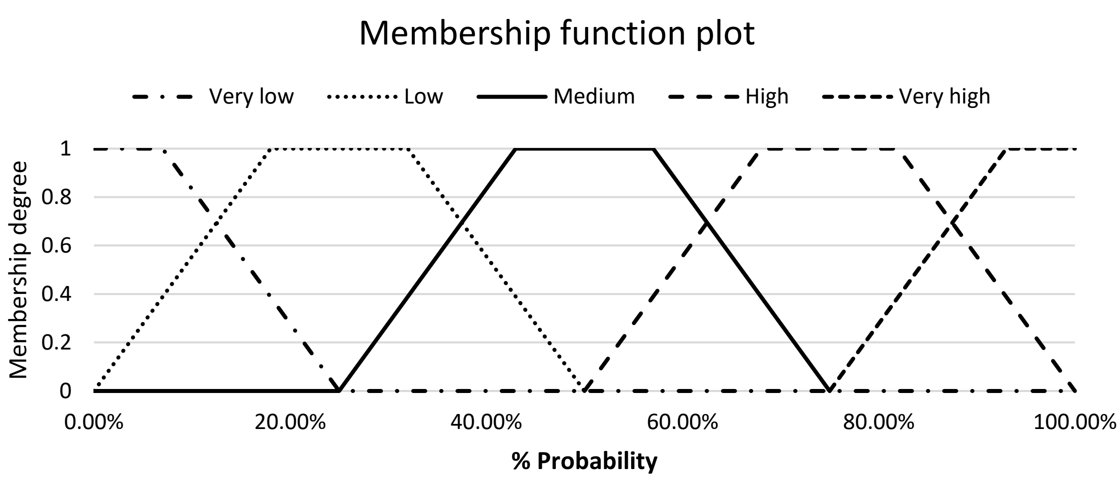


Figure 3.6 Membership functions of the linguistic terms for risk probability.

Different membership functions for probability and impact must be formed and aggregated to benefit from the knowledge and experience of all decision makers and SMEs on a project. Type-1 fuzzy sets project only one crisp number for the membership degree of each linguistic term, while interval type-2 fuzzy sets return an interval. Therefore, interval type-2 fuzzy sets are preferable, and they provide more information than type-1 fuzzy sets. An interval type-2 fuzzy set also covers all opinions. Figure 3.7 shows a hypothetical case study of various membership functions of the linguistic term *very low* for *risk probability* as determined by seven SMEs. For instance, in Figure 3.7, based on the opinion of SME 1, the risks with very low probability are those risks with an occurrence probability of less than 6 percent with the full membership degree in 0. Lower and upper limits of the intervals can be determined by the lowest and the highest height of the triangular membership functions built based on the opinions of different SMEs.

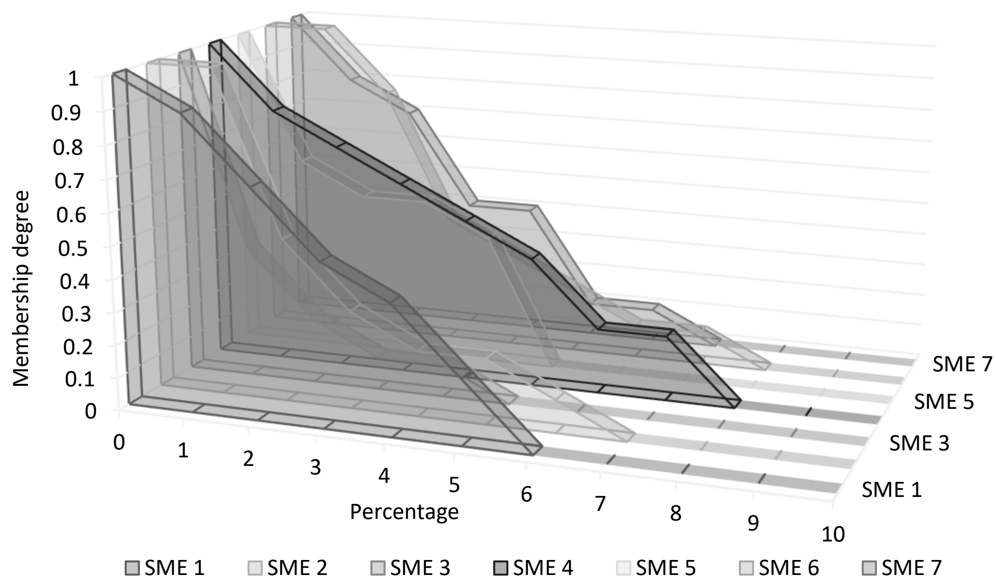


Figure 3.7 Suggested membership functions of the linguistic term very low for risk probability by seven subject matter experts (SMEs).

Then, the optimal lower and upper limits of the interval type-2 fuzzy set for each linguistic term are determined by maximizing the specificity and the coverage of each horizontal interval and simultaneously applying the principle of justifiable granularity (see Section 3.2.4). The intrinsic contradiction between the maximization of the coverage and the maximization of the specificity results in an optimization problem with a multiplicative form of the objective function. Having these two criteria in mind, a numeric representative, a robust estimator of the sample such as median *med (D)*, must be selected for each horizontal interval (horizontal information granule). The determination of the upper and lower bound must be realized independently but in the same way. The optimal upper bound must be obtained by maximizing the value of $V(b)$ in Equation (3.17). In the same way, the lower bound must be realized based on Equation (3.18). This process must be repeated for all intervals for each linguistic term. Then, the optimized horizontal intervals of each linguistic term are converted into interval type-2 fuzzy sets. Such a constructed optimized interval type-2 fuzzy set represents the aggregated opinions of all SMEs without the effect of outlier opinions. A statistically representative embedded set of the constructed optimized interval type-2 fuzzy set is used in the next steps of IT2FRAM.

In step 4, the probability and impact of events are assessed. Because of the neutral wording of events, each event can be evaluated simultaneously as a risk and an opportunity. An event allocation matrix (EAM) is employed to determine the relationships among the events and the project's work packages, activities, and tasks on the basis of expert judgment and project context. Events are categorized as local and global. The global events impact several work packages, activities, and tasks and are evaluated for the assigned group. On the contrary, local events can only be assessed individually for each work package, activity, or task and so are assigned individually to individual work packages, activities, and tasks. IT2FRAM considers two capabilities to improve the accuracy of the result: 1) determining the percentage value (between 0 and 100 percent) of each work package, activity, or task impacted by each local or global event, and 2) determining the portion of the estimated cost of the work package, activity, or task (in terms of a percentage or dollar value) affected by each local or global event.

Finally, the contingency of a work package, activity, or task is calculated applying the following fuzzy arithmetic procedure with respect to local events. (1) First, the probability and impact of the risk and opportunity events are evaluated by decision makers or SMEs in terms of the optimized linguistic scales which were established in step 3. Due to the neutral wording, the local events are assessed two times, both as risk and opportunity. (2) Risk and opportunity severities are calculated as a percentage by the multiplication of probability and impact fuzzy numbers. (3) The net severity percentage of each local event is calculated by a summation of risk severity and opportunity severity. (4) The fuzzy number of net severity dollar value is calculated for each local event by the multiplication of its net severity percentage by the affected cost of the work package, activity, or task. (5) The total local contingency in dollars of the work package, activity, or task is calculated by the summation of the net severity (in dollars) of all local events affecting it. (6) The same procedure (1–5) must then be used to calculate the total global contingency in dollars, with the only difference being that assessing the probability and impact of each global risk event is done for the affected group of work packages, activities, and tasks, instead of each work package, activity, or task individually. (7) Finally, the total contingency of the project is calculated by subtracting the total local contingency from total global contingency, reported in dollars (see Section 3.2.1 for detailed fuzzy arithmetic).

3.4. Implementation of IT2FRAM in FRA© and Discussion

In this section, a hypothetical case study is presented as an illustration of how to implement IT2FRAM in practice. FRA© is employed to implement the fuzzy arithmetic procedures of IT2FRAM. The three-level WBS of a hypothetical onshore wind farm project includes six work packages, 11 activities, and 42 tasks. The budget is CAD 554,628,000, and the work packages and their respective costs are presented in Table 3.1. The default two-level EBS in FRA© (see Figure 3.5) was modified resulting in new EBS with 26 risk and opportunity events, six of which were global and 20 were local.

Table 3.1 Cost of work packages.

Work Package Name	Total Cost (CAD)
Conceptional phase	$6,000,000
Design	$3,000,000
Contracting/procurement	$399,764,000
Construction	$135,664,000
Handover checklists	$5,000,000
Operation/maintenance	$5,200,000

For step 3, linguistic terms and their scales and respective fuzzy sets are established in order to evaluate the probability and impact of the risk and opportunity events. The opinions of different SMEs must be collected for the linguistic terms of probability and impact of events. In this hypothetical situation, it is assumed that there are seven SMEs whose opinions are essential for analyzing the risk and opportunity events. Table 3.2 summarizes their opinions about the membership function of the linguistic term *very low* for *risk probability*. Based on the opinion of SME 1, the linguistic term *very low* for *risk probability* ranges from 0 to 6 percent with the membership value of 1 in 0 percent. However, for SME 4 this value is different and ranges between 0 and 8 percent.

The interval type-2 fuzzy sets are used to consider all the membership functions suggested by different SMEs. As illustrated in Figure 3.8, an interval type-2 fuzzy set is formed by taking the minimum and maximum of each column in Table 3.2.

Table 3.2 The membership values of the very low risk probability suggested by seven SMEs.

Expert \ Percentage Value	0	1	2	3	4	5	6	7	8	9	10
SME 1	1	0.9	0.7	0.5	0.4	0.2	0	0	0	0	0
SME 2	1	1	0.5	0.3	0.2	0.2	0.1	0	0	0	0
SME 3	1	0.4	0.2	0.1	0.1	0	0	0	0	0	0
SME 4	1	0.8	0.7	0.6	0.5	0.4	0.2	0.2	0	0	0
SME 5	1	0.6	0.5	0.5	0.4	0	0	0	0	0	0
SME 6	1	1	0.8	0.4	0.3	0.2	0.1	0.1	0	0	0
SME 7	1	0.8	0.7	0.4	0.4	0.1	0.1	0	0	0	0

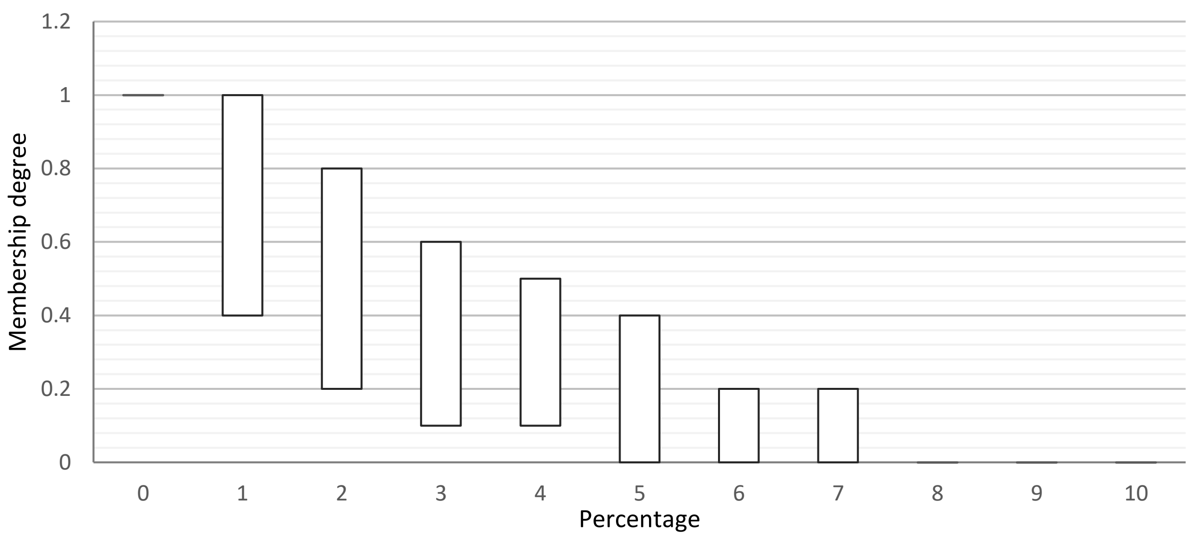


Figure 3.8 Membership function of interval type-2 fuzzy set of very low before optimization.

Then, by applying the principle of justifiable granularity and taking it as a multiplicative optimization problem, the tradeoff between specificity and coverage are performed. The lower and upper bounds of the interval type-2 fuzzy set membership function of all the intervals are calculated by maximizing the coverage and the specificity of the interval simultaneously (see Section 3.2.4). Figure 3.9 shows the trade-off results for horizontal intervals from 1 to 4 in Figure 3.8.

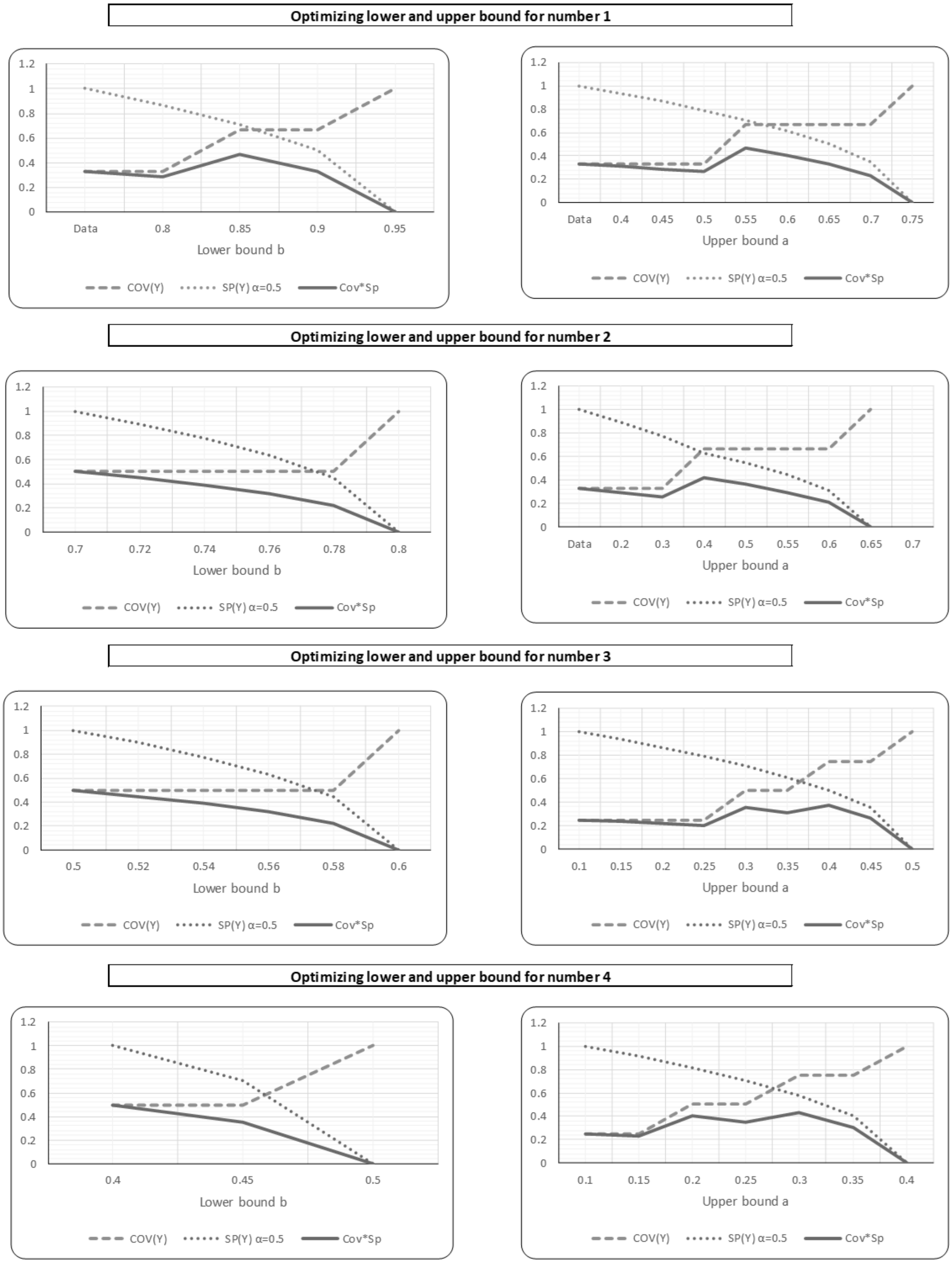


Figure 3.9 Optimizing the lower and upper bounds of interval type-2 fuzzy sets.

Figure 3.10 shows the optimized interval type-2 fuzzy set membership function of the linguistic term very low for risk probability.

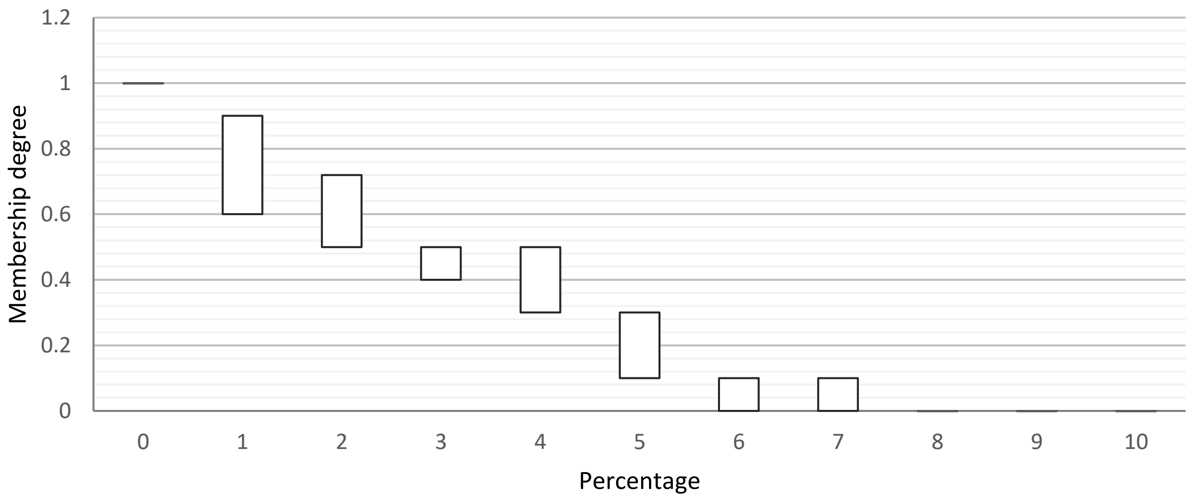


Figure 3.10 Optimized interval type-2 fuzzy set membership function of very low after optimization.

Based on the theories and concepts associated with interval type-2 fuzzy sets (Mendel 2001; Mendel & John 2002; Mendel et al. 2006), it is evident that interval type-2 fuzzy sets capture more uncertainty than their type-1 counterparts. Thus, interval type-2 membership functions are used to aggregate the opinions of all the SMEs. However, to minimize the effect of outlier opinions, the principle of justifiable granularity is used. These optimized membership functions are then type-reduced to standard membership functions for crisp output calculation. Figure 3.11 illustrates the process of converting interval type-2 membership function to type-1 membership function based on Sections 3.2.2 and 3.2.3.

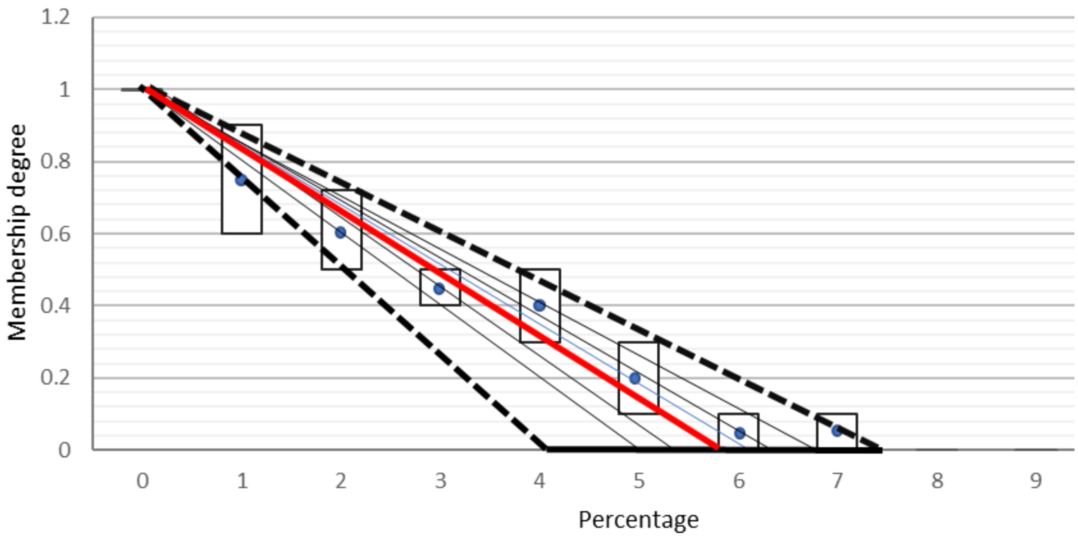


Figure 3.11 Converting the optimized interval type-2 fuzzy set membership function of very low to a type-1 fuzzy set.

The aim is to find the best fit line passing through these interval fuzzy values. Statistically, the interval fuzzy values are represented by the mean and spread. The interval sets are represented by their corresponding mean points in the *x*–*y* space, which are (0,1), (1,0.75), (2,0.6), (3,0.45), (4,0.4), (5,0.2), (6,0.05) and (7,0.05). The mean values of all the interval fuzzy sets might not lie on a straight line. To find the best fit linear equation, we solve linear equations between (0,1) and the mean point of each interval set that provides an intercept value at the *x* axis. Solving the linear equation between points (0,1) and (1,0.75) yields the intercept on the *x* axis at $x = 4$. We draw other lines by solving the line equations between (0,1) and the other mean points. The line between (0,1) and (7,0.05) gives the intercept value on the *x*-axis at $x = 7.37$. Thus, all the calculated intercepts on the *x*-axis are at $x = \{4, 5, 5.45, 6.67, 6.25, 6.31, 7.37\}$. This represents a region of uncertainty between $x = 4$ and $x = 7.37$, which is a direct consequence of the differences in opinion of the SMEs. This region of uncertainty forms the FOU of the interval type-2 fuzzy set with the triangular membership function. The interval type-2 set can be modeled as described in Section 3.2.3. Statistically, the word being modeled should be contained within $[x_m^l, x_m^r]$. Here, x_m^l is the mean of the left end points of the interval type-2 fuzzy set and x_m^r is the mean of the right end points. Assuming that the end point uncertainties disappear, then the above interval type-2 fuzzy set reduces to a type-1 fuzzy set with $a = b = x_m^r = x_m^l$. The mean of these points is at x_m^r = 5.86 with the standard deviation s = 1.046. The resulting type-1 fuzzy set is highlighted with red color. Similarly, the optimized membership functions are obtained for other linguistic terms. Figure 3.12 illustrates the optimized membership functions of all the linguistic terms for risk probability.

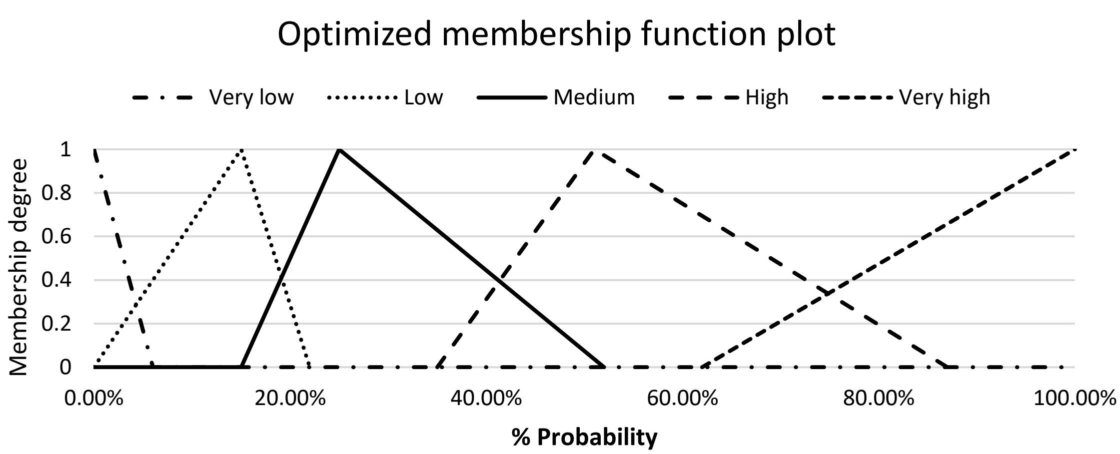


Figure 3.12 Optimized membership functions of the linguistic terms for risk probability.

In step 4, as illustrated in Figure 3.13, the identified local and global risk and opportunity events are assigned to work packages, activities, and tasks, and the probability and impact of these events are assessed on the basis of linguistic terms (type-1 fuzzy sets determined in step 3).

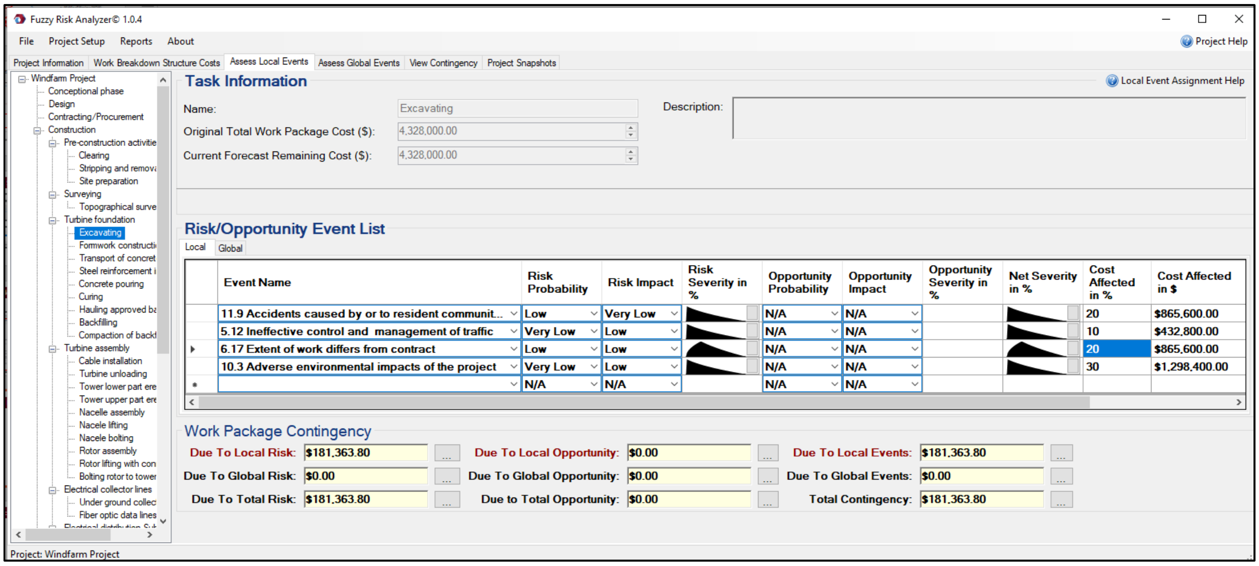


Figure 3.13 Assigning and assessing the local events.

Finally, fuzzy arithmetic is employed to calculate the work package and project contingency reserve using FRA©. IT2FRAM provides the user with the choice of standard fuzzy arithmetic or extended fuzzy arithmetic, the latter of which uses four different t-norms. The resulting fuzzy value of contingency reserve can be presented both as an interval value using the confidence level and as a crisp value based on the selection of a single value (defuzzification) method (Figure 3.14). The defuzzified single value of the total project contingency reserve based on the COA is CAD 7,307,032, and at an α-cut level of 0.50 there is a confidence level (possibility degree) of 0.5 that the project contingency will be between CAD 932,573 and CAD 9,890,760.

Figure 3.15 is the project summary graph report created by FRA© that provides a visualization of the defuzzified contingency values. This report is only available when a single defuzzified value is being used as the output in FRA©.

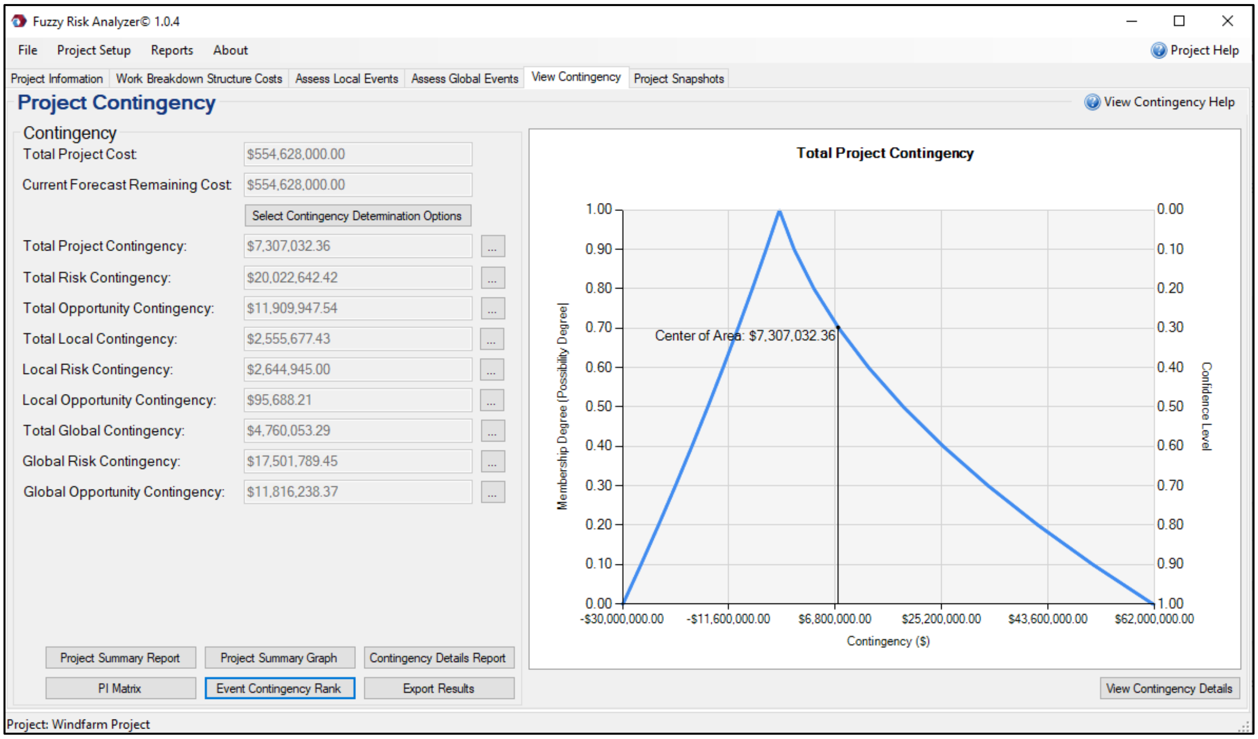
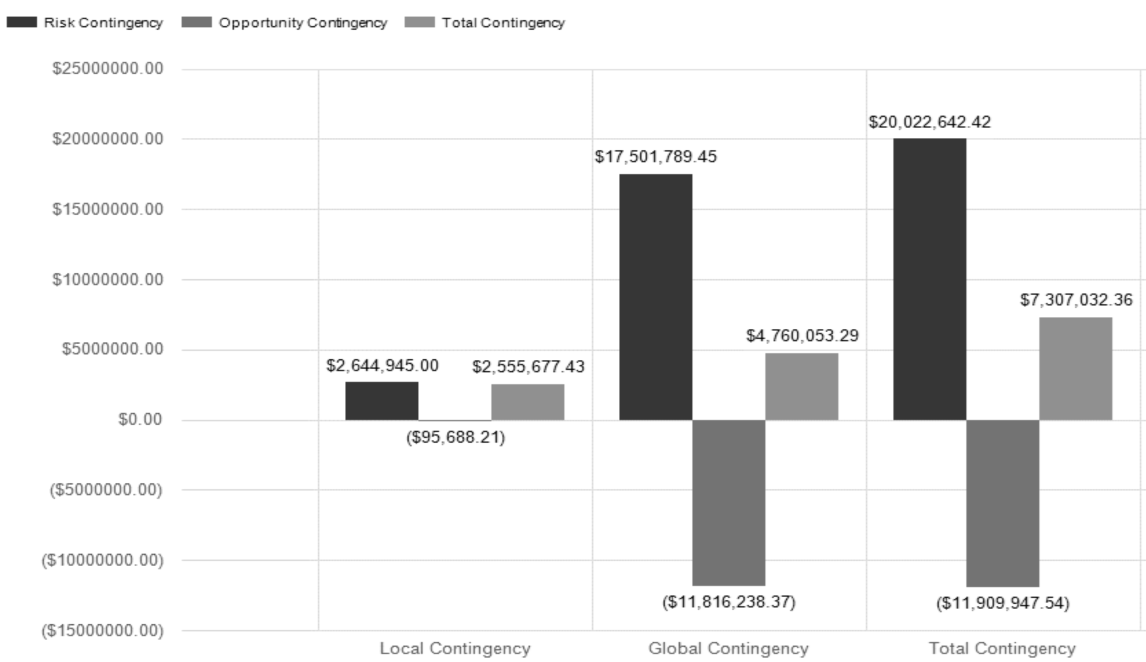


Figure 3.14 Assigning and assessing the local events.



	Risk Contingency	Opportunity Contingency	Total Contingency
Local Contingency	$2,644,945.00	($95,688.21)	$2,555,677.43
Global Contingency	$17,501,789.45	($11,816,238.37)	$4,760,053.29
Total Contingency	$20,022,642.42	($11,909,947.54)	$7,307,032.36

Figure 3.15 Local, global, and total contingency values.

FRA© also is able to calculate the confidence intervals of contingency reserve before defuzzification. The level of confidence associated with the range of output fuzzy number, represented by the confidence level, can be determined from the corresponding α-cut level (or possibility degree) and ranges between 0 and 1. The possibility degree is the difference between 1 and the confidence level (1—confidence level).

In Table 3.3, several contingency reserve determination methods are summarized and compared based on ten criteria. IT2FRAM provides a unique structured way to develop, optimize, and aggregate the linguistic terms. IT2FRAM addresses the limitations of the other methods of contingency reserve determination. The interval type-2 fuzzy sets in IT2FRAM capture more uncertainties, provide better knowledge representation, and consider several experts' opinions. The principle of justifiable granularity optimizes these interval type-2 fuzzy sets by maximizing the performance index of two criteria—coverage and specificity—which helps minimize the effects of outlier opinions of SMEs. IT2FRAM provides an alternative to other methods for the elicitation of membership functions such as fuzzy clustering and AHP, which cannot be effectively applied to form the membership functions of risk analysis linguistic terms. Based on Table 3.3, it is clear that IT2FRAM has greater advantages than the models developed in the past and extends FRAM (Fateminia et al. 2020a) by proposing a structured method to determine the membership functions of linguistic terms for probability and impact that are the foundations of its risk analysis process. Moreover, IT2FRAM fulfills the need to (1) aggregate the opinions of different SMEs about the membership functions of the identified linguistic terms and (2) remove outlier opinions.

Table 3.3 Comparison of the contingency reserve determination methods (modified from Fateminia et al., 2020).

Methods	Criteria	Providing quantitative analysis	Calculating contingency	Prioritizing risks	Considering range or distribution for contingency	Considering subjective uncertainty	Providing confidence level	Considering local and global risk and opportunity events	Having low reliance on data	Considering portion/percentage of affected work package, activity, or task	Providing a structured way to develop, optimize, and aggregate the linguistic terms
Deterministic approaches	Probability-impact matrix (PI matrix)	-	√	√	-	-	-	-	-	-	-
	Predefined percentages	-	√	-	-	-	-	-	-	-	-
Probabilistic approaches	Monte Carlo simulation (MCS)	√	√	√	√	-	√	-	-	-	-
Fuzzy-based approaches	Fuzzy failure mode and effect analysis (Fuzzy FMEA)	√	-	√	-	√	-	-	√	-	-
	Fuzzy fault tree analysis (Fuzzy FTA)	√	-	√	-	√	-	-	√	-	-
	Fuzzy risk analysis model (FRAM)	√	√	√	√	√	√	√	√	√	-
	IT2FRAM	√	√	√	√	√	√	√	√	√	√

3.5. Chapter summary

The uncertain events involved in projects make it challenging to achieve the project objectives without performing a risk and opportunity analysis and determining the contingency reserve. In this chapter, type-1 fuzzy arithmetic, interval type-2 fuzzy sets, and the principle of justifiable granularity are combined to improve the project contingency reserve determination. The new method, called interval type-2 fuzzy risk analysis model (IT2FRAM), is introduced in order to develop, optimize, and aggregate the membership functions for the probability and impact of risk and opportunity linguistic terms (e.g., *very low*). IT2FRAM is an extension of the fuzzy arithmetic-based risk analysis model proposed by Fateminia et al. (2020a), which addresses the limitations of traditional techniques of project contingency determination methods. Interval type-2 fuzzy sets are employed to capture more uncertainties, provide better knowledge representation, and consider several experts' opinions. The principle of justifiable granularity is employed to optimize interval type-2 fuzzy sets by maximizing the performance index of two criteria: coverage and specificity. IT2FRAM also provides an alternative to other methods for the elicitation of membership functions, such as fuzzy clustering and the analytical hierarchy process (AHP), which cannot be effectively applied to form the membership functions of risk analysis linguistic terms. A software tool, Fuzzy Risk Analyzer© (FRA©), was introduced to illustrate the implementation of IT2FRAM using a hypothetical case study.

The contributions of this chapter are in addressing the following challenges associated with previous methods of determining project contingency reserve: (1) considering the opinions of several SMEs to develop the membership functions of linguistic terms for the probability and impact of events, (2) decreasing the effect of outlier opinions in developing the membership functions of linguistic terms, and (3) aggregating non-linear membership functions into trapezoidal membership functions. Future research will focus on the validation of IT2FRAM using real project data and comparing the results with traditional contingency determination methods.

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Chapter 4: An Adaptive Hybrid Model for Determining Subjective Causal Relationships in Fuzzy System Dynamics Models for Analyzing Construction Risks[3]

4.1. Introduction

Decision-making procedures in construction projects are complex because a large number of factors and/or variables (e.g., risk events and work packages) are involved that have interrelationships and often-conflicting objectives (Abdelgawad & Fayek 2010; Fateminia et al. 2019a). Large projects with long durations entail a wide range of activities in different areas, as well as opposing stakeholder interests, making them particularly complex. Human actions and subjective reasoning complicate the interacting aspects that must be taken into consideration while making project management decisions (Fayek 2018). In construction projects, decisions are often made based on analysis of complex systems and imprecise or unstructured data (Fayek 2018). The influence of uncertainties on project objectives, which can be either positive or negative, may be managed through modeling complicated construction risk and uncertainty management systems comprising risk identification, quantitative and quantitative risk analysis, and planning risk responses (Ahmadi-Javid et al. 2019; Fateminia et al. 2020a). In construction, common types of uncertainty include random uncertainty and subjective uncertainty (Helton 1997). Random uncertainty has been widely investigated, necessitating enormous amounts of project data to

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accurately estimate it. However, numerical project data frequently falls short of the amount or quality requirements for successful modeling, or the data may not be fully representative of new project environments. Subjective uncertainty exists in many decision-making processes in construction projects, which stems from the use of approximate reasoning and expert knowledge, which are expressed linguistically (Fayek 2018). Helton (1997) characterized uncertainty's twofold nature by dividing it into "objective uncertainty" and "subjective uncertainty." The variability that arises from an environment's stochastic characteristics is referred to as objective uncertainty, and its concepts are based on probability theory. Subjective uncertainty, on the other hand, results from the use of approximate reasoning and linguistically articulated expert knowledge. Subjective uncertainty is classified by Fayek and Lourenzutti (Fayek & Lourenzutti 2018) as vagueness, ambiguity, and subjectivity. Vagueness arises from the absence of clear distinctions between important concepts. Ambiguity occurs when an object lacks specific distinctions that define it, from conflicting distinctions, or from both. Subjectivity arises as a consequence of the impact of personal beliefs or emotions rather than objective facts (Klir 2006).

Fuzzy system dynamics (FSD), a hybridization of system dynamics (SD) and fuzzy logic, is capable of capturing the dynamism and interactivity of real-world system components while addressing the limitations of SD, such as the lack of ability to deal with subjective uncertainties. FSD is concerned with system feedback loops and is capable of modeling systems in which the system variables change continuously through time (Fayek 2018). FSD can also keep track of the changes in the dynamics of variables (e.g., risk events, work packages) in construction projects. FSD is a suitable simulation approach when the primary areas of interest for the modeler are analyzing the changes in variables in the system over time, detecting the impacts of factors influencing the system's variables, and capturing vagueness, ambiguity, and subjectivity in linguistic terms (Fayek 2018; Raoufi et al. 2016). Causal loop diagrams (CLDs) are employed in FSD models to map soft (subjective) and hard (objective) causal relationships and causal structures among model variables. When the mathematical form of a causal relationship is known, it is said to be "hard" (e.g., relationship between risk severity and risk impact). Soft causal relationships, on the other hand, are those in which the mathematical form of the causal relationship is unknown (e.g., relationship between the probability of occurrence of a risk event and a secondary risk event) (Siraj & Fayek 2016, 2020). Soft causal relationships are expressed in linguistic terms. Regular or fuzzy arithmetic can be applied for hard relationships depending on the objectivity or subjectivity of variables. However, the literature reveals a lack of structured and systematic methods for constructing and analyzing complex soft relationships among the elements of a system in order to develop CLDs (Ahmadi-Javid et al. 2019; Fateminia et al. 2020b).

To develop a quantitative FSD simulation model, the crisp value of all causal relationships (i.e., soft and hard) needs to be calculated. To determine the crisp value of soft causal relationships in practice, it is necessary to determine the membership functions (MBFs) of linguistic terms resulted from a heterogenous expert's opinions (Siraj & Fayek 2016). The opinions of experts about forming MBFs of linguistic terms may differ based on their attitude, knowledge, and experience (Pedrycz 1994). Two main categories of MBF estimation are expert-driven approaches, in which MBF elicitation is considered a method of acquiring less or more sophisticated knowledge through interaction with a domain expert, and data-driven approaches, in which the elicitation of MBFs is based on organizing data into a structure (Fateminia et al. 2020b). The analytical hierarchy process (AHP) (Saaty 1987) is an expert-driven technique that enables experts to do pairwise assessments of alternatives in order to establish their MBF. There are some limitations to and eventual biases in the aforementioned techniques for eliciting MBFs (Pedrycz & Wang 2015). The expert-driven method may become broad in nature and may not even be necessarily reflective of the experimental data used to generate these fuzzy sets (Pedrycz 2005). This limitation is especially evident when such fuzzy sets are included in the resulting fuzzy model, which may occur as a result of the absence of experimental support for some MBFs (Fateminia et al. 2020b). For example, in a construction risk management system, AHP as an expert-driven method is not applicable in forming the MBFs of linguistic terms related to construction risks since employing AHP means all risks and opportunities must be considered as alternatives for pairwise comparison, which can be impossible or very time-consuming (Pedrycz 2020; Pedrycz & Gomide 1998); for example, for a project with 100 risk events, almost 4900 pairwise comparison among risk events must be performed by each expert to form only probability MBF, and the result is not necessarily linear. On the other hand, because of the difficulty of obtaining qualified numerical data on risk management for construction industry projects, data-driven methods are not applicable in the majority of cases (Fayek 2018; Pedrycz 2020). Additionally, using data-driven methods may result in semantically meaningless fuzzy sets (Pedrycz 2021), which implies that fuzzy clustering could result in some "crowded" fuzzy sets with ambiguous meaning that need to be tuned by an optimization method, such as simulated annealing algorithm, genetic algorithm, or tabu search (Pedrycz 2005; Pedrycz & Wang 2015). These limitations make data-driven methods inefficient and time consuming. As a result, their further modifications, when optimizing the fuzzy model that comprises the fuzzy sets, may significantly impair the interpretability of the fuzzy sets and the entire model (Pedrycz & Wang 2015). Aggregation methods used in previously published FSD approaches do not account for risk management experts' levels of expertise. In most instances, a moderator or project manager assigns importance weights to experts directly (Siraj & Fayek 2020). The principle of justifiable granularity (PJG) is a well-known paradigm and fundamental concept of granular computing, offering robust guidance for structuring information granules based on existing experimental data. PJG can be employed to optimize interval type-2 fuzzy sets and form type-1 MBFs (Fateminia et al. 2020b).

The current construction literature lacks a structured method for constructing and investigating soft causal relationships in FSD modeling of construction risk analysis. To form the soft causal relationships in an FSD model, MBFs of linguistic terms pertaining to these relationships must be determined. However, both expert-driven and data-driven methods have limitations to forming MBFs of linguistic terms of soft causal relationships by experts, which are necessary to assess them. To address these research gaps, the objective of this chapter is to propose an adaptive hybrid model for calculating crisp values of causality degrees of soft causal relationships in FSD modeling of construction risk management. The proposed model consists of fuzzy analytical hierarchy process (FAHP), weighted principle of justifiable granularity (WPJG), and fuzzy aggregation operators. FAHP enables the proposed model to calculate the level of risk expertise (importance weight) of different experts based on several factors and consider these importance weights in both processes of forming MBFs for linguistic terms and integrating experts' assessments of soft causal relationships. Moreover, WPJG (Pedrycz & Wang 2015) is applied to increase the accuracy of constructing MBFs of soft causal relationships by determining the optimum value of upper and lower bounds before converting them into type-1 MBFs. Furthermore, fuzzy aggregation operators are employed to aggregate the assessments of several heterogeneous experts' opinions using constructed fuzzy MBFs and the importance weight of each expert. The resulting crisp value of soft causal relationships then can be employed to form CLDs and run the FSD simulation model.

The rest of this chapter is organized as follows. First, the advantages and disadvantages of available methods of modeling complex systems in analyzing construction risks are reviewed and compared in Section 4.2.1. Second, Sections 4.2.2, 4.2.3, and 4.2.4 review and discuss the benefits, literature, and capabilities of techniques used in the proposed model, including FAHP, WPJG, and fuzzy aggregation operators, respectively. In Section 4.3, the proposed adaptive hybrid model is presented for calculating the causality degree of soft causal relationships in FSD modeling of construction risk management systems. Section 4.4 reports how the proposed model is implemented in a wind farm project to show how the adaptive hybrid model can be implemented in practice. Finally, Section 4.5 discusses the contributions, and results of this research are presented, along with potential future extensions.

4.2. Justification of Applied Techniques in the Proposed Model

This section first discusses the benefits and limitations of several modeling methods for complex systems. The concepts and techniques required for the proposed adaptive hybrid model are then discussed, and it is demonstrated that FSD is more capable than other mentioned techniques to model causal relationships among variables of construction risk analysis systems.

4.2.1. Reviewing and comparing fuzzy system dynamics and fuzzy cognitive maps capabilities to model construction risk management systems

SD, FSD, cognitive maps, and Fuzzy cognitive maps (FCM) methods allow modeling causal relationships among variables of a complex model. This subsection reviews the merits of mentioned techniques and compares their modeling capabilities.

The first cognitive maps were introduced in 1976 (Miller 1979) with the goal of representing social scientific knowledge through defined digraphs with arcs representing causal links between nodes. Modeling the knowledge associated with a complicated system is possible using these graph-based structures. There are two major downsides to cognitive mapping (León et al. 2010; Stach et al. 2010). The first is a lack of expression power, which causes their relationships (Papageorgiou et al. 2006). Casual signs are substituted by signed and weighted arrows that take values in the [–1,1] interval to address representation capability. Because both ideas and relations have corresponding numerical weights with a coherent meaning for the problem under analysis, simulations can be used to address the reasoning capability problem of cognitive maps. Some limitations when applying FCMs comprise: (1) weights relate the states of concepts rather than changes in state, (2) meaning of iterations and activation function is unclear, (3) a need exists to invert concepts to avoid negative weights, and (4) convergence can be problem and results may not make sense (Glykas 2010; Gregor 2017; Papageorgiou 2013).

On the other hand, SD, developed by Jay Forester in the 1950s (Sterman 2010), is a well-developed continuous simulation technique that can model the dynamic behavior of complex systems and is a viable simulation approach to modeling the complexity of projects (Siraj & Fayek 2016, 2020). One primary goal of SD is to capture how components in a system interact with one another and how changes in one variable influence another over time (Boateng et al. 2012; Nasirzadeh et al.). Xue et al. (2020) proposed an SD-based risk model to assess risks of high-speed rail (HSR) projects. However, their proposed model has certain limitations, such as ignoring unavoidable subjectivity in experts' risk evaluations. Complex construction processes involve subjective variables, which are qualitative in nature and are best expressed using linguistic words. Moreover, since most construction projects lack sufficient historical quantitative data, developing probabilistic distributions for system variables can be difficult (Raoufi et al. 2016). Furthermore, casual relationships of systems cannot be clearly calculated by statistical methods and represented as numerical values because of the lack of sets of similar data (Siraj & Fayek 2016). Therefore, to capture the subjective uncertainties of the subjective variables and relationships in the simulation model, SD must be integrated with fuzzy logic, resulting in FSD (Raoufi et al. 2016; Siraj & Fayek 2016). The FSD technique can capture the dynamism of construction uncertainties and the interactions among project components (Raoufi et al. 2016). FSD also addresses the limitations of FCM since (1) weights are similar to elasticities and their meanings are clear, (2) sensitivity functions modify weights as a function of concept value, (3) if a model contains one or more cycles, calculations are iterated to convergence, and (4) node values are in range of percent of maximum assumed real value (Gregor 2017).

4.2.2. Fuzzy system dynamics for construction risk management

FSD was first developed in 1990 (Levary 1990) by integrating SD with fuzzy logic, which results in improvements of SD technique's capabilities. System variables with subjective uncertainty and the uncertainty of the relationships among system variables can be represented in FSD models by MBFs rather than probabilistic distributions or deterministic values (Raoufi et al. 2016). Quantitative historical data are not widely available because construction projects are unique, which means there is a lack of data points from which to develop probabilistic distributions to represent the risk factors associated with these projects. Another issue is that the subjective impact of these risk factors is largely based on expert knowledge, and that also includes an uncertainty due to the nature of construction projects (Raoufi et al. 2016).

To develop and run an FSD model, both qualitative and quantitative FSD models must be built. The qualitative FSD model (system thinking) allows users to recognize system behavior, whereas the quantitative FSD model allows users to dynamically simulate system behavior and anticipate system state (Raoufi et al. 2016; Siraj & Fayek 2016, 2020). As illustrated in Figure 4.1, SD enables users to understand how components of a system interact with one another and how a change in one variable impacts another variable over time (Sterman 2010). Thus, utilizing feedback loops and stock and flow structures, a qualitative FSD model may be created. The qualitative model creation process begins with identifying system variables, such as risk events. The qualitative model illustrates the hard and soft relationships and interactions between model variables (Sterman 2010). Then, to support realistic representation, the initial model boundary and the amount of aggregation are determined. The model border denotes the modeling scope, whereas the aggregation level denotes the subdivision of activities into subsystems (Sterman 2010). Then, using CLDs and stock and flow maps, the interdependencies, causal structures, feedback structures, stocks, and flows are mapped. Following that, the qualitative model's layout is constructed (Siraj & Fayek 2020; Sterman 2010).

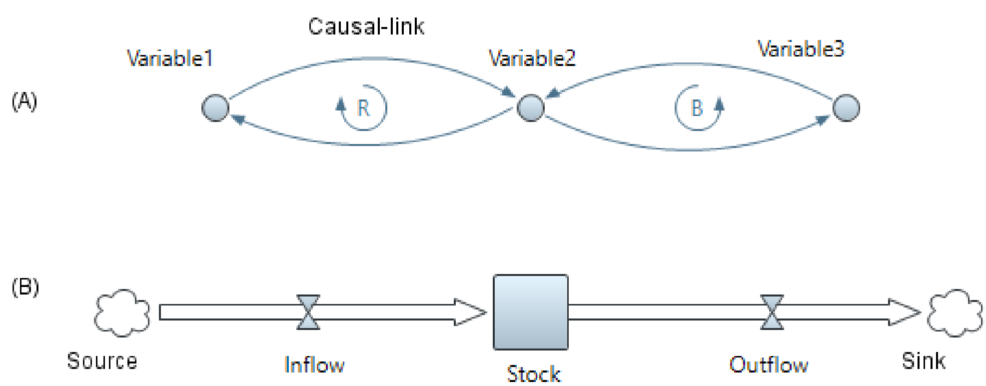

Figure 4.1 Components of system dynamics (SD): (A) Causal loop diagrams (CLDs) and (B) stock and flow diagrams (adapted from Sterman, 2010).

In order to construct the quantitative FSD model, it is necessary to formulate the variables and relationships of the qualitative model to simulate the model. Formulating the objective and subjective system variables and relationships is performed to develop the quantitative FSD model, in which the objective system variables are represented by crisp numbers (e.g., work package cost) and the subjective system variables are represented by MBFs, such as impact and probability of risk events, which are represented using linguistic terms, such as "Very Low" or "High." Moreover, hard (objective) relationships can be represented by equations, while crisp values of soft (subjective) causal relationships must be calculated initially. Then, an equation comprising the values of impacted and caused variables along with the crisp values of soft causal relationships can be determined, and the FSD simulation can be run (Siraj & Fayek 2020). Few research projects have investigated FSD's applicability to risk modeling and analysis. For example, Loh et al. (2020) proposed a framework that combines SD and fuzzy logic to facilitate the development of risk models for autonomous underwater vehicle (AUV) operations in the Antarctic. However, their proposed model does not suggest a systematic method for determining MBFs for linguistic terms representing the causality degree of soft relationships and the crisp value for the causality degree of soft relationships. In addition, Nasirzadeh et al. proposed a fuzzy-based SD approach (Nasirzadeh et al. 2008) for integrating risk management procedures for construction projects. In another study, an FSD model with a similar technique was used to establish the best risk allocation percentage between owners and contractors for construction projects (Nasirzadeh et al. 2014a). Very few fuzzy variables were considered in the FSD models in either technique. The project objective implications of the risks were evaluated at the project level, and opportunities in the evaluation process were not addressed. In both techniques, a fuzzy Delphi, requiring multiple rounds of modifications to attain an acceptable degree of agreement, was employed for aggregating expert input, but the experts' expertise levels were not considered. In another study using expert judgement and subjective evaluation, a hybrid FSD model 020 was designed to study the impacts of linked and interacting risk and opportunity events on work package cost in order to estimate work package and project contingencies (Siraj & Fayek 2020). However, the model was limited to risk assessment level and ignored risk response planning, which plays a vital role in managing risks.

4.2.3. Role of experts' level of risk expertise in FSD risk modeling

Level of experts' risk expertise must be considered to maximize knowledge elicitation and avoid biased assessments in both forming CLDs and assessing soft causal relationships in FSD risk modeling. Level of risk expertise can be determined based on multiple factors, such as knowledge, credentials, and experience of assessors. Various techniques have been used in construction for this goal. For example, Elbarkouky and Fayek (2011) employed a fuzzy expert system (FES) to aggregate expert opinions on roles and responsibilities in project delivery systems and calculated the experts' weights based on their qualification characteristics. In another study (Awad & Fayek 2012), a multi-attribute utility function (MAUF) was utilized to calculate the consensus weight factor for each expert based on their utility values and the relative weight of experience measures for contractor prequalification in surety bonding. Both FES and MAUF, however, have limits when dealing with many criteria. To propose a method for weighting experts according to their level of risk expertise while also handling a large number of criteria, this study employs an extended version of AHP.

AHP is a rational and straightforward measuring theory (Saaty 1987) that has been effectively implemented in the construction industry. AHP is capable of handling a large number of criteria by decreasing the number of necessary comparisons hierarchically. AHP is a structured yet flexible approach that can be easily updated or adjusted. However, the pairwise comparison may cause a dimensionality issue because of the large number of variables compared. Moreover, conventional AHP is incapable of accounting for the imprecise or vague nature of linguistic assessment and uncertainties inherent in expert evaluations. To alleviate this constraint, Laarhoven and Pedrycz (van Laarhoven & Pedrycz 1983) proposed a fuzzy analytic hierarchy process (FAHP) was proposed, which is an extended form of AHP that enables professionals to make decisions using linguistic terms represented by fuzzy numbers. Pedrycz and Laarhoven (1983) and Buckley (1985) modified

Saaty's importance rating scale (Saaty 1987) to allow experts to utilize linguistic terms, expressed as fuzzy number ratios instead of conventional AHP crisp ratios, in pairwise comparison matrices (Li & Zou 2011). Thus, fuzzy pairwise comparison matrices were constructed to approximate the imprecise and ambiguous value of human judgment (Li & Zou 2011). Given the complexity of construction methods and their inherent uncertainties and subjectivities, it is proposed that, rather than using AHP definite scales, FAHP linguistic scales be used for assigning importance weights to experts in order to more accurately capture their opinions in the proposed model (Chen & Wang 2009a). Additionally, the FAHP model has the benefit of allowing for overlapping linguistic terms that more accurately represent human perspectives, allowing for a smoother transition between diverse viewpoints than the crisp numerical representations of experts' opinions. In conclusion, the FAHP is a more appropriate model for calculating the level of risk expertise (importance weight) for each expert to be employed in forming MBFs of linguistic terms.

4.2.4. Weighted principle of justifiable granularity

Conventional approaches for creating fuzzy sets (or information granules) are limited in terms of forming MBFs of linguistic words, which are required for experts to evaluate soft relationships. Both expert- and data-driven approaches rely on expert (user) perception or data (data-driven constructs). PJG can be defined as the approach that maximizes the utility of available experimental data while augmenting the construct with domain knowledge, either in the form of a single component of the general criteria or additional problem-oriented domain knowledge. In this way, the concept can be thought of as representing a middle ground between the two previously mentioned data- and expert-driven approaches (Pedrycz 2021).

Granular computing, which incorporates fuzzy sets as a formal framework (Pedrycz & Gomide 1998; Pedrycz & Wang 2015; Zadeh 1975, 1999), is concerned with obtaining, processing, and transmitting information granules (Pedrycz & Homenda 2013). It becomes critical to identify (construct) information granules, which are utilized as conceptual entities in granular models, predictors, classifiers, and data descriptors as follows. The challenge of creating fuzzy sets has been a cornerstone of the field, serving as a requirement for any future uses of these information granules (Pedrycz & Wang 2015). A prominent tendency in granular computing that is also evident in fuzzy sets is to study and apply higher-order information granules (Pedrycz & Homenda 2013). Regarding intervals, a more advanced sort of construct presents itself in the form of granular intervals, that is, intervals whose limits are no longer integers but information granules. This trend toward increasing the variety of information granules is readily seen in the form of type-2 (particularly interval-valued) or order-2 fuzzy sets (Pedrycz 2018; Pedrycz & Wang 2015).

PJG (Pedrycz 2018; Pedrycz & Homenda 2013) is a prominent paradigm and one of the core foundations of granular computing, providing strong guidelines for dealing with constructing information granules in a structured way based on available experimental evidence (Pedrycz & Vukovich 2001; Pedrycz & Wang 2015). For further extensions and applications, refer to Pedrycz (2018, 2020, 2021). The PJG objective is to create an information granule that is empirically justifiable (i.e., can be justified by experimental data) and conceptually meaningful (i.e., having a well-defined semantics) (Pedrycz 2021). These two intuitive criteria are represented as the coverage criterion and the specificity criterion. The term coverage refers to the amount of data that is positioned behind the formed information granule; coverage indicates the degree to which an information granule is backed up by existing experimental data. Specificity is concerned with the semantics of the information granule, emphasizing the granule's meaning (Pedrycz 2021; Pedrycz & Wang 2015). PJG can be extended to accommodate scenarios in which individual data are linked with weights, which can be used to assess their quality, which may vary from element to element

(Pedrycz & Homenda 2013; Wang et al. 2018). Consequently, PJG and WPJG can be potential solutions in constructing MBFs of linguistic terms.

4.2.5. Fuzzy aggregation operators

The use of aggregation operators is key in every aggregation process. Aggregation operators are divided into two categories: crisp aggregation operators combine expert preferences expressed as crisp numbers, whereas fuzzy aggregation operators combine expert preferences expressed as linguistic phrases (which can be transformed to interval numbers, or fuzzy numbers). When group decision-making contains solution alternatives and options that cannot be accurately evaluated with a precise numerical value, linguistic evaluation and natural language are used in order to offer a more meaningful representation of experts' judgments. Therefore, in a group decision-making situation, fuzzy aggregation operators are employed to integrate the numerous experts' linguistically expressed preferences.

Several applications demand fuzzy aggregation in construction group decision-making procedures. A review of the literature confirms that numerous fuzzy aggregation operators have been proposed, comprising fuzzy weighted average (FWA) (Sadiq et al. 2004), fuzzy ordered weighted average (FOWA) (Yager 2004), fuzzy number-induced ordered weighted average (FN-IOWA) (Merigó & Casanovas 2009), fuzzy weighted geometric operator (FWG) (Gohar et al. 2012), and fuzzy similarity aggregation method (FSAM) (Hsu & Chen 1996). Selecting an aggregation operator depends on its characteristics and application.

Several properties for aggregation operators can determine the best option for each context. These properties comprise: (1) commutativity condition, which says the ordering or ranking of arguments is irrelevant and all criteria are equally important, (2) monotonicity, where the criteria and the aggregation output have a non-decreasing relationship in functions, (3) boundary condition, in which the outputs of the aggregation function are constrained to the minimal and maximum bounds of the function, and (4) idempotence, which is the strongest kind of agreement or unanimity, which is said to occur after the same initial value is aggregated n times and the outcome is the same as the initial value (Monzer et al. 2019). FOWA is commutative, monotonic, bounded, and idempotent.

Smolikova and Wachowiak (Smolikova & Wachowiak 2002) employed several aggregation operators to evaluate a case study, and they discovered that the FWG and FOWA operators provide more flexibility in fulfilling analysis requirements than FWA. The FOWA aggregation operator is the most often used aggregation operator in construction risk assessment (Monzer et al. 2019). Moreover, when working with fuzzy numbers, mathematical operations are critical because the fuzzy number format is not always preserved (e.g., multiplication of triangular fuzzy numbers). The FOWA aggregation operator simplifies the process of getting the product of two fuzzy numbers without modifying the fuzzy number format. Additionally, while evaluating reciprocal fuzzy pairwise comparison matrices in FAHP, the FOWA aggregation operator demonstrates exceptional efficiency and effectiveness. Furthermore, several fuzzy aggregation operators have been tested in the construction risk management domain, and the symmetric mean absolute percentage error (SMAPE) has been calculated, indicating that FOWA provides the smallest error (Monzer et al. 2019). As a result, FOWA is employed in this study as the aggregation operator for various assessments of heterogenous experts.

4.3. Methodology: Developing Adaptive Hybrid Model to Form CLDs in FSD Modeling

Development of an FSD model, as discussed in Section 4.2.1, is divided into two general phases: (1) creating a qualitative model and (2) developing a quantitative model. Qualitative modeling allows for identification of system variables and causal relationships, as well as the development of stocks and flows. In the quantitative modeling phase, the values of variables should be established using crisp numbers and probability distributions. Moreover, all causal relationships and interdependencies among the model variables should be formulated in order to run the model and identify the effect of variables (Sterman 2010). So, while mathematical equations are always used to define hard relationships, soft causal relationships can be determined in three steps, as illustrated in Figure 4.2.

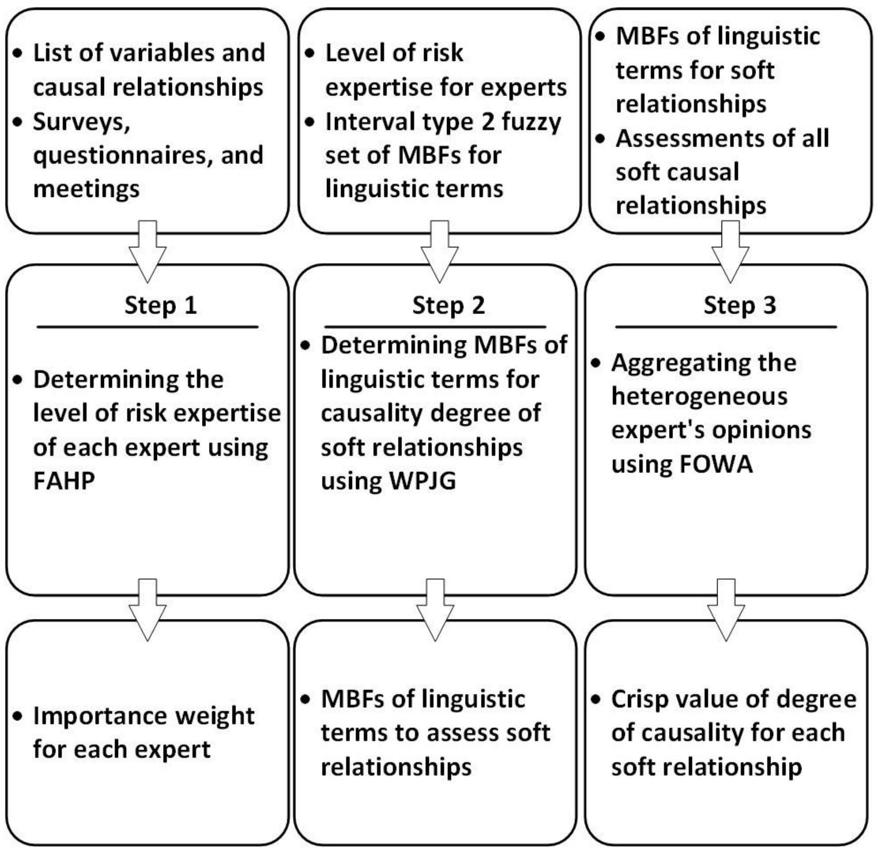

Figure 4.2 Inputs and outputs of all steps in adaptive hybrid model to determine soft causal relationships in fuzzy system dynamics (FSD) modeling.

The 3-step process for determining soft causal relationships begins with evaluating experts' risk expertise to enhance knowledge elicitation and avoid making faulty judgments using FAHP. The output of the first step, which is determining the importance weight for each expert, can be utilized in the second step where MBFs of linguistic terms (e.g., “Low” or “High”) for assessing causal relationships are built, optimized, and aggregated in order to use the knowledge and skills of all project decision makers and experts. In step 2, interval type-2 fuzzy sets are initially formed that contain all possible viewpoints of the experts. Then, constructed interval type-2 fuzzy sets are optimized and integrated using WPJG, resulting in MBFs of linguistic terms for the assessment of soft causal relationships. In the third step, all qualified experts are required to assess degree of causality for soft causal relationships based on optimized and aggregated MBFs in the second step. Then, the FOWA aggregation operator is used to aggregate the assessments of all experts. The output of the first step, importance weight for each expert, is utilized as one of inputs of third step, since FOWA is a weighted aggregation operator. Next, the aggregated fuzzy degree of causality between variables can be established and defuzzified to obtain the crisp degree of causality. The details of each step are described as follows.

4.3.1. Step 1—Determining the importance weight of each expert using FAHP

When aggregating expert judgments of the degrees of soft causal relationships among variables in the model, the importance weights of the experts must be accounted for. For example, Monzer et al. (2019) recommended assessing experts' level of risk expertise based on seven criteria comprising experience, knowledge, professional performance, risk management practice, project specifics, reputation, and personal qualities and skills. These criteria are employed in this chapter to calculate level of risk expertise (importance weight) for each expert. Each of the seven criteria has quantitative or qualitative sub criteria, and for each of the qualitative attributes assessed using a preset rating scale (1–5), detailed information can be found in Monzer et al. (2019). The importance weights of the experts, (Wk), are derived using FAHP weight-assigning approach after analyzing the experts' level of expertise based on the mentioned attributes. Unlike standard AHP, which utilizes crisp numbers, the FAHP approach allows experts to do pairwise comparisons using fuzzy linguistic evaluations (Mukherjee 2017). As a result, the FAHP approach is used to calculate the relative weights of qualifying attributes and criteria based on expert pairwise assessments. For further information about FAHP equations and concepts, refer to Monzer et al. (2019). The importance weight of each expert can be employed in both steps 2 and 3 in order to (1) form MBFs of linguistic terms for degree of causality and (2) aggregate several assessments of degree of causality.

4.3.2. Step 2—Forming MBFs of soft causal relationships using WPJG

Linguistic terms (e.g., "Very Low" or "Very High") for illustrating the causality degree of soft causal relationships are defined in order to enable experts to assess them. Defined linguistic terms for causality degree of soft relationships among variables are fuzzy numbers. These fuzzy numbers can be represented by triangular or trapezoidal fuzzy numbers, since the most popular forms for fuzzy numbers with open intervals of real numbers are triangular and trapezoidal (Fayek & Lourenzutti 2018; Pedrycz 1994). Trapezoidal fuzzy numbers are a subset of triangular fuzzy numbers. The degree of causality between variables is denoted in this model by five linguistic terms: "Very Low," "Low," "Medium," "High," and "Very High." Various MBFs for causal relationships are established and aggregated in order to benefit from the collective knowledge and expertise of all project decision makers and experts. A type-1 fuzzy set projects a single crisp number for the membership degree of each linguistic term, whereas interval type-2 fuzzy sets project an interval for the membership degree of each linguistic term (Mendel & Wu 2006, 2007; Mendel et al. 2006). Consequently, interval type-2 fuzzy sets are more appropriate because they give more information than type-1 fuzzy sets and are more accurate. In addition, an interval type-2 fuzzy set encompasses all possible viewpoints. Consequently, the intervals' lower and upper bounds are initially defined in this step by the lowest and highest heights of the MBFs constructed for linguistic terms (e.g., ”Low,” “Medium,” “High”) to assess degree of causality using the information from various risk experts.

After forming interval type-2 fuzzy sets of linguistic terms, the WPJG is applied in order to optimize these intervals and construct information granules. Coverage and specificity are two essential requirements invoked by the WPJG. The two criteria are at odds, which means that increasing coverage decreases specificity, and vice versa. Therefore, constructing information granules is a result of tradeoff between them, and there is an optimization problem with a multiplicative form of the objective function, shown by Equation (1), where D is an information granule based on the available experimental evidence resulting in a form of a collection of one-dimensional numeric data, and D = {x1, x2, ..., xN}, where xk ∈ R. Coverage is expressed as the cardinality (count) of the data X included in the interval [m,b], assuming m is the numeric representative of a data set, such as a median. In addition, specificity can be related directly with the length of the interval and define any decreasing function of the length that is |m−b| or |m−a|, where a and b are the optimized values of the lower and upper bounds of the interval, respectively.

$$V(b) = coverage \times specificity \tag{4.1}$$

Equation (1) can be implemented separately for the lower and upper bounds of the interval as follows:

$$V(b) = f1(card\{xkD|med(D) < xk \leq b\}) \times f2(|med(D)-b|), \tag{4.2}$$

$$V(a) = f1(card\{xk \in D|a \leq xk < med(D)\}) \times f2(|med(D)-a|). \tag{4.3}$$

By maximizing V(b), we achieve an optimal value of b, which is to say,

$$bopt = arg\ maxb\ V(b) \tag{4.4}$$

The optimal upper bound bopt can be obtained by maximizing the value of *V(b),* namely *V(bopt) = maxb>med(D)V(b).* The lower bound of the information granule is constructed in the same way: aopt, that is, *V(aopt) = maxa<med(D)V(a).*

The importance weights of each expert calculated in the last step using FAHP can be integrated with PJG, resulting in WPJG. To form WPJG, Equations (2) and (3) can be extended to deal with situations where data are associated with relative weights (Pedrycz 2021). In this case, given the data form (xi, wi), where wi represent weights in the range of an [0,1] interval, *w = [w1, w2, ..., wN]*, the upper and lower bounds can be determined by maximizing the performance index V as follows:

$$V(b) = f1\left(\sum_{xk:\, med(D) < xk \le b}^{N}{}_{k=1} w_k\right) \times f2(|med(D,w) - b|), \tag{4.5}$$

where med(D,w) is a weighted median as follows:

$$med(D,w) = argminy \sum_{k=1}^{N} w_k\,|x_k - y| \tag{4.6}$$

After implementing WPJG and optimizing the upper and lower bounds of interval fuzzy sets, MBFs are type-reduced to standard MBFs for the purpose of performing crisp output computation. In this research, the procedure described in Reference (Pedrycz 1994) is used to transform an interval type-2 MBF to a type-1 MBF.

4.3.3. Step 3—Aggregating the heterogeneous expert's opinions using aggregation operators

In step 3, MBFs of linguistic terms determined in the previous step are utilized to assess degree of causality for soft causal relationships. Assessments of several experts are aggregated using FOWA. The FOWA aggregation operator is a weighted aggregation operator for combining the linguistic opinions of diverse experts (Merigó & Casanovas 2009; Yager 2004), as a simple extension of the ordered weighted average (OWA) operator used in uncertain scenarios where the available data input and knowledge source may be evaluated using fuzzy numbers (Hsu & Chen 1996; Monzer et al. 2019). FOWA supports parameterization of a family of aggregation operators, including the fuzzy maximum, fuzzy minimum, and fuzzy average criteria. Additionally, FOWA shares many of the same characteristics as OWA (Yager 2004). Letting $f\colon \Theta n \rightarrow \Theta$, where Θ is the set of all fuzzy numbers, the formula for applying FOWA is:

$$f(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \sum_{j=1}^{n} w_j \tilde{b}_j, \quad (4.7)$$

where $w = (w1, w2, \dots, wn)$ is the weighting vector, and $\tilde{a}_i \in \Theta$, which means $\tilde{a}_i$ are fuzzy number representing experts' opinions. In addition, $w \in (0,1)$, and $\sum_{j=1}^{n} w_j = 1$, and $\tilde{bj}$ is the largest jth of the $\tilde{a}_i$ (Pedrycz 2020). Here, the weighting vector wj is calculated in Step 1 using FAHP. The aggregated fuzzy number of causality degree among variables can then be determined and is defuzzified to calculate crisp degree of causality. Consequently, crisp values of causality degree are employed to form CLDs and run the FSD model to assess construction risks.

4.4. Case Study: The Proposed Adaptive Hybrid Model

The main purpose of the case study was to illustrate how to implement the proposed model for analyzing risks of a construction project. The proposed model was employed as part of forming an FSD simulation model for analyzing construction risks of a real wind farm power generation construction project, since authors had access to some project information. However, the model can be implemented in any kind of construction project. Implementation of the proposed model is illustrated to (1) form MBFs of causality degree for soft causal relationships and (2) determine the crisp value of causality degree for soft causal relationships. To maintain confidentiality of project information, some actual information and value of used relationships and variables were substituted in the case study for some hypothetical data. Names and values of some variables comprising risks, risk responses, secondary risks, and assessments of causality degree for soft causal relationships are substituted. However, actual data and information were utilized to calculate experts' level of risk expertise. Moreover, the type of objective and subjective variables and the types of hard and soft relationships between them are real and were extracted from a risk analysis model of a real wind farm project in North America. The real wind farm project had eight construction work packages, which are categorized as civil, structural, and electrical.

FSD modeling begins with qualitative modeling, followed by quantitative modeling, to formulate all identified variables and relationships. The process of developing a qualitative model starts with the identification of system variables (e.g., risk events) and all hard and soft relationships and interactions between variables. Additionally, it incorporates the feedback structure for various variables (e.g., response actions that are available to address identified risks). The initial model boundaries, as well as the degree of aggregation, may then be determined in order to achieve the objective of realistic representation. Although the model boundary indicates the extent of the modeling exercise, the aggregation level indicates the breakdown of activities into subsystems. Using CLDs, stock and flow maps, and other tools, the interdependencies, causal structures, feedback structures, stocks, and flows are all visualized and represented graphically. Next, the layout of the qualitative model is developed. To formulate soft causal relationships in the quantitative modeling phase, the proposed model in this study is implemented in the following three steps.

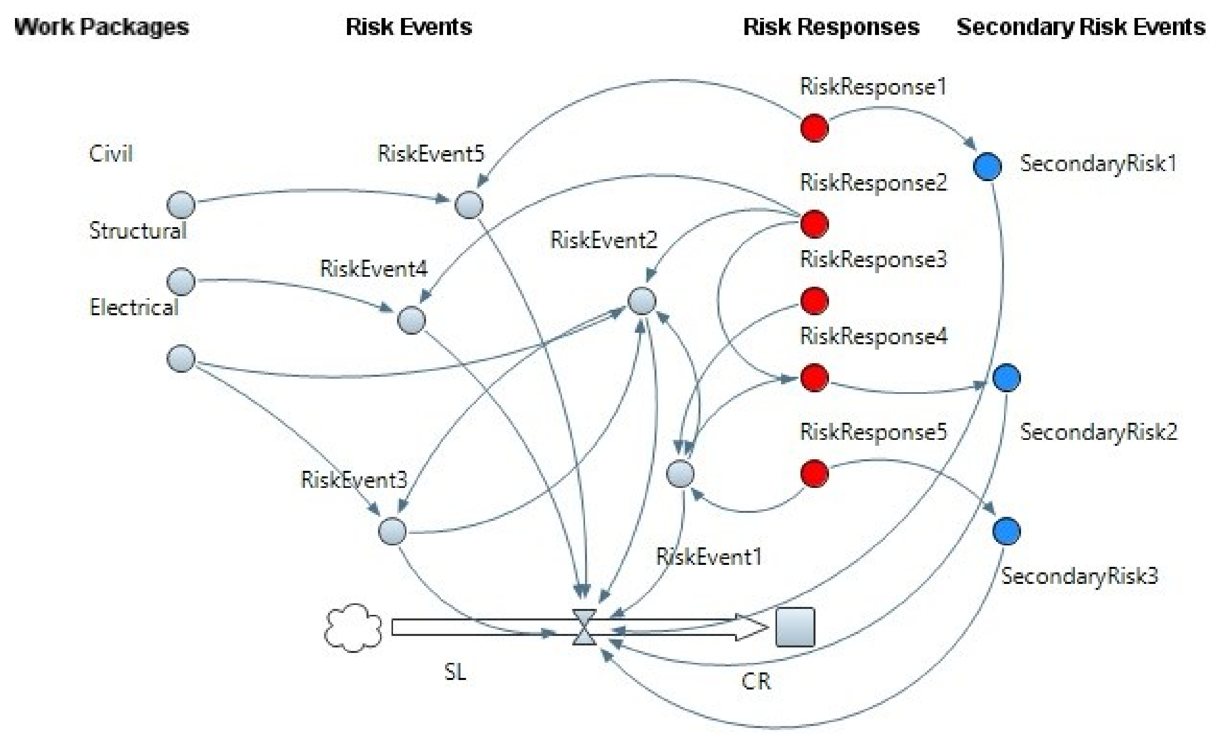

Figure 4.3 Graphical representation of FSD model in qualitative step in AnyLogic® software.

4.4.1. Step 1: Determining risk expertise

In the first step in formulating soft causal relationships, the experts' level of risk expertise (importance weights) is calculated. The criteria for choosing experts were their engagement in the project, their overall years of experience, their years of risk management experience, and the number of similar projects in which they had participated. A diverse group was established from four real experts who were actively involved in the project. Each expert was a part of the project team and had worked on more than five comparable-scale projects. They had an average of 23 years of total construction experience and an average of 12 years of risk management experience (Siraj & Fayek 2020).

In Step 1 of determining soft causal relationships, the risk expertise levels (importance weights) of the experts were determined using a combination of numerical and linguistics attributes, as detailed in Table 4.1. Next, the evaluation data were normalized to the range [0,1]. Then, the weights assigned to the criterion and sub criteria were used to compute the experts' level of risk expertise. The FAHP weight assignment technique was then used to compute the importance weights (Wk) of the four experts, W1, W2, W3, and W4. Calculated weights, such as each expert's importance weight (risk expertise), must be normalized before being used as the expert's importance weight. The experts' importance weights are relative weights that, when added, equal 1. This guarantees that the opinions of experts with a higher weight of importance have a greater effect on the experts' collective evaluation. The four experts' importance weights were 0.25, 0.27, 0.22, and 0.26.

Table 4.1 Numerical and linguistics attributes to determine the risk expertise levels (importance weights) of the experts.

Criteria No.	Criteria Name	Criteria Weight
1	**Experience**—Total years of experience, Diversity of experience, Relevant experience, Applied experience, Varied experience	0.17
2	**Knowledge**—Academic knowledge, Education level, On-the-job training	0.13
3	**Professional performance**—Current occupation, Years in current occupation, Expertise self-evaluation	0.12
4	**Risk management practice**—Average hours of work in risk per week, Level of risk training, risk conference experience, Risk identification and planning, Risk monitoring and control, Crisis management	0.18
5	**Project specifics**—Project size, Commitment to time deadlines, Commitment to cost budget, Safety adherence, Geographic diversity experience	0.16
6	**Reputation**—Social acclimation, Willingness to participate in survey, Professional reputation, Level of risk conservativeness	0.12
7	**Personal attributes and skills**—Level of communication, Teamwork, Leadership, Analytical skills, Level of ethics	0.12

4.4.2. Step 2: Constructing MBFs of soft causal relationships

In the second step, MBFs of linguistic terms for assessing causality degree of soft relationships are formed by expert opinions using WPJG. The following phase establishes linguistic terms, their scales, and associated fuzzy sets in order to analyze the degree of causality for project components with soft causal relationships. So, Step 2 begins with gathering opinions of several experts about the scales of linguistic terms of causality degree (e.g., "Very Low," "Low," "Medium," "High," and "Very High"). For example, based on the opinion of Expert 1, the linguistic term "Very Low" for causality degree ranges from 0 to 18 percent with the membership value of 1 in 0 percent. Then, interval type-2 fuzzy sets of each linguistic term are constructed for degree of causality in soft causal relationships. Interval type-2 fuzzy sets capture more uncertainty than their type-1 counterparts (Mendel & John 2002; Mendel & Wu 2006; Mendel et al. 2006; Wu et al. 2011). Thus, the opinions of all experts are employed to form interval type-2 fuzzy set. Since there were four experts in the project whose opinions were critical to risk modeling, interval type-2 fuzzy sets were employed to account for all MBFs these experts proposed. The interval type-2 fuzzy set was constructed by calculating the lowest and highest bounds of the proposed MBFs.

Then, the tradeoff between specificity and coverage of each interval is conducted using the WPJG and considering it as a multiplicative optimization problem (Pedrycz 2018, 2021; Wang et al. 2018). The parametric WPJG can mitigate the influence of irrelevant and biased opinions. Equations (5) and (6) are employed to determine the optimized upper and lower bounds of each interval by maximizing the performance index.

For crisp output calculation, type-2 fuzzy sets are subsequently converted to standard MBFs. The process of converting an interval type-2 fuzzy set to a type-1 fuzzy set, proposed by Fateminia et al. (Fateminia et al. 2020b) and Pedrycz (Pedrycz 2021), is applied in this study. The objective of the type reducing process is to determine the line that best fits these interval fuzzy values. Initially, mean and domain values are used to represent the interval fuzzy values statistically. The interval sets are represented by their corresponding mean points in the x–y space, which are (0,1), (10,0.75), (15,0.6), and (20,0.05). The mean values of all interval type-2 fuzzy sets may not be linear. Therefore, to get the best-fit linear equation, a linear equation between (0,1) and the mean point of each interval set is required to be solved for an x-axis intercept value. Statistically, the modeled linguistic term should fall inside the range $[x_m^l, x_m^r]$ (Fateminia et al. 2020b; Pedrycz 2021). Here, x_m^l is the mean of the interval type-2 fuzzy set's left endpoints, and x_m^r is the mean of the set's right endpoints. If the endpoint uncertainties are removed, the preceding interval type-2 fuzzy set degrades to a type-1 fuzzy set with a = b = x_m^r = x_m^l. The mean of these points is at x_m^r = 22 with standard deviation s = 3.06. Consequently, the optimized MBFs for various linguistic terms are similarly calculated as illustrated in Table 4.2. The optimized fuzzy numbers in Table 4.2 can be employed to assess risks and opportunities in the next step.

Table 4.2 Linguistic terms and fuzzy numbers for assessing the degree of causality.

Linguistic terms	**Fuzzy number**
Very low influence (VL)	(0.00 0.00 0.22)
Low influence (L)	(0.00 0.22 0.47)
Medium influence (M)	(0.22 0.47 0.72)
High influence (H)	(0.47 0.72 1.00)
Very high influence (VH)	(0.72 1.00 1.00)

4.4.3. Step 3: Aggregating assessments

In the third step of the model, several experts assess the causality degree of soft causal relationships based on linguistic terms constructed in Step 2 (Table 4.2). Then, FOWA is employed to aggregate the assessments of the four experts, resulting in creation of a single fuzzy number that reflects the group's opinion. Experts offer their evaluations of causality degree for soft causal relationships using linguistic terms that are represented by fuzzy numbers that are optimized and formed in step 2. The importance weights of the experts, calculated in Step 1 using FAHP, are utilized by FOWA as the weight vector for the experts' assessments in order to reflect their level of expertise. The aggregated fuzzy number of causality degrees across variables are then calculated. Finally, aggregated fuzzy number of causality degree is defuzzified to obtain the crisp value for degree of causality for the soft causal relationship.

4.5. Results and Discussion

The proposed hybrid model results in calculated the crisp value of causality degree for soft causal relationship among each pair of variables (e.g., variables 1 and 2) while considering the level of risk expertise for each assessor. Crisp values of causality degree for soft causal relationships are employed to formulate the value of the second variable (affected by first variable through a soft causal relationship) in different time steps of the FSD simulation. As a result, the FSD simulation model comprising of soft causal relationships can be quantified and run in simulation software (e.g., AnyLogic®) to evaluate construction risks.

The crisp value of causality degree for soft causal relationships among project components in this study are: 0.37 between risk event 2 and work package-electrical; 0.56 between risk event 2 and risk event 3; 0.6 between risk response 1 and secondary risk 1; and 0.40 between risk event 1 and risk response 5. The crisp value of causality degree can be utilized to formulate the soft causal relationships between interrelated variables in FSD modeling. The suggested adaptive hybrid model can provide industry professionals with a systematic and structured approach to modeling complex construction risk systems through FSD simulation comprising soft causal relationships. The model can be a potential alternative for traditional techniques (e.g., modified horizontal approach) for determining the MBFs of linguistic terms for degree of causality. Traditionally, modelers used to utilize the modified horizontal approach coupled with curve fitting, which is an expert-driven and direct method, to develop MBFs of linguistic terms. The modified horizontal approach is very straightforward to apply and enables condensing of many questions into a single one. However, it is highly reliant on expert judgments and is, thus, susceptible to mistakes owing to experts' subjectivity and inconsistency in responding to questions.

The interval type-2 fuzzy sets used in the proposed adaptive hybrid model capture more uncertainties compared to standard fuzzy sets, offer better knowledge representation, and accounts for the opinions of a larger number of experts compared to standard fuzzy sets. Moreover, WPJG optimizes these interval type-2 fuzzy sets by maximizing the performance indexes of two criteria—coverage and specificity—, thereby mitigating the impact of irrelevant and biased expert opinions. The suggested model is an alternative to existing techniques for eliciting MBFs, such as fuzzy clustering and AHP, which are ineffective for eliciting MBFs for risk analysis linguistic terms. Additionally, the proposed model meets the requirements for (1) aggregating expert opinions on the MBFs of identified linguistic terms, (2) aggregating expert evaluations of soft causal relationships, and (3) removing irrelevant and biased opinions.

4.6. Chapter Summary

Decision-making in construction projects is a complex process involving a large number of risks and uncertainty that requires efficient modeling and computing techniques to mitigate the impacts of risk and uncertainty on project objectives and to manage project contingency reserve. In this chapter, an adaptive hybrid model was proposed for improving the efficiency of constructing CLDs in FSD modeling of complex construction risk analysis systems. The model integrates FAHP, WPJG, and FOWA to (1) form and optimize the MBFs of linguistic terms and (2) aggregate assessments of causality degree for each soft causal relationship made based on the constructed MBFs. FAHP is employed to determine the level of risk expertise (importance weight) of various experts based on several criteria. WPJG is applied to determine the optimal value of the upper and lower bounds of interval type-2 MBFs of soft causal relationships, and FOWA is utilized to aggregate the opinions of heterogenous experts.

This study contributes to the modeling and analysis of risks in construction projects by proposing a systematic and organized technique via an adaptive hybrid model for calculating the crisp value of causality degree for soft causal relationships among the elements of construction projects. The proposed model can address the following issues with prior techniques: (1) considering the level of risk expertise (importance weights) of several experts in both developing the MBFs of linguistic terms and assessing the degree of causality based on constructed developed MBFs, (2) mitigating the influence of irrelevant and biased opinions on the development of MBFs for linguistic terms of causality degree , and (3) aggregating several expert's assessments of causality degree of soft causal relationships.

The results of the proposed adaptive hybrid model for FSD modeling of construction risks are: (1) optimized MBFs of linguistic terms for causality degree of soft causal relationships and (2) the crisp value of causality degree of soft causal relationships. The first result can be employed in assessing degree of causality of soft causal relationships among project variables by experts, and the second can be utilized in formulating the value of impacted variable based on the value of caused variable in each time step of the FSD simulation. The study results will enable risk analysts to: (1) calculate the crisp value of soft causal relationships when quantitative project data falls short of the quantity or quality required for effective modeling and (2) benefit from the opinions of several experts while modeling the dynamic behavior of complex construction projects using

FSD. The developed adaptive hybrid model was implemented on a hypothetical case study that was extracted from a real wind farm project.

When determining the degree of causality, the experts' importance weights were assumed to remain constant for a particular project, independent of the work package being evaluated. However, some experts are more informed than others or have more relevant backgrounds for a certain work package. Therefore, the weights assigned to experts must vary according to the work package being evaluated. Thus, future research should focus on the creation of a weighting technique that accounts for the level of expertise of the experts assigned to the work package under evaluation. Additionally, the proposed model can be implemented in several FSD models of construction risk analysis to compare the results with conventional methods (e.g., modified horizontal approach coupled with curve fitting).

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Chapter 5: Determining Contingency Reserve for Construction Projects Considering Time-dependence, Causal Relationships, and Linguistic Assessments of Risks and Responses [4]

5.1. Introduction

Uncertainty and risk are inherently part of all projects, and thus risk management plays a critical role in ensuring project success (Ahmadi-Javid et al., 2020). Risk refers to the situation in which a decision-maker is aware of decision outcomes and their probabilities of occurrence. Uncertainty refers to a situation in which a decision-maker is unaware of such information (Ahmadi-Javid et al., 2020). In construction projects, a wide range of activities exists across multiple knowledge areas (e.g., Civil works, Major equipment). This environment along with conflicting stakeholder interests make project management and decision-making processes highly complex (Fateminia et al., 2021). Moreover, the frequent need to use approximate reasoning and linguistic terms in construction projects that have imprecise or unstructured data increases the complexity of decision making and managing uncertainties (Fateminia, Sumati, et al., 2020). Construction projects have high levels of uncertainty due to their dynamic nature, multiple feedback processes, and the non-linear relationships and interactions among project components (Fateminia et al., 2021; Fateminia, Sumati, et al., 2020). Therefore, managing risks and uncertainties is crucial for construction projects to successfully achieve project goals in terms of time, cost, and quality.

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Risk management is ineffective without considering risk responses, which are critical in addressing the effects of identified risks on project goals (Fateminia et al., 2019; Fateminia, Siraj, et al., 2020; Hillson, 1999). Risk response planning is the process of developing, assessing, and selecting risk response strategies and actions that control the probability and impact of risks in order to increase the chance of achieving project objectives (Ahmadi-Javid et al., 2020; Fateminia, Siraj, et al., 2020; PMI, 2017). Contingency reserve is the budget calculated for implementing risk response actions (RRAs)and handling both secondary and residual risks (PMI, 2017). Contingency reserves must be calculated and considered in the project budget to cover the implementation cost of RRAs and the effects of risks on project objectives. Contingency reserve determination is a key tool for the decision makers of a project to respond to positive and negative risks (i.e., opportunities and threats) (Ahmadi-Javid et al., 2020; PMI, 2017).

Insufficiently allocating the contingency reserve amounts required for a project may result in significant financial losses and inefficient resource management (Salah & Moselhi, 2015). Current techniques for calculating contingency reserve, including deterministic and probabilistic approaches, are unable to capture the complex and dynamic of construction projects (Ahmadi-Javid et al., 2020; Fateminia, Siraj, et al., 2020). Deterministic approaches, which are based on the intuition and experience of experts, are simple and transparent to use. However, these approaches have difficulty calculating the exposure of risk events (REs) and are unable to consider positive risks, also known as opportunities (Iranmanesh et al., 2009). On the other hand, in probabilistic approaches a lack of quality and quantity of historical data can affect contingency reserve values, since these techniques rely significantly on such data (Fateminia, Siraj, et al., 2020; Salah & Moselhi, 2015). Additionally, probabilistic techniques assume that cost variations are inherently random. Many risk experts find it difficult to perform an accurate and precise risk assessment, since data are often scarce or of low quality (Hao et al., 2019). The probability of occurrence and impact of positive and negative REs change over time because of their dynamic behavior and time-dependent nature (Fateminia et al., 2021). However, traditional risk modeling and analysis approaches tend to focus on a static view of risks, rather than considering the time-dependent behavior of risks. Therefore, it is crucial to model and assess the interrelationships and interactions among risks as well as their dynamic nature in order to develop a realistic contingency reserve.

System dynamics (SD) (Sterman, 2000) and cognitive maps (CM) allow modeling of causal relationships among variables of a complex model. Two major downsides to cognitive mapping exist (León et al., 2010; Stach et al., 2010), in that they lack 1) expression power, which expresses causal relationships between two variables as positive and negative states, and 2) inference capabilities, which imply we cannot make decisions based on the model's relationships. Fuzzy cognitive maps (FCM) (Kosko, 1986) is an extension of CM that addresses some of their limitations. However, FCM has some limitations while. First, weights relate the states of concepts rather than changes in state. Second, the meaning of iterations and activation function is incomprehensible. Third, a need exists to invert concepts in order to avoid negative weights. Fourth, convergence can be problem and results may not make sense (Fateminia et al., 2021). SD also has some limitations. First, complex construction processes entail subjective, qualitative variables that are best represented through linguistic terms. Moreover, it is difficult to create probability distributions for system variables because most projects lack sufficient quantitative historical data (Raoufi et al., 2016). Additionally, due to a lack of similar data sets, the casual interactions of systems cannot be properly calculated using statistical methods and expressed as crisp values (Elbarkouky et al., 2016). Therefore, SD can be integrated with fuzzy arithmetic to capture subjective uncertainties associated with subjective variables and causal relationships in simulation models (Elbarkouky et al., 2016; Raoufi et al., 2016). Fuzzy system dynamics (FSD) technique addresses the limitations of SD, CM, and FCM (Fateminia et al., 2021; Gregor, 2017). In FSD, weights are similar to elasticities, and their meanings are clear. Moreover, sensitivity functions modify weights as a function of concept value, and if a model contains one or more cycles, calculations are iterated to convergence. Furthermore, node values are in range of percent of maximum assumed real value.

In summary, current methods of determining contingency reserves in the construction literature do not consider 1) RRAs, 2) subjective reasoning and linguistic evaluations, 3) causal interactions and dependencies between project components, and 4) the dynamic nature and time-dependent behavior of probability and impact of both positive and negative REs and RRAs. The objective of this paper is to propose a novel hybrid fuzzy arithmetic-based contingency reserve model (HFACRM) to determine contingency reserves throughout the lifecycle of construction projects. HFACRM takes RRAs into consideration while formulating variables, stocks and flows, and causal relationships among variables. The proposed model employs FSD to1) model the dynamic behavior of time-dependent components such as probability and impact of REs and 2) capture the interactions, relationships, and mutual impact of REs together and with RRAs over the course of project. HFACRM uses fuzzy logic and fuzzy arithmetic to capture the subjective uncertainties associated with assessing model variables (e.g., REs, RRAs) and causal relationships between them.

This paper is organized as follows. First, a brief literature review of traditional techniques of determining contingency reserve of projects is presented and their gaps are highlighted, followed by a discussion about the SD, FSD, and application and benefits of employing fuzzy arithmetic in the risk analysis process. Second, a fuzzy arithmetic-based contingency reserve model is proposed to determine contingency reserve of construction projects. Third, a case study is provided to illustrate how the proposed framework can be implemented in a wind farm project using AnyLogic®, a simulation software tool to run simulation models, and MATLAB. Then, results of this research are presented and discussed, and conclusions are presented along with potential future extensions.

5.2. Determination of Contingency Reserves in Risk Management for Construction Projects

5.2.1. Defining contingency reserves

To deal with uncertain events, construction projects have two types of reserves that must be calculated and considered in the project budget: management reserve and contingency reserve (Ahmadi-Javid et al., 2020; PMI, 2017). Management reserve is the amount of project budget or time buffers reserved for handling unforeseen events (PMI, 2017). Cost baseline is the sum of the cost estimates of all work packages and project contingency reserve (Ahmadi-Javid et al., 2020; PMI, 2017). Project budget is the sum of the cost baseline and management reserve. Contingency reserve is the budget typically used for implementing RRAs and handling both secondary and residual risks considering contingency plan or fallback plan (Ahmadi-Javid et al., 2020). A contingency or fallback plan can be developed and implemented when the selected response action turns out not to be fully effective or when an accepted risk occurs. Secondary risks are risks that arise as a direct result of implementing an RRA. Residual risks are risks that are expected to remain after planned response actions have been taken or risks that have been deliberately accepted (Ahmadi-Javid et al., 2020; PMI, 2017).

As shown in Figure 5.1, uncertain events in projects can be divided into two main categories: 1) unknown unknowns addressed with management reserve, and 2) known unknowns that must be responded to proactively or reactively. A proactive approach focuses on eliminating problems before they can occur by avoiding, mitigating, and transferring with respect to negative risks or exploiting, enhancing, and sharing with respect to positive risks. A reactive approach is based on responding to events after they happen by employing active and passive accepting strategies (Ahmadi-Javid et al., 2020). Workarounds are immediate RRAs for unidentified risks or identified risks that have been accepted passively (Ahmadi-Javid et al., 2020; Fateminia, Siraj, et al., 2020; PMI, 2017). Contingency reserve is used for events that are responded to with proactive response actions or active acceptance response actions.

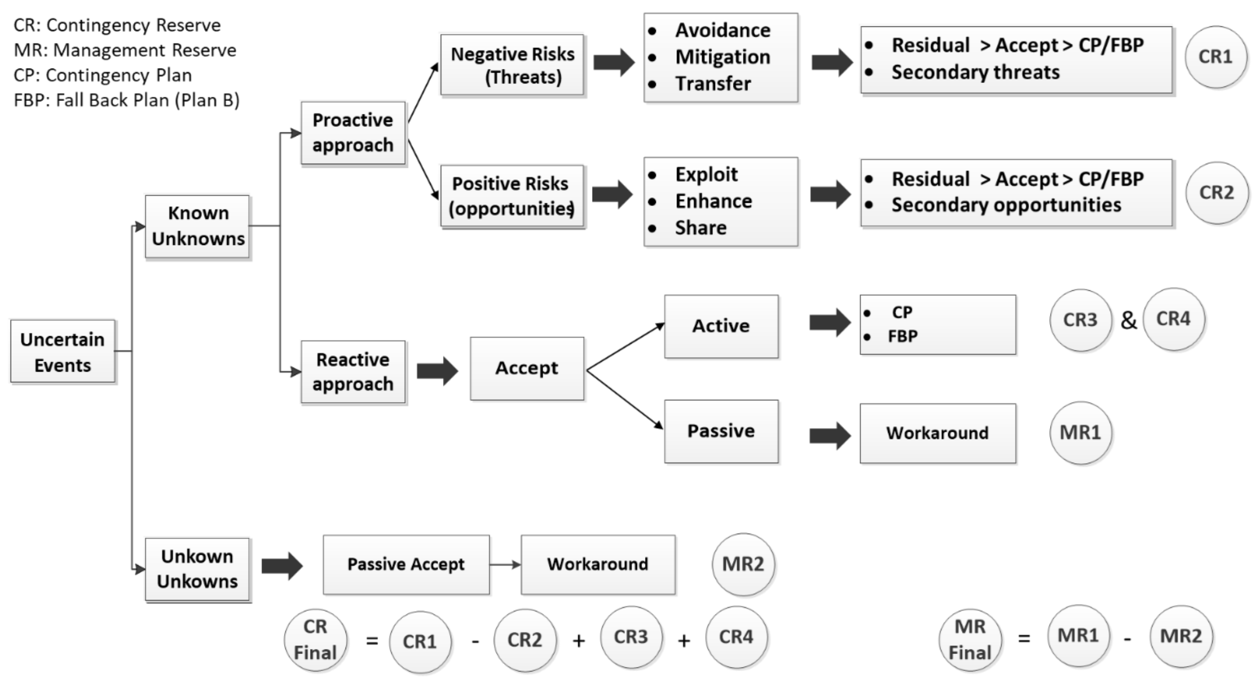

Figure 5.1 Contingency reserve and management reserve (adapted from Ahmadi-Javid et al., 2020; PMI, 2017).

5.2.2. Drawbacks of traditional methods to determine contingency reserve

Contingency determination methods can be categorized into two groups: deterministic techniques and probabilistic approaches. In deterministic techniques such as expert judgment and predetermined guidelines, contingency reserve is expressed as a predetermined proportion of the budget or as a single crisp number. Deterministic techniques are incapable of effectively addressing uncertainties (Mak & Picken, 2000), taking into account the unique effects of project complexity, market conditions, and location (Olumide et al., 2010), or accurately assessing risks (Kirchsteiger, 1999; Olumide et al., 2010). Additionally, they do not provide a confidence level for the predicted contingency's sufficiency and are incapable of considering positive risks (i.e., opportunities) (Ahmadi-Javid et al., 2020).

However, because probabilistic approaches rely heavily on probability theory, a lack of quality and quantity of historical quantitative data causes inaccurate and unreliable contingency reserve values (Fateminia, Siraj, et al., 2020; Salah & Moselhi, 2015). Probabilistic approaches can be classified as simulation-based methods (e.g., range estimating, integrated cost and schedule) and non-simulation-based methods (e.g., probability tree, analytic hierarchy process, expected value, regression) (Fateminia, Siraj, et al., 2020). Since probabilistic approaches presuppose that cost variations are intrinsically random, numerous risk specialists struggle to conduct an accurate and exact risk assessment because of a lack of data or poor-quality data (Hao et al., 2019). Standard probability theory does not provide techniques for deriving and computing from natural language-based data. Additionally, Monte Carlo simulation (MCS), which is the most common probabilistic technique, frequently fails in assessing risks of projects because of overconfidence bias (Flyvbjerg, 2021). Experts develop overconfidence bias by assuming thin-tailed risk distributions (normal or near-normal), whereas the true distributions are fat-tailed (lognormal, power law, or similar probability distribution) (Flyvbjerg, 2021). The error is not with MCS models per se, but with improper model input (Ahmadi-Javid et al., 2020; Flyvbjerg, 2021; Hillson, 1999). Additionally, neither deterministic nor probabilistic techniques can model subjective uncertainty.

5.2.3. FSD simulation advantages for construction risk management

Simulation methods are appropriate techniques to dynamically analyze and evaluate the performance of systems as they change over time and make future inferences (Helal, 2008). Simulation methods are more flexible than optimization models and do not generally require those assumptions and simplifications made with optimization models (Helal, 2008). Therefore, employing simulation methods can lead to more realistic modeling results.

The appropriate simulation technique must be selected to accurately mimic the complexity and uncertainty of construction projects. Large-scale construction projects belong to the class of complex, dynamic systems, which consist of multiple interdependent components (Fateminia, Siraj, et al., 2020; Fateminia, Sumati, et al., 2020). Moreover, highly dynamic construction projects entail various feedback loops and nonlinear interactions. (Fateminia, Sumati, et al., 2020). In discrete event simulation models, system performance can be evaluated for specific values of decision variables or control policies (Helal, 2008). However, determining the stability of the system in any region or neighborhood of those values or policies is not possible. This is critically important in dynamic, complex systems where performance may be driven by causal relationships that can be highly non-linear. In these systems, modest variations from the optimal decision point might result in disproportionately huge performance changes (Helal, 2008). In agent-based modeling (ABM), which is a type of bottom–up computational simulation modeling, individual entities are represented by discrete agents and interactions among agents, and macro factors cannot be modeled (Raoufi et al., 2016; Raoufi & Fayek, 2015, 2018). On the other hand, SD is a well-elaborated technique for continuous simulation that can model dynamic behavior of complex systems. Thus, SD represents a viable simulation technique for modelling the complexity of construction projects (Fateminia et al., 2021). SD allows representation of causal relationships between system variables, such as interdependencies between probability dependencies and impact dependencies among REs, RRAs, and secondary risks (Nasirzadeh et al., 2008; Sterman, 2000). Complex construction systems contain subjective variables of a qualitative nature, which are best expressed using linguistic terms. Since most construction projects lack sufficient historical quantitative data, the development of probabilistic distributions for system variables can be challenging (Raoufi et al., 2016). Furthermore, casual relationships of systems cannot be clearly calculated by statistical methods and represented as numerical values owing to the lack of sets of similar data (Fateminia et al., 2021; Fateminia, Sumati, et al., 2020).Therefore, to capture the subjective uncertainties of the subjective variables and relationships in a simulation model, SD can be integrated with fuzzy arithmetic, resulting in FSD (Fateminia, Sumati, et al., 2020; Raoufi et al., 2016). FSD is able to capture the time-dependent nature of construction uncertainties and interactions among the components influencing contingency (Raoufi et al., 2016).

The main feature of FSD is its ability to model continuous changes in system variables, deal with system feedback loops, and track the dynamics of construction variables (Fateminia et al., 2021). Therefore, FSD is the appropriate choice when modelers wish to assess changes of system variables over time and identify the effects of factors influencing these variables. Qualitative and qualitative FSD models are developed in the same way. However, quantitative FSD models are developed differently compared with quantitative SD models (Fateminia et al., 2021). Specifically, the subjective variables of FSD models are represented by fuzzy membership functions (MBFs) (Fateminia et al., 2021; Fateminia, Sumati, et al., 2020), rather than the deterministic or probabilistic values used in SD models (Raoufi et al., 2016). To design and run an FSD model, it is necessary to build both qualitative and quantitative FSD models. The qualitative FSD model (system thinking) enables users to perceive system behavior, whereas the quantitative FSD model enables users to simulate system behavior dynamically and predict system state (Fateminia et al., 2021).

The study of the literature indicates an increasing tendency toward overcoming the constraints of traditional risk analysis methods by integrating them with other techniques such as fuzzy logic. Nasirzadeh et al. (Nasirzadeh et al., 2014) employed a fuzzy-based SD technique in their FSD model to determine the optimal risk allocation percentage for construction projects between owners and contractors. In their proposed technique, very few fuzzy variables were included in the FSD models. The risk implications for the project's objectives were examined at the project level. Moreover, RRAs and opportunities were not addressed throughout the evaluation process. Siraj et al. (Siraj & Fayek, 2016) developed a hybrid FSD model combining expert judgement and subjective evaluation to investigate the influence of connected and interacting risk and opportunity events on work package cost in order to predict work package and project contingencies. However, the model was restricted to risk assessment and omitted risk response planning. Sadeghi et al. (Fateminia, Sumati, et al., 2020) suggested an approach for coping with both random and subjective uncertainties in estimating project contingency by combining fuzzy set theory and MCS. However, the proposed approach is incapable of evaluating the effect of individual REs; rather, it determines the range estimate of the combined effect of REs. Fateminia et al. (Fateminia, Siraj, et al., 2020) developed an arithmetic-based fuzzy risk analysis model (FRAM) to solve the research gap by resolving measurement imprecision and subjective uncertainty inherent in expert assessments. FRAM does not, however, take into account RRAs, causal relationships, or the complex and dynamic nature of construction project components. FRAM also serves as the foundation for the software application Fuzzy Risk Analyzer© (FRA©), a fuzzy arithmetic-based risk analysis software. FRA© employs linguistic terms represented by triangular and trapezoidal fuzzy numbers to assess the probability and impact of REs, as well as fuzzy arithmetic techniques based on the α-cut method to generate work package and project contingencies.

Other approaches to developing fuzzy hybrid models include integrating failure mode and effect analysis (FMEA), analytic hierarchy process (AHP), and fuzzy logic to assess risks and determine contingency (Raoufi & Fayek, 2018), prioritizing a project's risk factors using AHP and fuzzy set theory (Nasirzadeh et al., 2014), and quantifying REs using FMEA and fuzzy set theory (Siraj & Fayek, 2016). Table 5.1 compares different contingency reserve determination methods based on ten categories adopted from related literature (Ahmadi-Javid et al., 2020; Bakhshi & Touran, 2014; Fateminia, Sumati, et al., 2020; Salah & Moselhi, 2015; Teller et al., 2014). The Criteria are extracted from reviewing the literature of contingency determination methods and their capabilities and weaknesses. Table 5.1 summarizes how hybrid fuzzy techniques are more capable compared to deterministic and probabilistic approaches to consider subjective uncertainties. However, current methods of determining contingency reserve have shortcomings in incorporating RRAs into their risk analysis process. Moreover, current methods are limited in their ability to consider time-dependent behavior of REs and cause-and-effect relationships between project components. Furthermore, current contingency determination methods are based on one expert's assessment, which may cause biased assessments and decisions. Although hybrid fuzzy techniques use fuzzy logic and fuzzy arithmetic, the literature does not reveal a systematic method to develop, optimize, and aggregate the (MBFs) of linguistic terms used for risk assessments.

Table 5.1 Comparison of contingency reserve determination methods (adopted from Bakhshi & Touran, 2014; Fateminia 2020).

Methods	Criteria	Providing quantitative analysis	Calculating contingency	Prioritizing risks	Considers risk response actions	Considering subjective uncertainty	Considering causal relationships among project components	Considers time and dynamic nature of project (lifecycle of project)	Considering portion/percentage of affected work package	Providing a structured way to develop, optimize, and aggregate the linguistic terms	Considering the level of risk expertise
Deterministic approaches	Probability-impact matrix (PI matrix)		√	√							
	Predefined percentages		√	-							
Probabilistic approaches	Monte Carlo simulation (MCS)	√	√	√							
Fuzzy-based approaches	Fuzzy failure mode and effect analysis (Fuzzy FMEA)	√		√		√					
	Fuzzy fault tree analysis (Fuzzy FTA)	√		√		√					
	Fuzzy risk analysis model (FRAM)	√	√	√		√			√		
	Current study: Hybrid fuzzy arithmetic-based contingency reserve model (HFACRM)	√	√	√	√	√	√	√	√	√	√

5.3. Developing hybrid fuzzy arithmetic-based contingency reserve model (HFACRM)

HFACRM has four main steps: 1) preprocessing inputs, 2) developing qualitative FSD model, 3) developing quantitative FSD model, and 4) dynamic simulation of the model. Step 1 begins with calculating experts' risk expertise, then determining MBFs of linguistic terms and evaluating the effectiveness of RRAs. In Step 2, qualitative FSD model is developed resulting in stock and flow structures and identifying relationships between variables. In Step 3, all variables, relationships, and stocks and flows are formulated via quantitative FSD modeling. In Step 4, the cumulative and concurrent impact of REs on work packages and project cost is quantified by running the model across the duration of the project. Figure 5.2 provides an outline of the HFACRM process, and the steps are further described below.

5.3.1. Step 1, Preprocessing inputs

HFACRM employs fuzzy arithmetic to capture the subjective uncertainty of linguistic terms used to assess the risk expertise of each expert, probability and impact of REs, effectiveness of RRAs, and causality degree of causal relationships.

5.3.1.1 Evaluating risk expertise level of each participant

When aggregating expert opinions of the linguistic terms, importance weights must be assigned to the experts. For example, Monzer et al. (Monzer et al., 2019) suggested assessing experts' level of risk expertise based on seven criteria: experience, knowledge, professional performance, risk management practice, project specifics, reputation, and personal qualities and skills. In this study, these criteria are applied to calculate level of risk expertise (importance weight) for each expert. Each criterion has quantitative or qualitative subcriteria, and each qualitative attribute is assessed using a preset rating scale (1–5) (Monzer et al., 2019). The experts' importance weights (*Wk*) are derived using fuzzy analytical hierarchy process (FAHP) weight-assigning approach after analyzing each expert's level of expertise based on the mentioned attributes. Standard AHP utilizes crisp numbers, whereas FAHP allows experts to make pairwise comparisons using fuzzy linguistic evaluations (Fateminia, Sumati, et al., 2020). Therefore, FAHP is used to calculate the relative weights of qualifying attributes and criteria based on expert pairwise assessments.

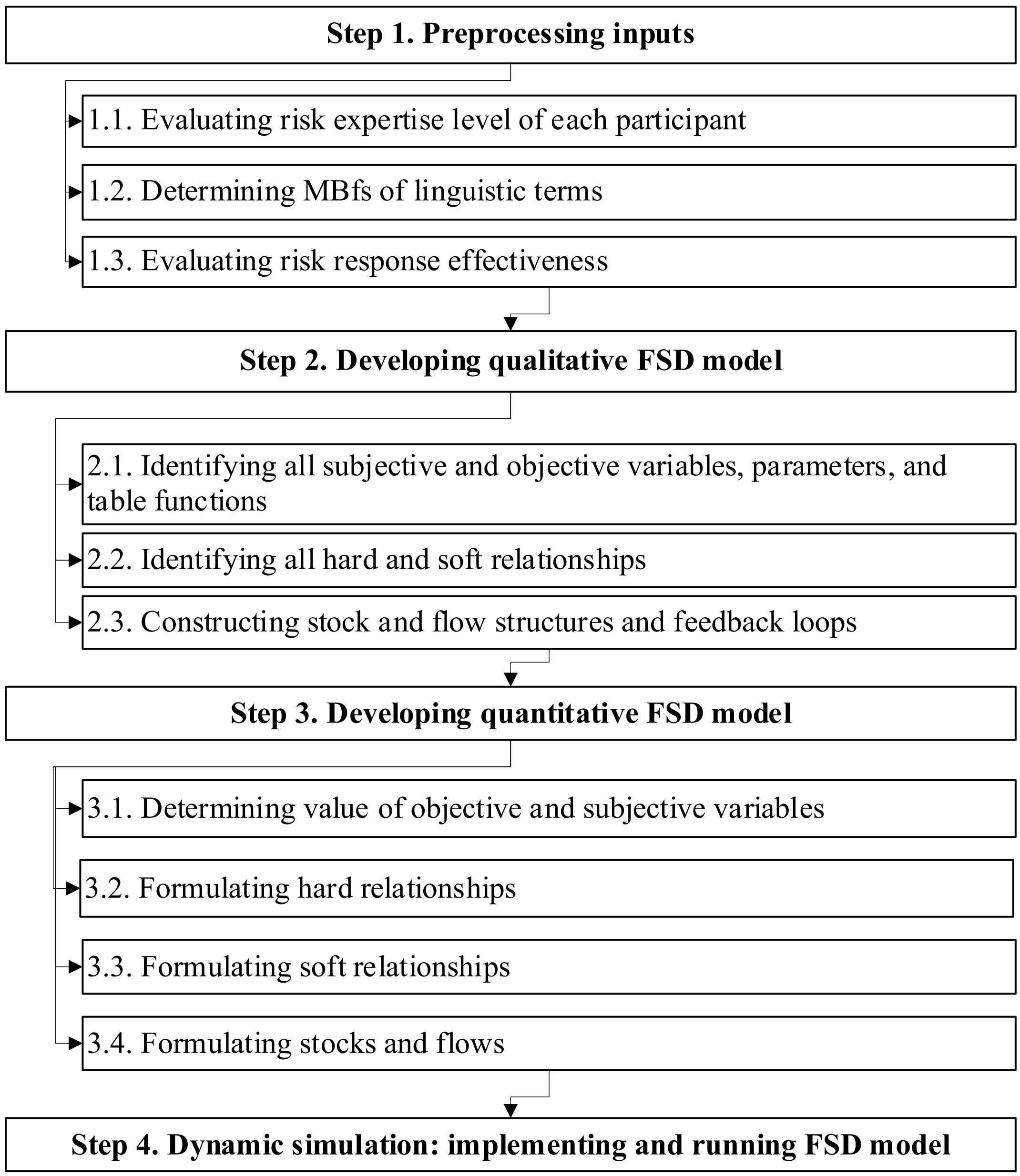

Figure 5.2 Steps of HFACRM.

5.3.1.2 Determining membership functions of linguistic terms

Expert-driven and data-driven methods both have limitations in their ability to form MBFs. For example, to form the MBF of probability by using an expert-driven method such as AHP in a project with 100 REs, almost 4,900 pair-wise comparisons among REs must be performed by each expert, and the results are not necessarily linear. Therefore, a fuzzy hybrid model proposed by Fateminia et al. (Fateminia, Sumati, et al., 2020) was employed to construct, optimize, and aggregate the MBFs of linguistic terms for the probability and impact of REs. This model uses interval type-2 fuzzy sets to provide broader knowledge representation and approximate reasoning for computing with words. It also employs weighted principle of justifiable granularity (WPJG) for determining the optimized interval type-2 MBFs of risk analysis concepts (i.e., linguistic variables including probability and impact). This principle provides an alternative to clustering methods in constructing information granules based on the criteria of coverage and specificity of data.

5.3.1.3 Evaluating risk response effectiveness

The application of complex quantitative models, such as optimization methods to select and rank RRAs for large-scale construction projects, can be a complex and costly process because of the effort and amount of data required. Moreover, these models account for only a limited number of criteria, which can lead to the selection of risk responses that are cost effective but unfeasible in terms of technology, environment, and achievability. Furthermore, most ranking and selection methods of RRAs are unable to consider linguistic terms. Therefore, a fuzzy model consisting of fuzzy rule-based system (FRBS) along with fuzzy ranking methods proposed by Fateminia et al. (Fateminia et al., 2019) is employed to evaluate the effectiveness of RRAs and rank them. The proposed FRBS uses three inputs as evaluation criteria and produces the effectiveness of risk responses as an output. The three inputs are the 1) affordability of each risk response, 2) the achievability of each risk response, and the 3) controllability of related REs. FRBS uses the estimated crisp values of these inputs to evaluate the effectiveness of risk responses according to the rules developed based on experts' opinions. The consistency of rules are examined using the inconsistency measure (Adilova, 2019) by calculating Similarity of Rule Premise (SRP) and Similarity of Rule Consequent (SRC). The output is a fuzzy set and is used as an input for three different fuzzy ranking methods, one based on the smallest of maxima (SOM), one on largest of maxima (LOM), and one on center of area (COA). This ranking determines the most effective risk response in terms of affordability, achievability, and controllability.

5.3.2. Step 2, Qualitative FSD model of HFACRM

The qualitative FSD model of HFACRM enables users to identify system behavior and can be developed in three major steps using focus groups, interviews, published literature, and surveys. First, subjective and objective variables, parameters, and table functions such as REs and RRAs are identified. Variables are identified using the most common REs in construction projects, which have been categorized into eleven groups (Siraj & Fayek, 2019): Resource-related, Management, Technical, Construction, Site conditions, Contractual and legal, Economic, Financial, Environmental, Social, Political, and Health and safety (Siraj & Fayek, 2019). Then, an initial model boundary and the level of aggregation are established to achieve realistic abstraction and representation. The model boundary reflects the modeling scope, and the level of aggregation deals with grouping of activities into subsystems (components). Next, causal relationships and logical interactions among the model variables are determined. Corresponding causal loop diagrams (CLDs) of identified variables and relationships between them are then constructed, by determining feedback loops and stock and flow structures. Figure 5.3 shows the required inputs, procedures, and outputs of each step for the qualitative FSD model of HFACRM.

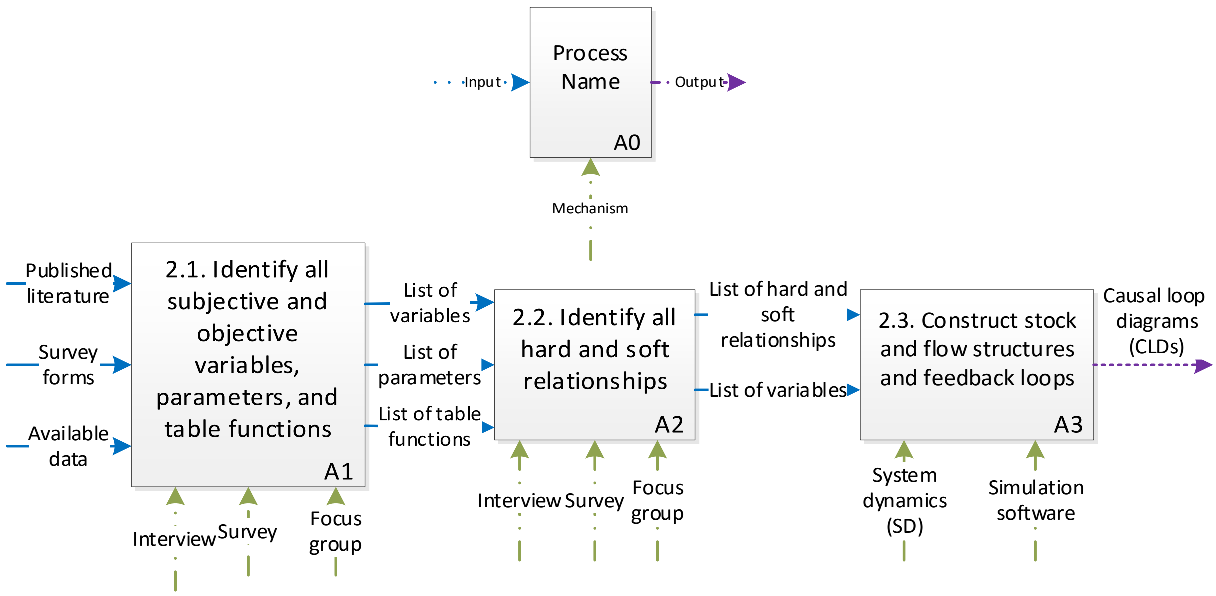

Figure 5.3 Inputs, procedures, and outputs of qualitative FSD model of HFACRM.

5.3.3. Step 3, Quantitative FSD model of HFACRM

The quantitative FSD model of HFACRM comprises four steps. First, the value of subjective and objective variables is determined. Between model variables, both soft and hard causal relationships exist. When a causal relationship's mathematical form is known, it is said to be "hard" (e.g., relationship between risk severity and risk impact). Soft causal interactions are those in which the mathematical form of the causal relationship is unclear (for example, the relationship between the probability of occurrence of two risk events) (Fateminia et al., 2021; Fateminia, Sumati, et al., 2020). In the second and third steps, the soft and hard relationships between variables identified in the qualitative phase are formulated. Fourth, all stocks and flows are formulated using both crisp and fuzzy arithmetic. These four steps of quantitative FSD modeling of HFACRM are described in the following subsections in detail.

5.3.1.4 Determining value of objective and subjective variables

In quantitative FSD, objective system variables are represented by crisp numbers (e.g., work package cost). However, the subjective system variables are represented by MBFs, such as impact and probability of REs, which are represented using linguistic terms such as "Very Low" or "High." Figure 5.4 shows the required inputs, procedures, and outputs of the first quantitative FSD modeling step of HFACRM.

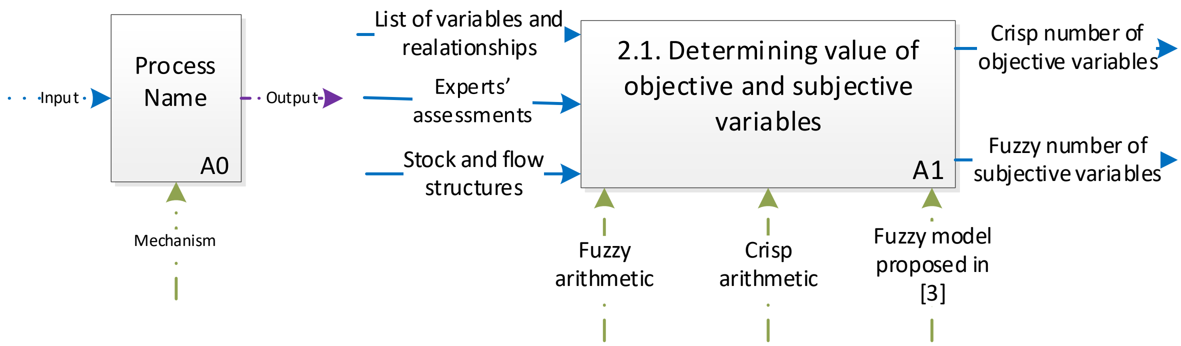

Figure 5.4 Inputs, procedures, and outputs of first step of the quantitative FSD model.

5.3.1.5 Formulating hard relationships in FSD model of HFACRM

Second, hard causal relationships are formulated using a contingency determination fuzzy procedure and both crisp and fuzzy arithmetic, resulting in mathematical equations of the hard causal relationships. This procedure starts with calculating the threat risk severity and opportunity risk severity of implementing related RRAs. For any positive and negative RE impacting a given work package, the fuzzy number representing its impact is multiplied by the fuzzy number that represents its probability; the product gives the risk or opportunity severity as a percentage. Then, net severity percentage is computed for each RE by subtracting its opportunity severity percentage from its threat severity percentage. To determine each RE's net severity in a currency denomination (e.g., Canadian or U.S. dollars), its net severity percentage is multiplied by the expert-determined impacted portion of the estimated cost of the work package as a result of that event and expressed as a fuzzy number. The fuzzy number that represents the contingency amount of the work package is determined by adding the net severity of all events impacting that work package.

Table 5.2 presents a list of all sets and variables required in the FSD model of HFACRM. The equations of the quantitative FSD model of HFACRM are described and expressed as follows.

Threat severity after implementing *k*th RRA (RRA_k):

$$RST_{rij} = PT_i^k \times IT_i^k \qquad i = \{1, \dots, n\}, j = \{1, \dots, m\}, k = \{1, \dots, l\}, r = \{1, \dots, f\} \tag{1}$$

$$RST_{rj} = \sum_{r=1}^{f} RST_{rij} \qquad j = \{1, \dots, m\} \tag{2}$$

Opportunity severity after implementing *k*th RRA (RRA_k):

$$RSO_{rij} = PO_i^k \times IO_i^k \qquad i = \{1, \dots, n\}, j = \{1, \dots, m\}, k = \{1, \dots, l\}, r = \{1, \dots, f\} \tag{3}$$

$$RSO_{rj} = \sum_{r=1}^{f} RSO_{rij} \qquad j = \{1, \dots, m\} \tag{4}$$

Net severity of *r*th category of REs for *j*th work package:

$$RSN_{rj} = RST_{rj} - RSO_{rj} \qquad r = \{1, \dots, f\}, j = \{1, \dots, m\} \tag{5}$$

Total threat contingency of *j*th work package:

$$CTWP_j = \sum_{r=1}^{f} RST_{rj} \times WPC_j \times WPIC_j \tag{6}$$

Total opportunity contingency of *j*th work package:

$$COWP_j = \sum_{r=1}^{f} RSO_{rj} \times WPC_j \times WPIC_j \tag{7}$$

Total net contingency of *j*th work package:

$$CWP_j = CTWP_j - COWP_j + \left(\sum_{r=1}^{f} \sum_{i=1}^{n} \sum_{k=1}^{l} RRAC_{ikr}\right) \quad (8)$$

Total net contingency of project:

$$CRT = \sum_{j=1}^{m} CWP_j \quad (9)$$

Figure 5.5 shows the required inputs, procedures, and outputs of the second quantitative FSD modeling step of HFACRM.

Table 5.2 Sets and variables required in the FSD model of HFACRM, where i = {1,… ,n}, j = {1,… ,m}, k = {1,… ,l}, and r = {1,… ,f}.

Category	Symbol	Description
i. Required sets	E	The set of all risk events (REs)
	A	The set of all risk response actions (RRAs)
ii. Threats (negative risks)	PT_i	Probability of ith threat before implementing RRA
	IT_i	Impact of ith threat before implementing RRA
	PT_i^k	Probability of ith threat after implementing kth RRA (RRA_k)
	IT_i^k	Impact of ith threat after implementing kth RRA (RRA_k)
iii. Opportunities (positive risks)	PO_i	Probability of ith opportunity before implementing RRA
	IO_i	Impact of ith opportunity before implementing RRA
	PO_i^k	Probability of ith opportunity after implementing kth RRA (RRA_k)
	IO_i^k	Impact of ith opportunity after implementing kth RRA (RRA_k)
iv. Work packages	WPC_j	Cost of jth work package
	$RRAC_{ikr}$	Implementation cost of kth RRA for ith risk in rth category of risks
	$WPIC_{ij}$	Impacted cost of jth work package by the ith risk
v. Threat risk severity	RST_{rij}	Threat risk severity of ith threat in rth category of REs for jth work package
	RST_{rj}	Threat risk severity of rth category of REs for jth work package
vi. Opportunity risk severity	RSO_{rij}	Opportunity risk severity of ith opportunity in rth category of risks for jth WP
	RSO_{rj}	Opportunity risk severity of rth category of REs for jth work package

vii. Total risk severity	RSN_{rj}	Net risk severity of rth category of REs for jth work package
viii. Contingency reserve	$CTWP_j$	Threat contingency reserve of jth work package
	$COWP_j$	Opportunity contingency reserve of jth work package
	CWP_j	Total contingency reserve of jth work package
	CRT	Total contingency reserve

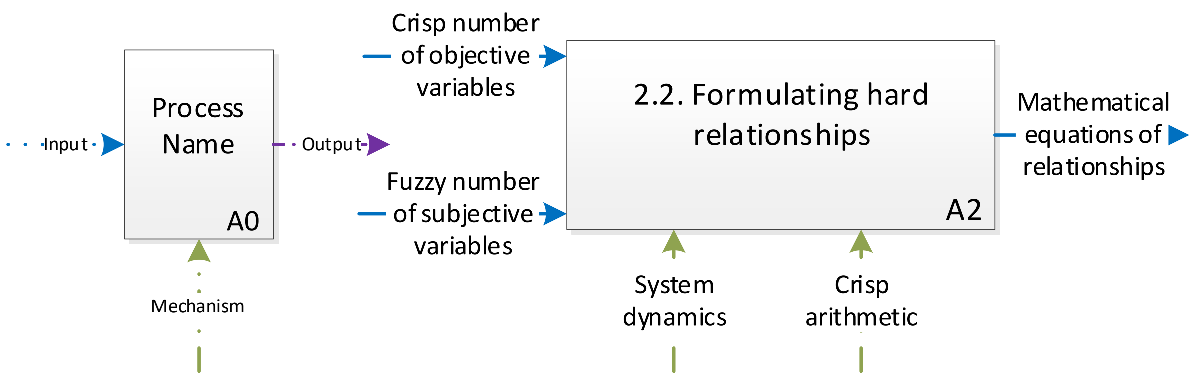

Figure 5.5 Inputs, procedures, and outputs of second step of the quantitative FSD model.

5.3.1.6 Formulating soft causal relationships in FSD model

Third, soft causal relationships are formulated using fuzzy arithmetic and a fuzzy model proposed by Fateminia et al. (Fateminia et al., 2021), which uses FAHP, WPJG, and fuzzy aggregation operators. This study employs the model in order to obtain crisp causality degree values and optimized MBFs for soft causal relationships. Since linguistic terms are used to express soft causal relationships, fuzzy arithmetic is employed to formulate linguistic assessments. By employing fuzzy arithmetic, the HFACRM addresses the limitations of traditional risk analysis methods, such as a high reliance on historical data and the inability to account for the subjective uncertainty associated with assessing risk and opportunity events. Also, a fuzzy decision-making trial and evaluation laboratory method (FDEMATEL) is employed to demonstrate the importance degree of REs in terms of their causal relationships. Using graph and matrix theory, FDEMATEL efficiently structures and analyzes complex causal relationships between a system's main components (Seker & Zavadskas, 2017). REs with high importance degree values have more causal relations with the other risk and opportunity events. Figure 5.6 shows the required inputs, procedures, and outputs of third step in the quantitative FSD modeling step of HFACRM.

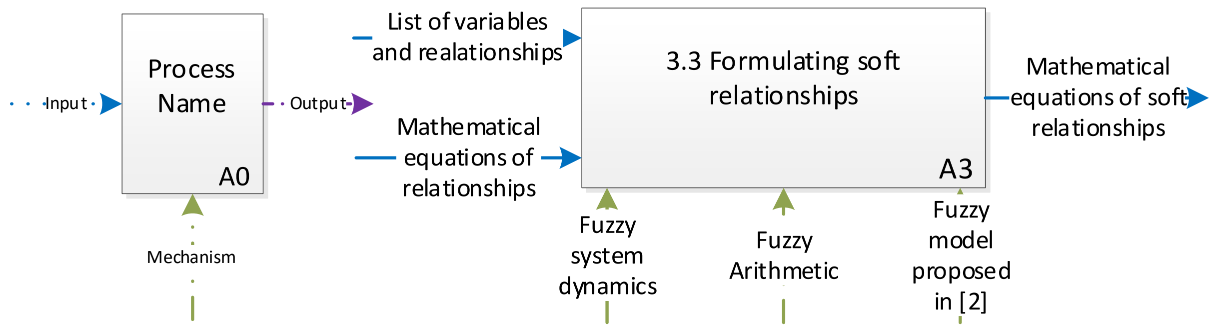

Figure 5.6 Inputs, procedures, and outputs of third step of the quantitative FSD model.

5.3.1.7 Formulating stocks and flows in FSD model

Fourth, stocks and flows are formulated using both crisp and fuzzy arithmetic. CLDs have the ability to show relationships among the elements of a system using features such as loop polarity. However, they fail at quantifying the elements of the system. If a component increases or decreases due its causal variable, it is important to know how much and at what rate it changed. Stocks and flows are the concepts that account for such quantities. Each stock is considered the accumulation of each element size in the system. Thus the system is said to have memory or history. Two types of flows exist: inflows and outflows. Inflows and outflows usually vary with time. Inflows and outflows are the rates at which a given quantity is being added to or subtracted from the stock. Therefore, a stock is the integral of the net flow added to the initial value of the stock. The net flow is eventually the outflow subtracted from the inflow. The net flow is therefore the derivative of the total stock with respect to time:

$$\mathrm{stock(t)} = \mathrm{S}_0 + \int_{t_0}^{t} (inflows(t) - outflows(t))dt \qquad (10)$$

Both inflow and outflow arrows contain a valve that dictates the rate of the flows entering or leaving a stock. In short, stock and flow diagrams not only show the structure's components and their relationships, they draw more attention to accumulation and flow processes. All equations for required flows in HFACRM are described and expressed as follows.

Threat risk severity for each work package:

$$CTWP_j = \sum_{r=1}^{f} RST_{rj} \times WPC_j \times WPIC_j \qquad (11)$$

Opportunity risk severity for each work package:

$$COWP_j = \sum_{r=1}^{f} RSO_{rj} \times WPC_j \times WPIC_j \qquad (12)$$

Net risk severity for each work package:

$$CWP_j = CTWP_j - COWP_j + \left(\sum_{r=1}^{f} \sum_{i=1}^{n} \sum_{k=1}^{l} RRAC_{ikr}\right) \qquad (13)$$

Total project risk severity:

$$CRT = \sum_{j=1}^{m} CWP_j \qquad (14)$$

Monthly planned cost of project:

$$MPCP = \sum_{j=1}^{m} WPC_j \qquad (15)$$

Monthly actual cost of project:

$$MACP = \sum_{j=1}^{m} WPC_j + CWP_j \qquad (16)$$

All equations for required stocks in HFACRM are described and expressed as follows.

Threat contingency reserve of each work package:

$$\int_{t_0}^{t} CTWP \quad (t)\, dt \qquad (17)$$

Opportunity contingency reserve of each work package:

$$\int_{t_0}^{t} COWP \quad (t)\, dt \qquad (18)$$

Total contingency reserve of each work package:

$$\int_{t_0}^{t} CWP \quad (t)\, dt \qquad (19)$$

Total contingency reserve:

$$\int_{t_0}^{t} CRT \quad (t)\, dt \qquad (20)$$

Total planned budget of project:

$$\int_{t_0}^{t} MPCP \quad (t)\, dt \qquad (21)$$

Total actual budget of project:

$$\int_{t_0}^{t} MACP \quad (t)\, dt \qquad (22)$$

Figure 5.7 shows the required inputs, procedures, and outputs of the fourth step in quantitative FSD model of HFACRM.

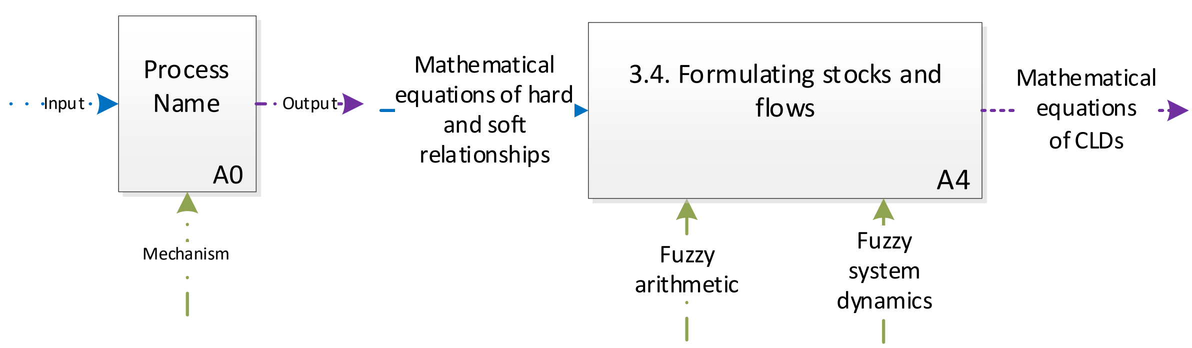

Figure 5.7 Inputs, procedures, and outputs of fourth step of the quantitative FSD model.

5.3.4. Step 4, Dynamic simulation

After constructing the quantitative FSD model, the cumulative and concurrent impact of REs on work packages and project costs is calculated by simulating the quantitative model throughout the project's entire duration. The proposed models are implemented using simulation software. In this study, AnyLogic® simulation software was applied to implement the model. In this study, fuzzy calculations are restricted only between two fuzzy numbers, because the outputs of a single implementation of a fuzzy operation (e.g., fuzzy multiplication) are irregularly shaped fuzzy numbers, and the α-cut method is the only possible arithmetic. The α-cut method is the most commonly used arithmetic method in FSD models. The minimum t-norm gives the same result as the α-cut method. Moreover, the support of the fuzzy numbers obtained by using the minimum t-norm and the product t-norm are the same. Hence, the accumulations of fuzziness due to the minimum t-norm and the product t-norm are similar to the α-cut method (Hanss, 2005). Fuzziness is the quality of being indistinct and without sharp outlines. Therefore, this study implemented the α-cut method to carry out fuzzy arithmetic operations involving trapezoidal fuzzy numbers in the FSD model. For any trapezoidal fuzzy number represented by a tuple *(a, b, c, d), a* and *d* represent the lower and upper bound of the support (i.e., the set of all elements of the universe of discourse that have a non-zero membership degree in the fuzzy number), respectively. The parameters *b* and *c* denote the lower and upper mode of the core (i.e., the set of all elements of the universe of discourse that have a membership degree of 1 in the fuzzy number), respectively. The four defuzzification methods of COA, SOM, middle of maxima (MOM), and LOM are employed to defuzzify the final output (fuzzy numbers) of the FSD model that represents work package and project contingency values in terms of cost. To choose the best defuzzification approach, a compromise must be made between accuracy and computational complexity. COA can be considered as the most accurate defuzzification method while the calculation process is harder than others.

5.4. Case Study: Implementing HFACRM with an Actual Wind Farm Project

The proposed model and methodology were applied to analyze REs and determining contingency reserve on the construction of a 97.2-megawatt wind farm power generation project in Alberta, Canada which can be categorised as large construction project. Large-scale construction project means a construction project for which the total estimated cost of the construction contract is $35 million or more based on the Federal Acquisition Regulatory Council (FAR Council). The estimated overall cost of the project was around CAN$165 million, and the planned project duration was 12 months. The cost breakdown of the wind farm project consisted of four major categories: *Civil works, Electrical and grid connections, Major equipment,* and *Owners' cost*. These four categories were considered as higher-level work packages in the model. Table 5.3 presents the project cost breakdown structure.

Table 5.3 Cost breakdown structure.

Category	Percent (%)	Cost (CAN$)
Civil works	8	13,200,000
Electrical and grid connections	12	19,800,000
Major equipment	75	123,750,000
Owners' cost	5	8,250,000
Total project cost	100	165,000,000

5.4.1. Preprocessing inputs

A data collection protocol comprising several different data collection forms was developed to describe the methodology and data collection process and collect required data for developing HFACRM. Data collection forms were designed to 1) collect project and work package characteristics, 2) evaluate risk expertise level of each participant based on experience, knowledge, professional performance, risk management practice, project specifics, reputation, and personal attributes and skills, 3) identify a list of REs, 4) evaluate the probability of occurrence of identified REs and their impact on work package cost using linguistic terms represented by fuzzy numbers, 5) determine RRAs for each RE, 6) evaluate the effectiveness of RRAs using linguistic terms represented by fuzzy numbers, 7) assess the REs after implementing each risk response using linguistic terms represented by fuzzy numbers, 8) identify causal relationships between REs together and with RRAs, and 9) assess degree of causality, type, and polarity of soft causal relationships using pairwise comparison matrix and linguistic terms represented by fuzzy numbers..

5.4.1.1. Evaluating risk expertise level of each participant

To identify REs, RRAs, and causality degree of causal relationships, a heterogeneous group was formed consisting of three experts who were directly involved in the project. There is no ideal number of SMEs. However, authors' recommendation is 3 to 5 experts. Expert selection strategies are not provided by this study. However, if there is only one qualified expert among heterogeneous experts, the model can be regarded reliable since the weights are distributed appropriately, reducing the effect of biased judgments. The importance weight (experts' level of risk expertise) of each expert was calculated based on the seven qualitative and quantitative criteria and the FAHP weight assigning method proposed by Monzer et al. (Monzer et al., 2019). Experts were selected based on their participation in the case study project, total years of experience, years of experience in risk management, and number of similar projects they had participated in. More than 15 individual and group meetings were held to fill out the forms. For Experts 1, 2, and 3, total expert scores were 0.62, 0.66, and 0.59, respectively, and the expert weight importance was 0.33, 0.35, and 0.32, respectively. The process of calculating importance weight is developed to increase the effect of qualified experts (based on criteria) and decrease the effect of experts with lower risk expertise. In cases that the importance weights of experts are close together, this indicates that they have a comparable impact on the formation of MBFs and the evaluation of risk events and risk response activities.

The experts initially identified 90 REs and 72 RRAs with the corresponding causal relationships between all variables during several focused group meetings and interviews and reviewing risk management documents of similar projects. The relevance of the identified REs and their categorization with respect to the wind farm project were validated by another qualified expert from the project's company. Consequently, the final number of REs and RRAs were reduced to 77 REs and 57 RRAs. Table 5.4 shows the list of construction risk events.

Table 5.4 Construction REs identified for the case study.

RE no.	RE name
RE 3.1	Delays and interruptions causing cost increase to the work package/project
RE 3.2	Poor workmanship and construction errors leading to rework
RE 3.3	Unreasonably tight project schedule causing cost increase to the work package/project
RE 3.17	Roads: poor quality gravel crane pads
RE 3.18	Roads: problem with public roads
RE 3.19	Roads: high WTG turnarounds
RE 3.20	WTG erection: additional crane path reclamation
RE 3.21	WTG erection: additional crane breakdowns (based on crossing agreements)
RE 3.22	WTG erection: problem with aviation lights

RE 3.23	Collection system: relocation of junction boxes due to not getting landowner sign-off
RE 3.24	Collection system: cable spec change
RE 3.25	Collection system: 1.5–3% scope change based on final design. add fault indicators
RE 3.26	Collection system: above ground and underground directional drilling crossings
RE 3.27	Substation: operation of substation during commissioning
RE 3.28	Substation: additional reclamation not including in contract (laydown and batch plant)

Note: WTG = wind turbine generator

5.4.1.2. Determining membership functions of linguistic terms

The MBFs of subjective variables were calculated to develop the quantitative FSD model of HFACRM and assess REs, RRAs, and causality degree of soft causal relationships based on the models proposed by Fateminia et al. (Fateminia et al., 2021; Fateminia, Sumati, et al., 2020). In these models, WPJG and fuzzy aggregation operators were employed to optimize and construct MBFs. The resulting optimized MBFs of linguistic terms to evaluate REs and RRAs are presented in Figure 5.8.

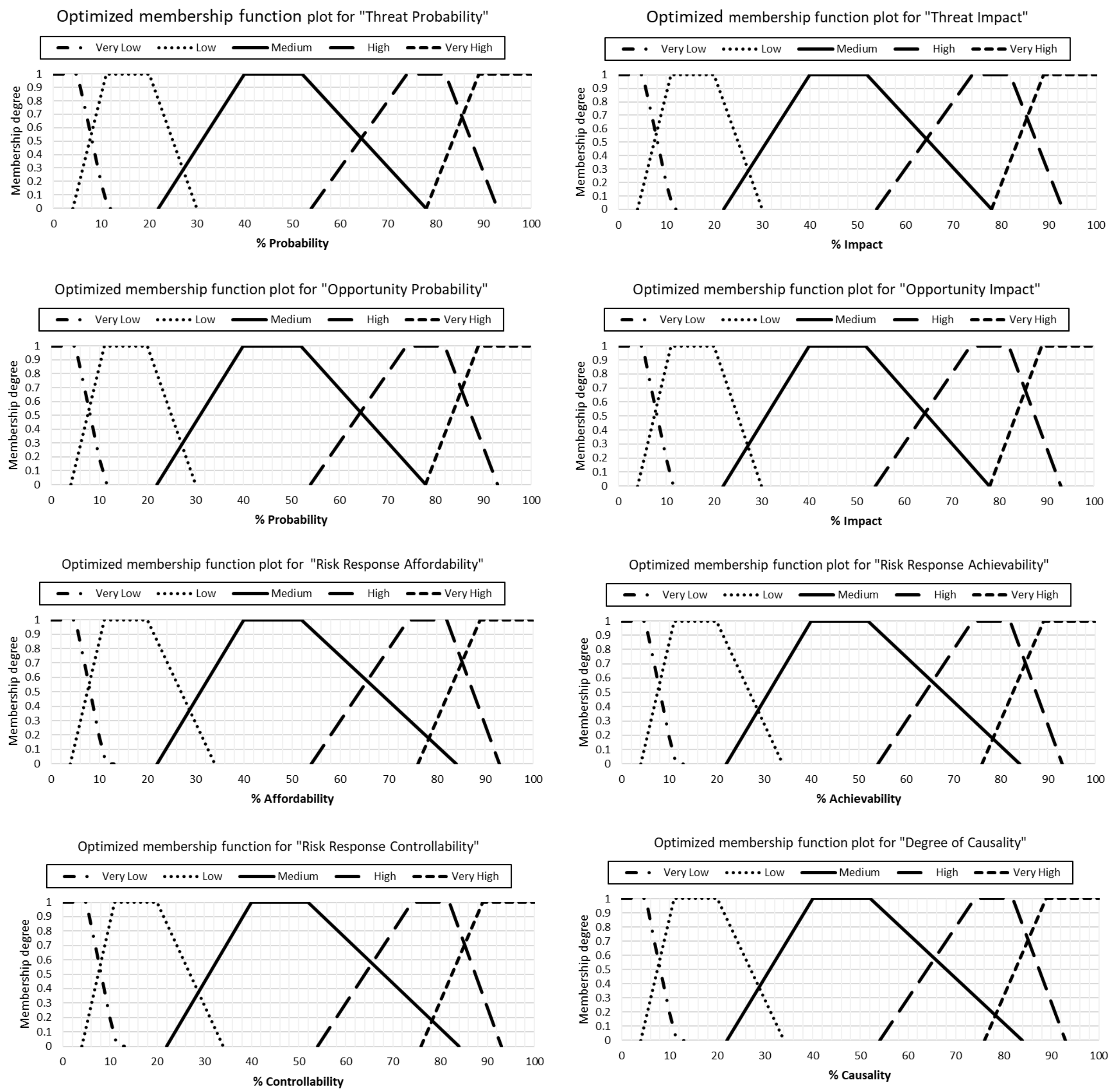

Figure 5.8 Optimized membership functions for linguistic terms used to evaluate risk events (REs) and risk response actions (RRAs).

5.4.1.3. Evaluating risk response effectiveness

Using the linguistic terms and their related optimized fuzzy MBFs, the experts evaluated the probability of occurrence of REs and their corresponding impacts on civil works, electrical and grid connections, major equipment, and owners' costs. An FRBS proposed by Fateminia et al.

(Fateminia et al., 2019) was implemented in MATLAB and applied to evaluate the effectiveness of RRAs based on their achievability and affordability as well as the controllability of correspondence REs. Then, the most effective risk response action for each RE was selected. Table 5.5 presents the effectiveness of suggested RRAs for some of construction REs. For example, RRA 3.1.1 and RRA 3.1.2 are suggested for RE 3.1 with the aggregated effectiveness of 46.5 and 48.9, respectively.

Table 5.5 Effectiveness of suggested RRAs for construction REs. Under Defuzzified value, A = Affordability of RRAs, B = controllability of REs, and C = achievability of RRAs.

Risk response actions (RRAs) for *Mitigation* response strategy	**Defuzzified value**			**Aggregated effectiveness (based on FRBS)**
	A	***B***	***C***	
3.1.1 Liquidated damages clause to accelerate the delivery and decrease the effects of delays	66.4	41.3	66.4	46.5
Consider time contingency for deliveries	66.4	48.4	66.4	48.9
3.2.1 Implement QA/QC procedures measures to limit rework	46.2	37.2	55.7	48.6
3.3.1 Keeping contractors up to date to provide cost schedule impacts	52.1	27.7	56.9	41.7
3.3.2 Proportional liquidated damages clause in relation to construction impact	55.7	37.8	47.3	48.6

5.4.2. Qualitative FSD model of HFACRM

The qualitative FSD model of contingency reserve determination has two components: cause-and-effect diagrams, and stock and flow diagrams. The cause-and-effect diagrams were developed to capture causal relationships between system variables. The stock and flow diagrams were developed to show the contingency determination process. Then, causal relationships and logical interactions among the model variables were determined. Finally, corresponding CLDs of identified variables and relationships between them were constructed by determining feedback loops and stock and flow structures. The identified REs and corresponding selected RRAs were considered as model dynamic variables. The total contingency reserve values required for each work package, risk category, and project were considered as stocks of the simulation model. The severity of negative and positive risks per time were considered as flows of the model. Then, experts identified and evaluated the types of causal relationships (degree of causality, polarity of causal links) between REs together and with RRAs for each risk category. A combination of the fuzzy model developed by Fateminia et al. (Fateminia et al., 2021) and FDEMATEL (Seker & Zavadskas, 2017) was applied for each work package to construct the CLDs.

Figure 5.9 presents, for brevity, only the CLDs of the Management RE category for the Civil works work package associated with the corresponding causal relationships between variables. There are nine Management REs, represented by black circles, for the Civil works work package. Seven of these are mitigated by selected RRAs, represented by white circles. The cause-and-effect soft causal relationships are displayed by bold gray links between REs together and with RRAs. Gray circles are fuzzy arrays used in the simulation software to represent the MBFs of fuzzy numbers such as the probability and impact of REs.

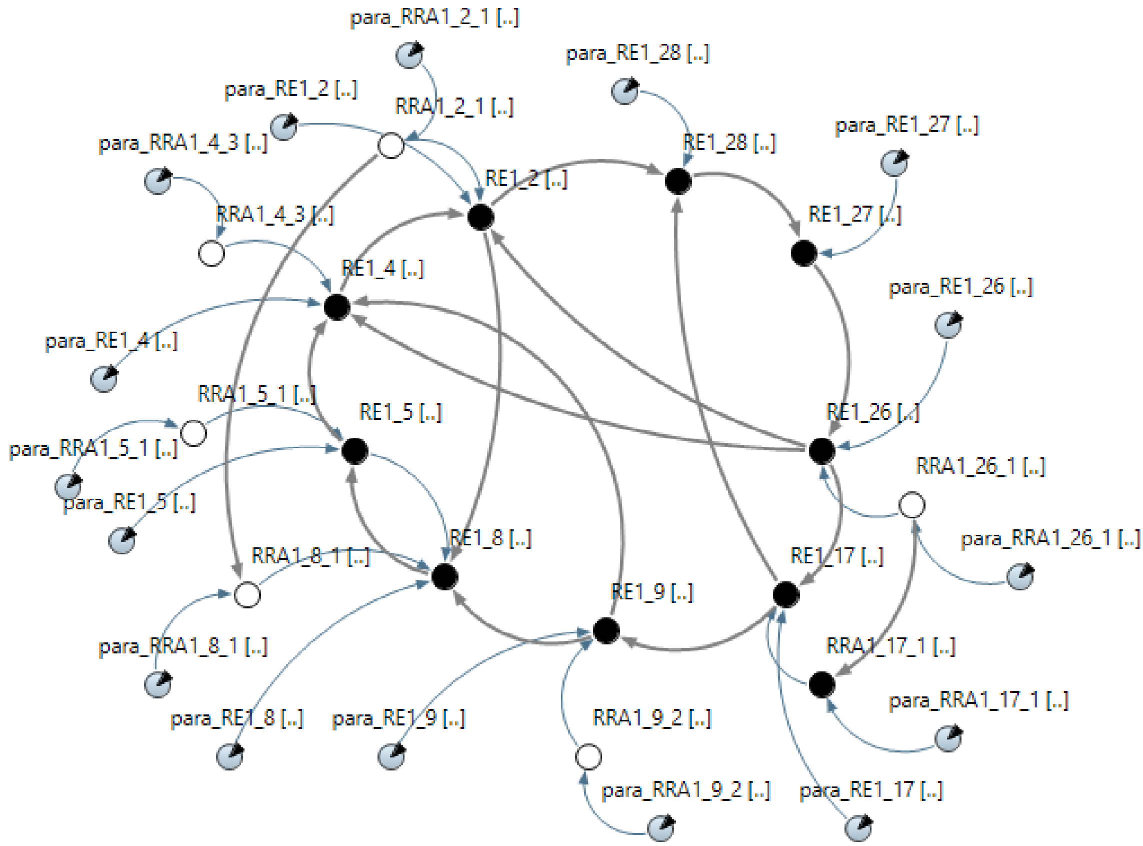

Figure 5.9 Management risk category CLDs for the Civil works work package, created in AnyLogic®.

5.4.3. Quantitative FSD model of HFACRM

The quantitative FSD model was developed in four steps and began with determining the value of subjective and objective variables. Hard and soft causal relationships between variables, identified in the qualitative phase, were formulated in the second and third steps. Finally, all stocks and flows were formulated using both crisp and fuzzy arithmetic.

5.4.3.1. Determining value of objective and subjective variables

Values for the objective model variables were determined using crisp numbers for objective variables, such as work package cost and RRA implementation cost. Values for subjective model variables were defined using fuzzy MBFs, such as impact and probability of REs, which are represented using linguistic terms such as "Very Low" or "High." Subjective (fuzzy) variables were also represented by fuzzy arrays in the proposed method. Fuzzy arrays allow storage of multidimensional data pertaining to a given system variable, so they can provide the advantage of representing a large number of fuzzy variables with several attributes (dimensions) while keeping the FSD model compact and efficient.

5.4.3.2. Formulating hard relationships in FSD model of HFACRM

Next, hard causal relationships and stocks and flows were formulated. Figure 5.10 illustrates the hard causal relationships and stocks and flows for the Management risk category for the Civil works work package in AnyLogic®. Each RE was modeled as a dynamic fuzzy array defined by the probability and impact of REs and their corresponding fuzzy MBF parameters. The affected percentage of work package cost and the degree of causality for soft causal relationships between REs were represented by crisp values, whilst the remaining attributes were represented by trapezoidal fuzzy numbers. All flow and stock variables in the FSD model were fuzzy variables, since risk severity numbers employed in the equations were also fuzzy numbers. The weighted risk probability and weighted risk impact, which reflect the effect of a preceding RE on the subsequent RE, were calculated for each RE at each timestep. Then, fuzzy multiplication and sum functions were employed to calculate weighted risk severity percentage and in Canadian dollars (CAN$) at each timestep. The aggregation of these severity values in the work package and project levels resulted in the risk contingency and net contingency. .

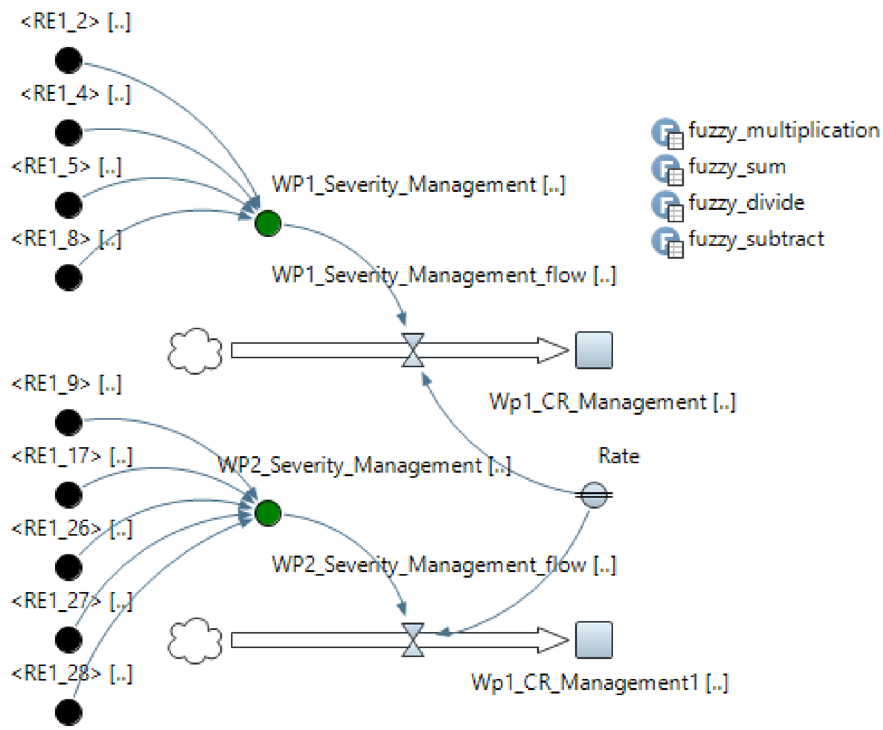

Figure 5.10 Flows and stocks for the *Management* risk category for work packages 1 and 2 in AnyLogic®.

5.4.3.3. Formulating soft causal relationships in FSD model

A degree of causality form (described in subsection 4.1) was completed by three of the experts involved in the risk assessment and prioritization stage. Each expert determined the causality degree between REs together and with RRAs using the fuzzy linguistic scales depicted in Figure 5.8 (see also subsection 4.1). The experts also determined the polarity and types of causal relationships as “Positive,” “Negative,” or “Not applicable (N/A).”

Then, the model proposed by Fateminia et al. (Fateminia et al., 2021) was employed to determine the crisp value of causality degree for soft causal relationships between REs together and with RRAs. In this respect, fuzzy ordered weighted average (FOWA) was applied to aggregate the evaluations of the three experts, resulting in a single fuzzy number that reflects their opinion. The experts’ importance weights were employed by FOWA as the weight vector for the experts’ assessments, to show their level of expertise. The aggregated fuzzy numbers of causality degrees between variables were then calculated. Finally, the aggregated fuzzy number of causality degree was defuzzified to obtain the crisp value for degree of causality for the soft causal relationship.

The FDEMATEL was employed to calculate the prominence and relation of REs and RRAs based on each risk category. Figure 5.11 shows that REs having the highest values of prominence, such as RE1.4, have the highest level of causal interactions with the rest of the REs. In contrast, REs with the lowest values of relation are the most affected by the rest of the REs.

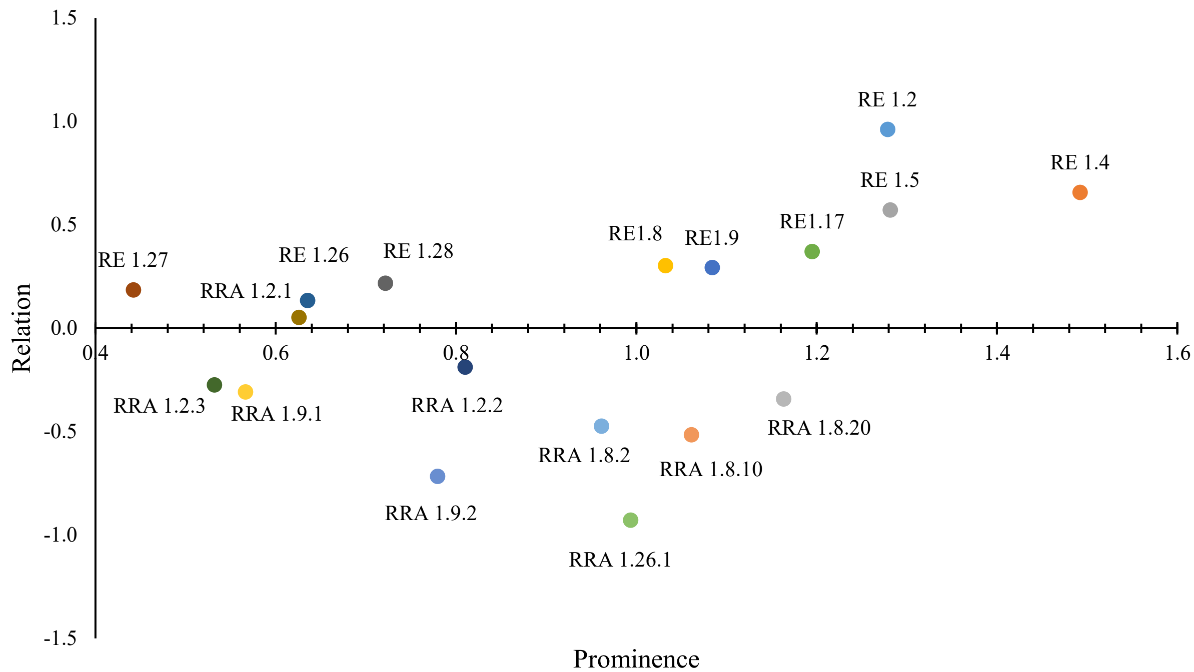

Figure 5.11 Influence relation map of risk events for the *Management* risk category.

The constructed CLDs in the qualitative step were modified based on the defuzzified total-relation matrix values. A threshold value of 0.070, which is the 75th percentile of the defuzzified total-relation matrix, was set for each risk category so the strongest causal relationships were selected, reducing the complexity of the final CLDs.

5.4.3.4. *Formulating stocks and flows in FSD model*

As illustrated in Figure 5.12, green circles are the fuzzy arrays of work packages 1 and 2 risk severity for the *Management* risk category, which are added together, resulting in fuzzy total contingency reserve for *Management* for all work packages. Then, all fuzzy numbers were defuzzified using the four defuzzification methods. Additionally, to calculate the actual cost of each work package, the monthly progress percentage of each work package is multiplied by the cost of related work package and added to the contingency reserve.

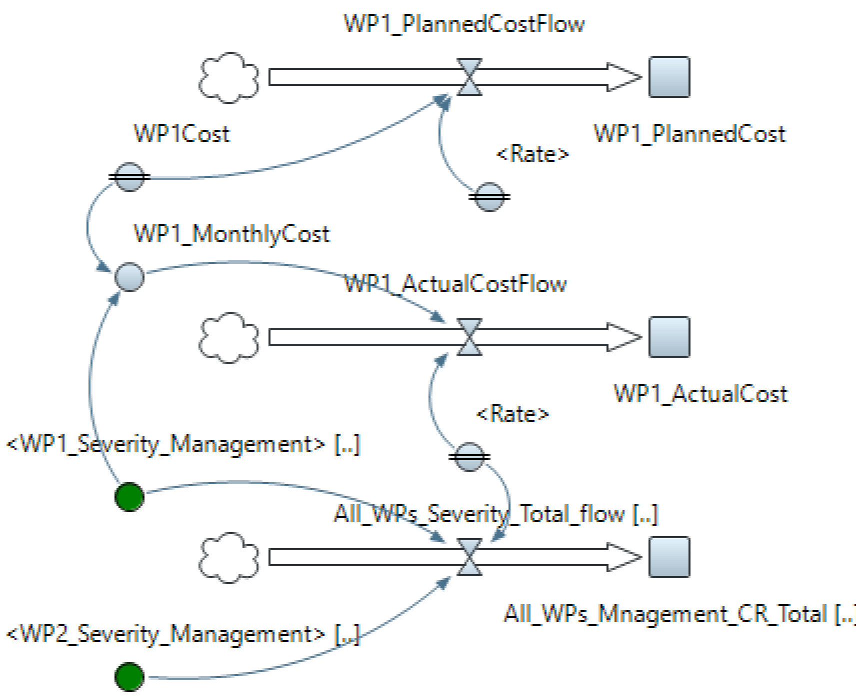

Figure 5.12 Flows and stocks for the *Management* risk category for the *Civil works* work package, created using AnyLogic®.

5.4.4. Dynamic simulation

The proposed model was implemented in AnyLogic® simulation software. Linking the simulation software with a mathematical software was necessary to perform fuzzy arithmetic, since simulation software are not capable of performing fuzzy arithmetic. Therefore, MATLAB was linked to

AnyLogic® to perform fuzzy arithmetic operations using the α-cut method. Moreover, MATLAB defuzzification functions were linked to AnyLogic® to determine contingency values using defuzzification methods. Matlabcontrol (a Java application programming interface) allowed for calling MATLAB from AnyLogic®.

The concept of risk events' "dynamic nature" is distinct from "reactive". To construct a reactive system, a system must observe, comprehend, and analyse events before adjusting itself based on the new condition. Considering the dynamic nature of risks, however, means that the probability and impact of risk events might alter throughout the simulation as a result of the influence of events and conditions.

At each timestep, fuzzy arithmetic equations containing fuzzy variables were calculated, and the appropriate output fuzzy numbers or defuzzified values were produced. Since the probability and impact of the REs were assessed using linguistic scales represented by trapezoidal fuzzy numbers, the REs were considered as subjective variables in the FSD model and represented by fuzzy arrays. The contingency values of the work packages and the project were determined by simulating the quantitative FSD model over the project duration.

5.5. Results and discussion

HFACRM calculates total contingency reserve for threats, total contingency reserve for opportunities, and total net value of contingency reserve at the work package and project levels for each risk category for the *i*th work package and all work packages. To maintain confidentiality of the results, the contingency reserve values presented in the following are ratios of actual numbers.

The result is defuzzified in the final step of calculation. Defuzzification is the process of converting the degrees of membership of output linguistic variables within their linguistic terms into crisp numerical values. The defuzzified total contingency for the project was CAD$3,708,990 based on the α-cut fuzzy arithmetic method, as shown in Figure 5.13. The level of confidence associated with the range of output fuzzy number, represented by the confidence level, can be determined from the corresponding α-cut level (or possibility degree) and ranges between 0 and 1. However, due to the software limitations, the confidence level can not be calculated in this case study.

According to contingency reserve accumulation s-curve in Figure 5.13, almost 70 percent of contingency reserve budget is required between months 7 and 10 to implement risk response actions. It also highlights the vital role of exploiting opportunities (positive risks) as they can compensate a significant cost of threats' adverse effects (i.e., almost 45 percent of CAD$6,300,000).

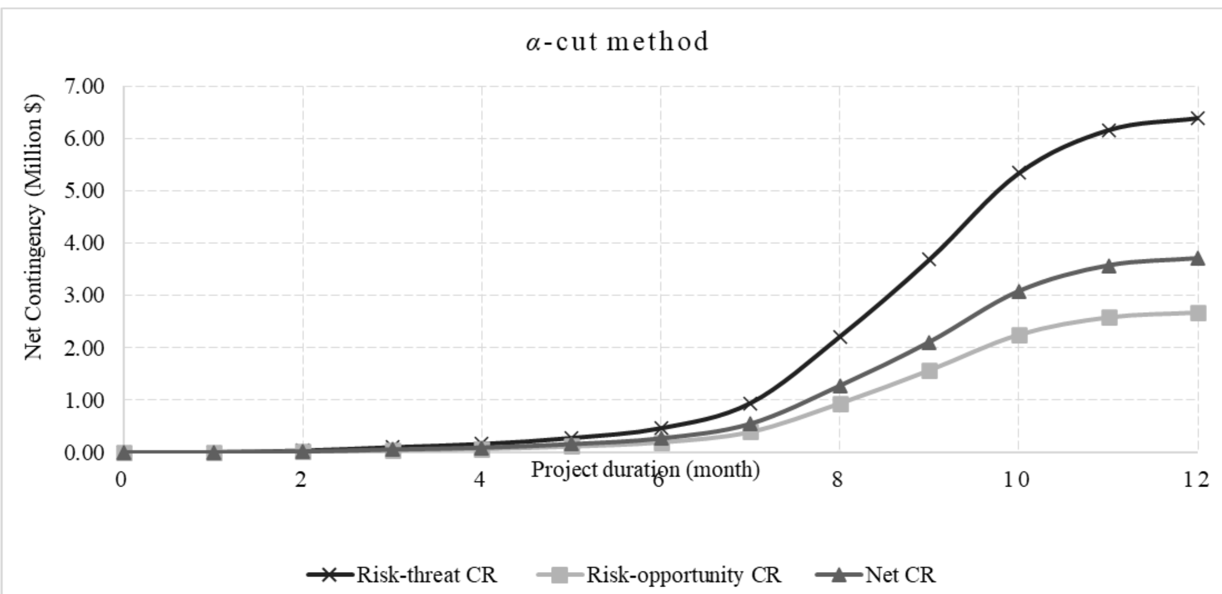

Figure 5.13 Total net contingency based on the α-cut method.

The drawdown curve of contingency reserve can be illustrated based on the contingency reserve values acquired by the simulation software for every time step of the project. Assuming that threat contingency absolute value is bigger that opportunity, the drawdown graphs for all three contingency declines. On the contrary, if threat contingency absolute value is smaller that opportunity contingency, the drawdown curve can increase.

The model provides project decision makers with a blueprint of the contingency reserve values from different point of views. In addition to the total contingency reserve for the project, the model calculates the total contingency reserve for each work package, category of REs, and work package as well as for each RE category, based on the α-cut fuzzy arithmetic method. Table 5.6 presents contingency reserve values for each RE category and work package.

Table 5.6 Contingency reserve values for each category of risk events.

Risk Category	**Contingency Reserve Value (CAN$)**
Construction	456,205.77
Management	318,973.14
Resource	1,453,924.08
Technical	359,772.03
Contractual	307,846.17
HSE and Site conditions	352,354.05
Economical and Financial	459,914.76

After implementing the proposed HFACRM and running it in AnyLogic® simulation software, the resulted defuzzified net project contingency values were compared to the 1) actual amount of project contingency reserve after completion of the project, 2) estimated value of contingency reserve resulted from MCS, and 3) estimated value of contingency reserve resulted from the defuzzified contingency values using FRA©. The symmetric mean absolute percentage error (SMAPE) was utilized to compare the results and quantify the error by measuring the level of agreement between results. SMAPE overcomes the drawbacks of other error measurement methods such as asymmetry and impact of outliers, associated with other error measurements, including the mean absolute error (MAE), mean absolute percentage error (MAPE), and the root mean square error (RMSE) (Willmott & Matsuura, 2005). MAPE is asymmetric, and it puts a heavier penalty on negative errors (when forecasts are higher than actuals) than on positive errors. This is caused by the fact that the percentage error cannot exceed 100% for forecasts that are too low. While there is no upper limit for the forecasts which are too high. To calculate SMAPE, the baseline value is the actual net contingency value from the project and the result of proposed HFACRM was compared to the outputs of the other methods. In general, the value of SMAPE ranges from 0% to 200% and a value of 0% implies a perfect agreement.

Table 5.7 shows the SMAPE values among the actual net contingency results after completion of the project compared to the estimated net contingency value resulted from the proposed HFACRM, MCS P50, MCS P95, and FRA©. Per Table 5.7, the degree of agreement between the actual value of net contingency reserve and other methods varied between 8.47% and 76.61%. Comparing the SMAPE derived from HFACRM with the estimated net value of contingency reserve calculated by MCS P50 (confidence level of 0.5), MCS P95 (confidence level of 0.95), FRA© demonstrates that HFACRM results have the lowest SMAPE which is the highest level of agreement with the actual net contingency value from the project. This means that the level of agreement between HFACRM results using MOM defuzzification method and the actual contingency reserve is higher than the other contingency determination methods using different defuzzification methods. Therefore, the accuracy of the HFACRM result is much higher for forecasting the total contingency value. SMAPE results show that FRA© results in a lower level of agreements compared to MCS 95 when using SOM, and higher level of agreement when using LOM, MOM, and COA defuzzification methods.

Table 5.7 SMAPE: Comparison of actual net contingency with the result of HFACRM, MCS P50, MCS P95, and FRA©.

Method	HFACRM				MCS P50	MCS P95	FRA©			
	SOM	MOM	LOM	COA			SOM	MOM	LOM	COA
Actual value of net contingency reserve (after completion of the project)	14.31	8.47	18.56	12.93	28.31	42.47	76.61	30.14	41.33	33.40

To ensure the accuracy of the qualitative and quantitative FSD models, they were tested with structural, behavioral validation techniques. The CLDs, flow and stock diagrams, and mathematical equations conducted structural validation, which included structural verification, parameter verification, and dimensional consistency. In order to determine how precisely the FSD model represents the system's variables and interactions, structural verification was performed at multiple points in the development process. In order to identify risk response strategies/actions and assess REs and RRAs, surveys, focus groups, and interviews were employed. Furthermore, all the parameters used in the FSD model (e.g., work package cost) were obtained from project documents and verified by the project manager of the case study under consideration. Additionally, all equations in the FSD model were inspected, and automatic dimensional analysis was carried out using AnyLogic® simulation software. Fuzzy arithmetic examples from Lin et al. (Lin et al., 2011) and Pedrycz and Gomide (2007) were used to evaluate the accuracy of the Java-based fuzzy arithmetic functions designed to implement the α-cut method.

The extreme condition test was utilised to evaluate parameters under extreme conditions and determine the validity of the result. Using the boundary parameter values, it was determined whether the results remained consistent. For instance, for the management risk category, we reduced to zero the cost of implementing risk response actions and the cost associated with each risk event. As a result, the value of the contingency reserve for the management risk category became zero. The extreme condition test results were found to be within the upper and lower limits of the expected contingency reserve, indicating plausibility.

The model for the project was decomposed into subsystem models for each RE category and for each work package, so the FSD model's aggregation level could be tested for mathematical precision. After simulating each subsystem model separately, the resulting work packages' contingency reserve were aggregated and compared with the project's contingency reserve acquired from simulating the entire project model. For behavior validation, the FSD model was examined to determine if it reproduces the expected system behavior. To do this, the predicted contingency values of the work packages and the project were plotted and compared with the shape of the forecasted S-curves for the work package and project costs. In addition, an integration error test was undertaken on the FSD model by running the model with several timesteps and numerical integration methods to ensure that the model was insensitive to the choice of timestep or integration method (Sterman, 2000). Although the proposed method is implemented in a large scale construction project, the HFACRM can also be applied in small projects with less complexity which shows the flexibility and adoptability of the method.

In the FSD model and based on the research objectives, we were not looking for optimizing variables and parameters based on the characteristics of the model. Instead, calibration of the SD model was performed to ensure that it could replicate the project's behavior under various conditions. Calibration of SD means the process of evaluating and optimizing certain variables so that the model can mimic the exact behavior of the project under investigation.

5.6. Chapter summary

To deal with REs and RRAs of construction projects, insufficient allocation of contingency reserves has a significant adverse effect on achieving project objectives and can lead to poor resource management (e.g., budget). This paper proposes a hybrid fuzzy arithmetic-based SD method called HFACRM for improving the accuracy and effectiveness of calculating contingency reserve in complex construction projects. The proposed HFACRM: 1) constructs the MBFs of linguistic terms used to evaluate the components of risk analysis model, 2) determine the effectiveness of RRAs and rank them, 3) determine the crisp value of causality degree for soft causal relationships between REs together and with RRAs, and 4) formulate hard causal relationships, stocks and flows of quantitative FSD model.

This study contributes to current literature and methods of risk analysis and contingency determination in construction projects in both academic and industrial aspects. From academic perspective, it proposes a systematic and structured fuzzy method that integrates four different fuzzy models to calculate contingency reserve. The proposed HFACRM considers time-dependent behavior of probability and impact of REs and RRAs, since their value changes during the lifecycle of the project. HFACRM can model dependent variables and capture the cause-and-effect relationships and dependencies among subjective and objective variables that affect contingency since the occurrence of an RE may increase the probability of occurrence for another RE. HFACRM captures the subjective uncertainty associated with linguistic evaluations of risk analysis model. Finally, it incorporates RRAs into the process of calculating contingency reserve. From an industrial perspective, HFACRM contributes to the current methods of determining contingency reserve by 1) employing expert judgment and linguistic terms instead of historical quantitative data that are either scarce or of low quality, 2) determining the value of contingency reserve at different stages of a project from initiation to completion, 3) providing a validated risk assessment and risk response planning model to assist practitioners in modeling project risks and RRAs.

The proposed adaptive hybrid model calculates: 1) the total amount of contingency reserve for negative risks (threats), 2) the total amount of contingency reserve for positive risks (opportunities), and 3) the total net value of contingency reserve. All of these three contingency reserves can be calculated for the work package and project levels as well for each risk category for the *i*th work package and all work packages. The comparison of the SMAPE values between the contingency reserve resulted from the proposed model with the contingency reserve calculated by MCS P50 (confidence level of 0.5), MCS P95 (confidence level of 0.95), FRA©, and the actual value of contingency reserve confirms that HFACRM results have the highest level of agreement with the actual value of contingency reserve. This means that taking risk responses into account as well as considering soft causal relationships among project components and time-dependent factors such as probability and impacts of REs can significantly increase the accuracy of calculating contingency reserve in construction projects. HFACRM results provide a better understanding of the required amounts of contingency throughout the duration of project and can lead to more accurate budgeting and planning in construction projects.

Linking the simulation software with MATLAB was necessary to perform fuzzy arithmetic. However, MATLAB fuzzy arithmetic package is based on the α-cut method. Moreover, fuzzy calculations were restricted only between two fuzzy numbers because the outputs of a single implementation of a fuzzy operation (e.g., fuzzy multiplication) will be irregularly shaped fuzzy numbers, and only possible arithmetic is the alpha-cut method. Future research can focus on the fuzzy arithmetic aspect of model using the effect of different methods of fuzzy arithmetic operations (i.e., extension principle and Yager t-norms) on the final value of contingency reserve. Investigating consecutive fuzzy arithmetic operations and implementing them in the HFACRM can also address the issue of extra programming both in Java and MATLAB. Furthermore, the FSD model only addresses subjective uncertainties, so this research can be expanded to account for both probabilistic (i.e., randomness) and subjective uncertainties in FSD.

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Chapter 6: Conclusions and Recommendations

6.1. Introduction

This chapter provides the summary of the work conducted in this research, the academic and industrial contributions of the research, limitations of the research, and recommendations for future research and development.

6.2. Research Summary

Managing risks and uncertainties have long been a major research interest in the large construction engineering domain. Large-scale construction project means a construction project for which the total estimated cost of the construction contract is $35 million or more based on the Federal Acquisition Regulatory Council (FAR Council). Contingency reserve is a key tool for the decision makers of a project to deal with positive and negative risk events A review of previous research revealed that current methods of determining contingency in construction projects had limitations to incorporate risk response planning into their calculations. Moreover, previous methods considered the probability and impact of risk events as static and independent variables. However, in practice, the probability and impact of risk events and risk response actions can change during the project duration and can be affected by their cause-and-effect relationships with other risk events and risk response actions. Furthermore, previous methods of determining contingency had high reliance on quantitative historical data. In practice, however, construction projects suffer from lack of quantitative data. Therefore, the previous models that have been developed for developing contingency reserve cannot accurately estimate the value of contingency reserve in construction projects. To address the identified gaps, this research incorporated risk response planning into risk identification and assessment by developing a hybrid fuzzy arithmetic-based contingency reserve method (HFACRM) to determine a contingency reserve throughout the life cycle of construction projects. The proposed HFACRM is a combination of four fuzzy models, one to determine effectiveness of risk response actions, one for determining MBFs of linguistic terms, one to determine causality degree of soft causal relationships, and one to formulate stocks, flows, and hard relationships of FSD model. The objectives of this research were achieved as described below.

a. An extensive was conducted on the processes entailed in risk management in general, with a specific focus on contingency determination methods and risk response planning in construction projects. Previous studies focusing on hybrid fuzzy techniques for risk management and contingency determination were closely examined to identify research gaps. The identified gaps were presented in chapter 1. Criteria for assessing the effectiveness of risk response actions were identified and were presented in chapter 2. The proposed study used three criteria to evaluate risk response actions: affordability of the risk response action, achievability of the risk response action, and controllability of risk events.

b. Next, four fuzzy models were developed to prepare the required inputs for the main model to determine contingency reserve. These four fuzzy models were proposed to calculate (1) the effectiveness of risk response actions, 2) form the MBFs of linguistic terms used to evaluate model variables, 3) calculate the crisp value of causality degree for soft causal relationships between model variables, and 4) formulate stock, flows and hard relationships of quantitative FSD model.

   i. The first fuzzy model consisting of FRBS and fuzzy ranking methods was developed to evaluate the effectiveness of risk response actions and rank them based on their effectiveness. The proposed FRBS has three inputs as evaluation criteria and produces effectiveness of risk responses as an output. The three inputs are identified critical criteria for evaluating risk response actions. The FRBS uses the estimated crisp values of affordability, achievability, and controllability to evaluate the effectiveness of risk responses according to the rules developed based on experts' opinions. The output, which is a fuzzy set, is used as an input for three different fuzzy ranking methods based on the SOM, LOM, MOM and COA to determine the most effective risk response.

ii. Second hybrid fuzzy model was developed to integrate, optimize, and construct MBFs of linguistic terms used to evaluate the probability and impact of risk events and the identified criteria of assessing risk response actions using Interval type 2 fuzzy sets and principle of WPJG.

iii. Third hybrid fuzzy model was developed to calculate the crisp value for the causality degree of soft relationships between risk events together and with risk response actions in quantitative FSD models using WPJG, FAHP, and fuzzy aggregation operators.

iv. Fourth fuzzy model was developed to formulate the stocks, flows, and hard relationships in quantitative FSD model. A contingency determination fuzzy procedure and both crisp and fuzzy arithmetic were applied resulting in the mathematical equations of stocks, flows, and hard relationships.

c. Then, the FSD model of HFACRM was developed using four proposed fuzzy models by developing the qualitative and quantitative parts.

d. A data collection protocol was prepared to describe the methodology and data collection process for developing the FSD model. Several data collection forms were designed for (1) collecting project and work packages characteristics, (2) evaluating risk expertise level of each participant based on experience, knowledge, professional performance, risk management practice, project specifics, reputation, and personal attributes and skills, (3) identifying the list of risk events, (4) evaluating identified the probability of occurrence of identified risk events and their impact on the work package cost using linguistic terms represented by fuzzy numbers, (5) determining risk response actions for each risk event, (6) evaluating the effectiveness of risk response actions using linguistic terms represented by fuzzy numbers, (7) assessing the risk events after implementing each risk response using linguistic terms represented by fuzzy numbers, (8) identifying causal relationships between risk events together and with risk response actions, and (9) assessing degree of causality, type, and polarity of soft causal relationships using pairwise comparison matrix and linguistic terms represented by fuzzy numbers. A candidate project for a case study was selected during a meeting attended by top management from the participating company. The surveys were done in the form of a structured interview survey to a group of experts who were directly associated with the selected project.

e. Next, the qualitative and quantitative FSD models of HFACRM were validated by conducting structural and behavioral validations. Structural validation (i.e., structural verification, parameter verification, and dimensional consistency) is performed on the CLDs, flow and stock diagrams, and mathematical equations. For behavioral validation, the performances of the HFACRM model (i.e., the defuzzified net project contingency values) were compared to the actual amount of project contingency reserve (after completion of the project), the outcomes of Mont Carlo Simulation (MCS) and Fuzzy Risk Analyzer© (FRA©). FRA© is a fuzzy arithmetic-based risk analysis software developed at the University of Alberta. The symmetric mean absolute percentage error (SMAPE) was utilized to quantify the error and measure the level of agreement between results.

f. The proposed HFACRM method was implemented in simulation programme AnyLogic®. MATLAB was linked to AnyLogic® through Matlabcontrol to perform fuzzy arithmetic operations using the α-cut method and to determine contingency values using defuzzification methods. Matlabcontrol is a Java application programming interface that allows MATLAB to be called from Java-based AnyLogic®. At each time step, fuzzy arithmetic equations involving fuzzy variables were calculated, and the corresponding fuzzy output numbers or defuzzified values were generated.

Three outputs from the proposed HFACRM are the total amount of contingency reserve for negative risks (threats), the total amount of contingency reserve for positive risks (opportunity), and the overall net value of contingency reserve. All these three contingency reserves can be calculated in work package and project level as well for each category of risk for *i*th work package and for all work packages. Comparing the SMAPE values of the contingency reserve derived from the proposed model with the contingency reserve calculated by MCS P50 (confidence level of 0.5), MCS P95 (confidence level of 0.95), FRA©, and the actual value of contingency reserve demonstrates that HFACRM results have the highest level of agreement with the actual value of contingency reserve. It means that taking risk responses into account, along with considering soft causal relationships among project components and time-dependent factors such as the probability and impacts of risk events, can significantly improve the accuracy of calculating contingency reserve in construction projects. The results of HFACRM provide a better knowledge of the required amounts of contingency all across the project's life cycle and can result in more accurate budgeting and planning for construction projects.

Table 6.1 Linking research activities, outcomes, and contributions

Research activities	Outcomes	Contributions
Comprehensive literature review	Identified gaps Research objectives Possible techniques	Proposing criteria to evaluate the effectiveness of risk response actions
Developing a fuzzy model to determine the effectiveness of risk response actions	Effectiveness of risk response actions List of selected risk response actions	Propose a systematic way to evaluate the effectiveness of risk response actions Applying an expert driven FRBS and a group of fuzzy ranking methods can help automate the evaluation of risk response actions.
Developing a fuzzy model to determine the membership functions for the linguistic terms	Optimized membership functions for linguistic terms used to describe the probability and impact of risk events, the causality degree of causal relationships, and the effectiveness of risk response actions	Opinions of several subject matter Reducing the effect of outlier opinions Aggregation of non-linear membership functions into trapezoidal membership functions
Developing a fuzzy model to determine the degree of causality for soft causal relationships	The crisp value degree of causality for soft causal relationships	The proposed model improves efficiency and effectiveness of developing FSD quantitative modeling by (1) considering the level of risk expertise (importance weights) of multiple experts in assessing the degree of causality based on constructed developed MBFs, (2) mitigating the influence of irrelevant and biased opinions on assessing the causality degree of soft relationships, and (3) aggregating multiple experts' assessments of causality degree of soft causal relationships
Developing a fuzzy model to formulate stocks, flows, and hard relationships	Equations of all stocks, flows and hard relationships in quantitative FSD modeling	Employing fuzzy arithmetic procedure solved the problem of substantial reliance on historical data in probabilistic methods by employing expert judgment and linguistic terms
Developing data collection protocol and forms	Data collection protocol data collection forms	Illustrating how to collect data for analyzing risks of a construction project

Implementing qualitative and quantitative FSD model of HFACRM in AnyLogic®	validating of proposed method	Illustrating how to implement the proposed model for analyzing risks of a construction project

6.3. Research Contributions

The academic and industrial contributions of this research relevant to academic researchers and construction industry practitioners, respectively are presented in the following subsections.

6.3.1. Academic contributions

The academic contributions of this research are as follows:

1) *Developing a methodology for evaluating the effectiveness of identified risk responses by employing an FRBS and fuzzy ranking method to determine the effectiveness of risk responses and select the most effective risk responses.* The previous studies focused on employing complex quantitative models such as optimization methods to select and rank risk response actions for large-scale construction projects can be a complex and costly process because of the effort and amount of data required. Moreover, these models accounted for only a limited number of criteria, which can lead to the selection of risk responses that are cost effective but unfeasible in terms of technology, environment, and achievability. Optimization models have low transparency (i.e., they operate in such a way that it is not easy for others to see what actions are performed) during the process of selecting risk response actions. Furthermore, current ranking and selection methods of risk response actions can not consider linguistic terms. Applying an expert driven FRBS and a group of fuzzy ranking methods can help automate the evaluation of risk response actions.

2) *Developing a hybrid fuzzy model which contributes the advancement of the state of the art in forming fuzzy MBFs by considering the opinions of several subject matter experts to*

develop the MBFs of linguistic terms, reducing the effect of outlier opinions in developing the MBFs of linguistic terms, and enabling the aggregation of non-linear MBFs into trapezoidal MBFs. Previous studies (i.e., both expert driven, and data driven methods) had limitations in their ability to form MBFs of linguistic terms. For example, to form the MBF of probability by using an expert-driven method such as analytical hierarchy process (AHP), almost 4,900 pair-wise comparisons among risk events must be performed by each expert for a project with 100 risk events, and the results are not necessarily linear.

3) *Proposing an adaptive hybrid fuzzy model to calculate the crisp value for the causality degree of soft relationships between different variables in FSD models using FAHP and aggregation operators. The proposed model improves efficiency and effectiveness of developing FSD quantitative modeling by (1) considering the level of risk expertise (importance weights) of multiple experts in assessing the degree of causality based on constructed developed MBFs, (2) mitigating the influence of irrelevant and biased opinions on assessing the causality degree of soft relationships, and (3) aggregating multiple experts' assessments of causality degree of soft causal relationships.* The literature review revealed a lack of structured and systematic methods for constructing and analyzing soft causal relationships among the elements of an FSD model. Since most construction projects suffer from lack of sufficient historical quantitative data, the casual relationships of systems cannot be clearly calculated by statistical methods and represented as numerical values owing to the lack of sets of similar data. Consequently, to capture the subjective uncertainties of the subjective variables and relationships in the simulation model, soft causal relationships must be expressed in linguistic terms. FAHP enabled the proposed model to calculate the level of risk expertise (importance weight) of different

experts based on several factors and to consider these importance weights in the process of aggregating experts' assessments of soft causal relationships. Furthermore, fuzzy ordered weighted average was employed to aggregate the assessments of several heterogeneous experts' opinions using constructed fuzzy MBFs and the importance weight of each expert.

4) *Developing a hybrid fuzzy model to formulate stocks, flows, and hard relationships of quantitative FSD model for determining contingency reserve in construction projects. The proposed model (1) considered the time-dependent nature of risk events and risk response actions, (2) modeled the cause and effect relationships and dependencies among subjective and objective variables that affect contingency, and (3) addressed subjective uncertainty associated with linguistic evaluations in risk management.* Reviewing the literature showed a lack of research in FSD quantitative model development for contingency determination in construction projects. Subjective variables of FSD models are fuzzy numbers represented by fuzzy MBFs rather than deterministic or probabilistic values. Therefore, a fuzzy arithmetic-based model was required to formulate stocks, flows, and hard relationships of quantitative FSD model as well as analyze risk events and risk response actions to determine construction project contingency reserve.

6.3.2. Industrial Contributions

The industrial contributions of this research are as follows:

1) *Employing fuzzy arithmetic procedure solved the problem of substantial reliance on historical data in probabilistic methods by employing expert judgment and linguistic terms.* Many risk experts find it difficult to perform an accurate and precise risk assessment, since the data are either scarce or of low quality.

2) *Incorporating risk response planning into risk identification and assessment to determine and manage contingency reserve all over the life cycle of construction projects.* Reviewing the risk-related literature acknowledged that current techniques of determining contingency reserve have not paid much attention to risk response actions. Incorporating risk response planning into risk assessment can improve the accuracy of determining contingency reserve and the effectiveness of risk management.

3) *Identification of most critical criteria to evaluate the effectiveness of risk response actions.* Previous studies focused on the limited criteria which can lead to the selection of risk responses that are cost effective but unfeasible in terms of technology, environment, and achievability. This study suggested three criteria to evaluate risk response actions: affordability of the risk response action, achievability of the risk response action, and controllability of risk events. There is a positive correlation between the controllability of a risk event and the effectiveness of its risk response action. Even if a risk response action will be implemented with high affordability and high achievability, the risk response action will not be effective in addressing a risk with low controllability.

4) *Capturing the soft and hard causal relationships and interactions between risk events together and with risk response actions. Previous studies on risk analysis had limitations capturing the complexity and causal relationships of the components of construction projects.*

5) *Considering positive risks (opportunities) as well as negative risks and their respective risk response actions in determining contingency reserve.* Ignoring opportunities in risk management process can lead to inaccurate contingency reserve amounts and waste of project budget.

6) *Providing construction industry organizations with:*

   a. *An integrated risk assessment and risk response planning model to determine and manage the value of contingency reserve in construction projects with better transparency and visibility to understand the effects of causal interactions,*

   b. *A validated risk assessment and risk response planning model to assist practitioners in modeling project uncertainties.*

   c. *Determining the value of contingency reserve at different stages of a project and throughout the life cycle of a construction project from project initiation to the end.*

   d. *Increasing the accuracy of managing contingency reserve in construction projects significantly.*

7) *Applying an expert-driven FRBS and fuzzy ranking method delivers an expert-level risk management tool to a non-expert in the field.*

6.4. Research Limitations and Suggestions for Future Research

Research limitations and the recommendations for future research are presented in this section.

6.4.1. Computational Methods for Implementing Fuzzy Arithmetic Operations

- In this research, linking the simulation software with MATLAB was necessary to perform fuzzy arithmetic since simulation software are not capable to perform fuzzy arithmetic. However, MATLAB fuzzy arithmetic package is based on the α-cut method. Future research can focus on the fuzzy arithmetic aspect of model using the effect of different methods of fuzzy arithmetic operations (i.e., extension principle and Yager t-norms) on the final value of contingency reserve.

- Fuzzy calculations were restricted only between two fuzzy numbers because the outputs of a single implementation of a fuzzy operation (e.g., fuzzy multiplication) are irregularly shaped fuzzy numbers, and only possible arithmetic is the alpha-cut method. Future research can focus on investigating consecutive fuzzy arithmetic operations and implementing them in the proposed contingency determination model which can address the issue of extra programming both in JAVA and MATLAB.

6.4.2. Further Expansion of the Developed Model

- In this thesis, the hybrid fuzzy contingency determination model was developed and validated by field data that were collected from a case study of windfarm construction project. However, the MBFs, number od variables and types of relationships and their influence on contingency reserve varies from one context to another. In future research, the hybrid FSD model of determining contingency developed in this research can be adapted for other contexts using field data collected from construction activities in different contexts.

- In this thesis, a hybrid fuzzy model was developed to determine contingency reserve in work package and project levels. Future development of the model can investigate the determination of contingency reserve in portfolio-level, that is, a contingency determination model can be developed using the FSD technique as an integration of the several project-level FSD models of contingency determination.

- In this thesis, the hard and soft causal relationships were considered between risk events of each risk category together and with their selected risk response actions. Future development of the model can be done by considering the causal relationships between all risk events of the project together and with their selected risk response actions.

- Through the behaviour reproduction test, the behavioural validity of the FSD model was evaluated in this thesis. To increase trust in the results of the FSD model, the behaviour validation of the model can be studied further using the behaviour sensitivity test (Bala et al. 2017). The behaviour sensitivity test assesses the sensitivity of simulation results to changes in system variable values and compares the model's behaviour sensitivity to that of the actual system.
- This thesis established an FSD model that only addresses subjective uncertainties. In order to account for both probabilistic (i.e., randomness) and subjective uncertainties in the FSD, this research should be expanded.
- This thesis's FSD model is only capable of estimating the impact of interacting risk events on work package and project costs. Risk events may affect two or more project objectives simultaneously (i.e., concurrent impact). In addition, the cumulative impact of linked and interacting risks on two or more project objectives differs from the total of the individual impacts of independent risks on a particular project goal (Boateng 2012). Therefore, future research should be conducted to develop an FSD model for determining the concurrent and cumulative impact of risk and opportunity events on two or more project objectives (e.g., cost, schedule, quality, and safety and health). Specifically, the FSD model will be expanded to identify not only the severity of risk and opportunity events in terms of cost, but also their impact on the project's schedule, including time extensions.
- The cross validating of FSD model with other methods that use bottom up approach can be investigated in the future research. Agent based modeling is a type of bottom–up computational simulation modeling. Individual entities are represented by discrete agents and agent interactions, therefore macro variables cannot be modelled in ABM. However,

SD is a continuous simulation technique that can model the dynamic behaviour of complex systems. Therefore, a hybrid Fuzzy SD-ABM can be developed to get a deeper insight into system and to study the effect of productivity of the person who is responsible for implementing risk response actions on the value of contingency reserve by considering the effect of micro elements such as temperature and working environment on the productivity.

- To collect required information and implement and run the proposed method, several interviews, meetings, and surveys are required for each project separately which can be time consuming. The collected information can be used to form MBFs of linguistic terms, assess the probability and impact of risk events, assess the effectiveness of risk response actions, and evaluate the causality degree of soft causal relationships. A retrospective study costs less and takes less time than a prospective study. This is because a retrospective study doesn't involve observing and interviewing participants, so there's less time and cost spent on data collection. Therefore, a retrospective case-control study can be performed in the future to determine a set of standard values for variable of models in different conditions. In a retrospective case-control study the investigator can quickly estimate the effect of an exposure on outcome status. Cases and controls are established based on the presence of the condition, and exposure is assessed by looking back over time. It is very important in a case-control study that the cases be as similar to the controls on all factors except the outcome of interest.

6.4.3. Incorporating risk Response Planning

- In this thesis, expert knowledge and approximate reasoning were employed to develop FRBS rules due to lack of quantitative historical data. Therefore, FRBS rules must be customized based on the opinions of each group of experts in each project. However, the data-driven FRBSs are more accurate, as compared to the expert-driven FRBSs; while the expert-driven FRBSs are more interpretable, as compared to the data-driven FRBSs (Guillaume & Magdalena 2006). Further research can be performed to investigate the possibility of hybrid methods (i.e., using data and expert knowledge simultaneously) for developing the FRBSs that determine the effectiveness of risks response actions. In order to accurately represent linguistic terms, the hybrid approaches modify the fuzzy membership functions using expert knowledge. These methods additionally make use of expert knowledge to alter the rule base if the sample data (i.e., those used to create the data driven FRBS) is not a thorough representation of all possible input and output variable values(Guillaume & Charnomordic 2012).

6.4.4. Development of MBFs for Linguistic Terms

- In this thesis, the proposed model for determining MBFs can be implemented on triangular and trapezoidal fuzzy numbers, which are commonly observed in engineering applications. The proposed computational approach can be developed in future study to implement operations on Gaussian fuzzy numbers, the other prevalent form of fuzzy numbers used in engineering applications.

- The proposed method for determining MBFs employed interval type-2 fuzzy sets in order to provide a broader knowledge representation and approximate reasoning for computing with words. The proposed model employed also WPJG for determining the optimized interval type-2 MBFs of risk analysis concepts (i.e., linguistic variables including probability and impact). This principle provides an alternative to clustering methods in constructing information granules based on the criteria of coverage and specificity of data.

However, fuzzy arithmetic using type-2 fuzzy numbers and WPJG versus type-1 fuzzy numbers is computationally more demanding. Future research could be conducted to produce an interactive and user-friendly programme that automatically does all essential computations to construct optimized MBFs for linguistic terms.

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Appendices

Appendix A. Data collection protocol

[Company X (Co. X)], as an independent power supplier, must guarantee that its strategic objectives are met during project implementation. As a result, [Co. X] has tried to investigate its risk assessment and management processes in order to evaluate their applicability and capacity to effectively forecast and mitigate future threats.

In order to help [Co. X]improve its risk assessment and management processes, the Natural Sciences and Engineering Research Council of Canada Industrial Research Chair in Strategic Construction Modeling and Delivery (NSERC-IRC-SCMD) has developed Fuzzy Risk Analysis Model (FRAM) and the Fuzzy Risk Analyzer© (FRA©). These tools were designed to help [Co. X]discover and analyze events that might potentially affect its projects, and then estimate the contingencies of these events at both the work package and project levels.

Risk analysis is greatly influenced by the causal relationships and dependencies among risk events, risk response actions, and other components of construction projects. To avoid overestimating or underestimating risk contingency, these causal relationships and dependencies must be taken into account. Moreover, incorporating risk response planning into risk identification and assessment can improve the accuracy of determining contingency reserve by considering (1) the effects of risks on project goals before and after implementing risk response actions and (2) the implementation cost of risk response actions in the total contingency reserve amount. However, FRAM and FRA© are not able to capture the causal relationships and take risk response actions into consideration. Overall, FRAM and FRA© have the following limitations:

1. The risk response actions have not been considered.
2. There is not a systematic method to form and aggregate the membership functions of linguistic terms required to describe subjective variables.
3. The risks/opportunities are treated as stand-alone items (i.e., causal interactions and dependencies between risks/opportunities are not considered).
4. The dynamic nature of risks that result from various feedback processes are not considered.
5. The risk expertise levels of experts are not considered in assessing the probability and impact of the risks.

A new Hybrid Fuzzy Arithmetic-based Risk and Response Analysis Method has been developed to address all above-mentioned limitations in calculating contingency reserve throughout the life cycle of construction projects. Proposed method is the integration of several fuzzy models in order to determine contingency reserve in construction projects. It addresses the gaps in different steps of developing a fuzzy system dynamics simulation that can be run using AnyLogic© simulation software. This data collection protocol details the methodology and data collecting procedure for constructing the proposed method.

Introduction

Construction projects have high levels of uncertainty due to their dynamic and complex nature, multiple feedback processes, and non-linear relationships and interdependencies among project components. Therefore, managing risks and uncertainties is crucial for construction projects to successfully achieve project goals in terms of time, cost, and quality. Risk management is recognized as an essential contributor to project success, since it addresses uncertain events so as to control their impact and probability of occurrence (Ahmadi-Javid et al. 2020).

A new Hybrid Fuzzy Arithmetic-based Risk and Response Analysis Method has been developed to address limitations in calculating contingency reserve throughout the life cycle of construction projects. The proposed method will consider the dynamic behavior, causal interactions, and interdependencies among work packages, risk events, and risk response actions. Moreover, it employs a systematic method for forming and aggregating the membership functions of linguistic terms required to describe subjective variables. Furthermore, assessors' risk expertise levels are considered both in forming membership functions of linguistic terms and in aggregating their evaluations. The proposed method is more accurate and will provide better transparency and visibility in tracking the impact of dynamic and interacting risks over time, compared to other risk assessment tools. Proposed method integrates several fuzzy models (Fateminia et al. 2019b, 2020b,a, 2021) in order to determine contingency reserve in construction projects. It addresses the gaps in different steps of developing a fuzzy system dynamics simulation that can be run with AnyLogic© simulation software.

This data collection protocol details the methodology and data collecting procedure for constructing a dynamic risk analysis model that will be used to calculate the contingency reserve throughout the life cycle of construction projects. The proposed hybrid method determines the impact of risk events and risk response actions on work packages while considering their dynamic behavior, causal interactions, and interdependencies. The data collection process consists of eight main steps:

1. Identifying a candidate project and work packages with [Co. X]
2. Conducting a survey to determine the research participants' level of risk expertise
3. Conducting a survey to form membership functions of linguistic terms
4. Identifying and assessing both positive and negative risk events affecting the selected work packages before implementing risk response actions
5. Identifying and assessing response strategies for the most critical risks
6. Conducting assessment for both positive and negative risk events affecting the selected work packages after implementing risk response actions
7. Conducting a survey to determine the causal interactions among work packages, risk events, and risk response actions together and with each other
8. Gathering data about work package contingency reserve status and cost performance assessment

The data collection methodology will be based on the completion of nine data collection forms, as summarized in Table 1.

Table 1. Summary of Data Collection Forms

Appendix	Form No.	Description	Frequency
A	1	Project and work package characteristics	Initially
B.1	2	Expertise level assessment (self-evaluation form)	Initially

B.2	3	Expertise level assessment (supervisor evaluation form)	Initially
C	4	Membership functions of linguistic terms	Initially
D	5	Identification and assessment of both positive and negative risk events before implementing risk responses	Initially for three work packages (civil, mechanical, and electrical)
E	6	Identifying risk response actions and assessing their effectiveness	Initially
D	7	Identification and assessment of both positive and negative risk events after implementing risk responses	Initially
F	8	Determining causal relationships and their degree of causality among project components	Initially
G	9	Work package contingency reserve status and cost performance assessment	Initially

The rest of this data collection protocol document is organized as follows. Each section details one major step in the data collection process. Section 1 describes the process of identifying a candidate project and work package for the research. Section 2 discusses the data collection forms for determining the expertise level of the participants in risk management. Section 3 presents details of data collection for constructing membership functions of linguistic terms. Section 4 discusses the data collection form for identification and assessment of both positive and negative risk events before implementing risk response actions. Section 5 discusses the data collection form for identification and assessment of risk response actions. Section 6 discusses the data collection form for identification and assessment of both positive and negative risk events after implementing risk response actions. Section 7 presents the details of data collection for determining causal relationships and their degree of causality. Finally, Section 8 discusses the data collection form for work package contingency reserve status and cost performance assessment.

1. Identifying a Candidate Project and Work Packages

The data collection will begin by identifying a candidate project and work packages with [Co. X] through a meeting in the presence of senior management staff from [Co. X]and the research supervisor and/or principal investigator. The criteria for selecting a project and work packages for the research are summarized in Table 2. Please refer to *Form 1: Project and Work Package Characteristics* .

Table 2. Project and Work Package Selection Criteria

Item	Criteria	Preferable amount
Project	• At least three-month project duration • Risk analysis is carried out and an amount is assigned for contingency	One project
Work package	• Critical work packages that contain a large portion of the project cost and/or contingency • Work packages that are affected by several risks • Preferably common among several power projects • Have a construction deliverable	Minimum of three work packages

2. Evaluating the Level of Risk Expertise for Research Participants

The expected participants of this research are senior managers, managers, project managers, and project engineers who have direct involvement with the project and work packages selected. In order to aggregate individual opinions to get a collective assessment, it is essential to account for the different expertise level of the research participants (which will later be used to assign weights to research participants). The expertise level of the research participants in risk management is assessed based on certain qualification attributes such as experience, knowledge, professional performance, risk management practice, reputation, project specifics, and personal attributes and skills. The qualification attributes are of two types: quantitative (i.e., numerical) and qualitative (i.e., linguistic). A predetermined rating scale of 1–5 is established for assessing each qualitative qualification attribute. The criteria and sub-criteria used for the qualification attributes and their respective data source are provided in Table 3. The assessment of the expertise level will be carried out using Data Collection Forms 2 and 3. The research participants will carry out self-evaluation based on the qualification attributes using Form 2. An immediate supervisor will evaluate some qualitative qualification attributes of the team member participating in the research using Form 3. The expertise level assessment should be done initially and when there are changes to the research participants.

Table 3. Qualification Attributes for Expertise Level Assessment [6]

Criteria	***Sub-criteria***	***Data source***
1. Experience	1.1 Total years of experience	Expert
	1.2 Diversity of experience	Expert
	1.3 Relevant experience	Expert
	1.4 Applied experience	Expert
	1.5 Varied experience	Expert
2.Knowledge	2.1 Academic knowledge	Expert
	2.2 Education level	Expert
	2.3 On-the-job training	Expert
3.Professional performance	3.1 Current occupation in the company	Expert
	3.2 Years in current occupation	Expert
	3.3 Expertise self-evaluation	Expert
4.Risk management practice	4.1 Average hours of work in risk per week	Expert
	4.2 Level of risk management training	Expert
	4.3 Risk management conferences experience	Expert
	4.4 Risk identification and planning	Expert and Supervisor
	4.5 Risk monitoring and control	Expert and Supervisor
	4.6 Crisis management	Expert and Supervisor
5. Project specifics	5.1 Project size limit	Expert
	5.2 Commitment to time deadlines	Expert
	5.3 Commitment to cost budget	Expert
	5.4 Safety adherence	Expert
	5.5 Geographic diversity experience	Expert
6.Reputation	6.1 Social acclamation	Supervisor
	6.2 Willingness to participate in survey	Expert and Supervisor
	6.3 Professional reputation	Supervisor
	6.4 Enthusiasm and willingness	Expert and Supervisor
	6.5 Level of risk conservativeness	Supervisor
7.Personal attributes and skills	7.1 Level of communication skills	Supervisor
	7.2 Level of teamwork skills	Supervisor
	7.3 Level of leadership skills	Supervisor
	7.4 Level of analytical skills	Supervisor
	7.5 Level of ethics	Supervisor

3. Membership Functions of Linguistic Terms

Form 4 (Appendix C (Fateminia et al. 2020b, 2021)) is used to construct membership functions of linguistic terms(e.g., “Very Low” or “Very High”). Linguistic terms for describing the probability and impacts of risk events, the effectiveness of risk response actions, and the causality degree of soft causal relationships among variables in the model must be defined in order to enable experts to assess them. The probability and impacts of risk events, the effectiveness of risk response actions, and the causality degree of soft causal relationships are denoted in this model by five linguistic terms: “Very Low,” “Low,” ”Medium,” “High,” and ”Very High.”

Each expert is required to estimate the values for lower bound, lower modal, upper modal, and upper bound for each linguistic term. For example, in Figure 1, for linguistic term “Medium” for “Percentage of risk impact,” the lower bound is 25%, lower modal is 45%, upper modal is 55%, and the upper bound is 70%. This means that based on the opinion of Expert 1, the risks with “Medium” impact are those risks with an impact of less than 70 percent and more than 25 percent with the full membership degree between 45 and 55 percent, which are the lower and upper limits.

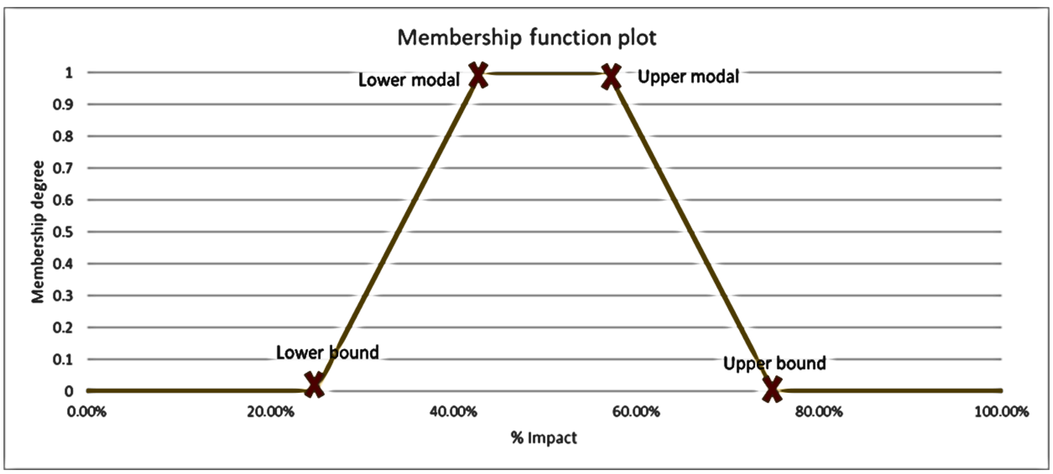

Figure 1. The lower and upper modal and bounds of linguistic terms

4. Risk Identification and Assessment Before Implementing Risk Response Actions

Form 5 (Appendix D (Nasir & Fayek 2019)) is designed to assess the probability of occurrence of potential risks/opportunities and their impact on the selected work package cost. The risks/opportunities were identified through extensive literature review and grouped under 11 different risk categories comprising *Management*, *Technical*, *Construction*, *Resources related*, *Site conditions*, *Contractual and legal*, *Economic and financial*, *Social*, *Political*, *Environmental*, and *Health and safety* (Table 4).

Table 4. Number of Identified Risk Events in Each Category (Siraj & Fayek 2019)

Risk category	No. of identified risks
Management	26
Technical	19
Construction	16
Resources related	30
Site conditions	18
Contractual and legal	21
Economic and financial	20
Social	12
Political	14
Environmental	9
Health and safety	15
Total:	**200**

Research participants are asked to assess the probability of occurrence and impact of each risk and/or opportunity on work package cost on a scale of 1–5 where 1 = "Very Low," 2 = "Low," 3 = "Medium," 4 = "High," and 5 = "Very High." If the risk event does not affect the work package, participants are asked to assign "N/A" ("Not applicable"). Participants are also asked to determine the percentage of the work package cost that may be affected by each risk/opportunity. Refer to Form 5 included in Appendix D.

5. Identification of Risk Response Actions and Assessing their Effectiveness

Once risk events have been identified and prioritized, risk response actions for the most severe risks, which may impact the work package cost, will be identified and assessed using Form 6. The research participants from [Co. X]are asked to assess the effectiveness of the recommended risk response actions to be implemented based on three criteria: (1) affordability of the risk response, (2) achievability of the risk response, and (3) controllability of risk events. *Affordability* refers to the cost-effectiveness of risk responses, where the amount of time, effort, and money spent on addressing a risk should not exceed the available resources for implementing risk responses. *Achievability* refers to the feasibility of a risk response in terms of three considerations: (a) the technical complexity of the proposed risk response, (b) the capability of the respondent, and (c) the authority of the respondent. *Controllability* refers to the likelihood that the probability of occurrence of a risk event can be changed.

[Co. X] research participants are asked to evaluate all three criteria on a scale of 1–5, where 1 = "Very Low," 2 = "Low," 3 = "Medium," 4 = "High," and 5 = "Very High." Also, the cost of implementing the response strategies is required. Refer to Form 6 (Appendix E).

6. Risk Identification and Assessment After Implementing Risk Response Actions

The research participants from [Co. X] are asked to evaluate the impact of selected risk response strategies on risk events. Therefore, the probability and impact of both negative and positive risk events must be assessed after implementing risk response strategies. Refer to Form 7 included in Appendix D.

7. Conducting a Survey to Determine Subjective (Soft) Causal Relationships

There are two types of causal relationships among model variables in FSD models: soft (subjective) and hard (objective). When the mathematical form of a causal relationship is known, it is said to be "hard" (e.g., relationship between risk severity and risk impact). Regular or fuzzy arithmetic can be applied for hard relationships depending on the objectivity or subjectivity of variables. "Soft" causal relationships, on the other hand, are those in which the mathematical form of the causal relationship is unknown (e.g., relationship between the probabilities of a risk event and another risk event). Soft causal relationships are expressed in linguistic terms.

To determine the causal interactions among work packages, risk events, and risk response actions together and with each other, data is collected using Form 8 included in Appendix F.

Research participants are asked to evaluate causal relationships on a scale of 1–5, where 1 = "Very Low," 2 = "Low," 3 = "Medium," 4 = "High," and 5 = "Very High." Also, the cost of implementing the response strategies is required. Refer to Form 8 (Appendix F).

8. Work Package Contingency Reserve Status and Cost Performance Assessment

Form 9 is designed to assess the contingency reserve status and cost performance of the work package at different completion percentages of the work package (i.e., 25%, 50%, 75%, and 100%). The first section of this form documents the estimated work package contingency to be spent and the actual work package contingency expended at the specified percentage completion of the work package. The second section of this form records cost information such as actual total work package cost, actual work package direct and indirect cost, cost of approved changes to work package, total value of variations in work package cost, and construction cost of rectifying all work package defects at specified percentages of work package completion. This form is to be filled in by the project manager when the company data related to the work package performance are not available. Refer to Form 9 (Appendix F).

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Appendix B.

Form 1: Project and Work Package Characteristics

Please provide a description of the selected project and work package by providing appropriate answers to the questions below.

1. Project Characteristics

1.1. Please indicate the name of the project: ____

1.2. Please indicate the project location: ____

1.3. What role does your organization play in the project?

☐ Owner ☐ Main contractor

☐ Sub-/Specialty contractor ☐ Consultant

☐ Project management service ☐ Supplier

☐ Financier ☐ Other (please specify): ___________________

1.4. Please specify the total contract value of the project: ______________________

1.5. Please specify the percentage of the allocated project contingency relative to the total project cost: __________________________________

1.6. Please specify the contract duration of the project: _______________________

1.7. Please specify the project start date (for construction work): _______________________

1.8. Please specify the approximate percent complete to date in the ***construction work*** for this project: ____________________________

1.9. Please indicate below the project delivery system employed for the project.

☐ Traditional Design-Bid-Build ☐ Design-Build (EPC)

☐ Construction Management at Risk ☐ Parallel Primes

☐ Build, Own, Operate and Transfer (BOOT) ☐ Integrated Project Delivery (IDP)

☐ Public–Private Partnership (P3) ☐ Other (please specify): ________________

1.10. Please indicate below the contract type used in the project.

☐ Unit Rate ☐ Lump Sum

☐ Cost Plus ☐ Time and Material

☐ Guaranteed Maximum Price ☐ Other (please specify): ___________________

1.11. Please specify the number of similar projects completed by your organization: _______________________

1.12. Please specify the number of work packages involved in the project: _________________

1.13. How would you rate the level of complexity of the project with respect to the number of work packages involved?

Low	Somewhat Low	Average	Somewhat High	High
1	2	3	4	5

1.14. How would you rate the overall complexity of the project?

Low	Somewhat Low	Average	Somewhat High	High
1	2	3	4	5

2. Work Package Characteristics

The project manager will complete this section of the form for EACH selected work package initially.

2.1. Please indicate the name of the work package: _____________________________________

2.2. Please provide a full description of the work package:

____

____

____

____

____

____

____

____

2.3. Please indicate below the contract type used in the work package:

□ Unit Rate □ Lump Sum

□ Cost Plus □ Time and Material

□ Guaranteed Maximum Price □ Other (please specify): ____________

2.4. Please indicate the estimate type used for the work package:

□ Indicative □ Estimate

□ Historical □ Other (please specify): ___________________

2.5. Please specify the total work package cost: ____________________________

2.6. Please specify the percentage of the total cost of the selected work package relative to the total project cost: __________________________________

2.7. Please specify the values of the cost components for the selected work package:

Cost component	Amount (Canadian dollars)
Labour total cost	
Materials total cost	
Equipment total cost	
Subcontract total cost	
Indirect total cost	

2.8. Please specify the estimated duration of the work package: ___________________________

2.9. Please specify the start date of the work package (for construction work): _______________

2.10. Please specify the approximate percent complete to date in the ***construction work*** for this work package: ____________________________

2.11. Please specify the cumulative budgeted cost of the work package at different completion stage (percentage):

Percentage completion of the work package (%)	Cumulative budgeted cost of the work package (Canadian dollars)
10	
20	
30	
40	
50	
60	
70	
80	
90	
100	

2.12. Please rate the level of complexity of the selected work package based on the following descriptions using the predetermined rating scale (1–5):

No.	Description	Level of complexity				
		Low	Somewhat Low	Average	Somewhat High	High
2.12.1	The level of complexity of the selected work package in terms of number of activities involved	1	2	3	4	5
2.12.2	The level of complexity of the selected work package with respect to the work scope	1	2	3	4	5
2.12.3	The level of complexity of the selected work package with respect to the construction methods	1	2	3	4	5
2.12.4	The level of difficulty of the selected work package with regard to the constructability	1	2	3	4	5

2.13. Please rate the criticality of the work package based on the following descriptions using the predetermined rating scale (of 1–5):

No.	Description	Level of criticality				
		Low	Somewhat Low	Average	Somewhat High	High
2.13.1	The criticality of the selected work package in terms of its share of the total project cost	1	2	3	4	5
2.13.2	The criticality of the selected work package in terms of its share of the total project contingency	1	2	3	4	5

2.13.3	The criticality of the selected work package in terms of its proneness to several risks	1	2	3	4	5

Appendix B. Form 2: Expertise Level of the Experts in Risk Management (completed by research participants)

B.1. Form 2: Self-evaluation form

1. Name of research participant: ____

2. Demographic information

Your age: ☐ 20–30 ☐ 31–40 ☐ 41–50 ☐ 51–60 ☐ Over 60

Your gender: ☐ Male ☐ Female ☐ Other / prefer not to say

3. Supervisor's name: ____________________________________

4. Please enter numerical data values for the quantitative qualification attributes and assign a data value for each qualitative qualification attributes based on the corresponding predetermined rating scales provided.

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
1. Experience	1.1 Total years of experience	Number of years you have been working in this discipline	Integer		N/A
	1.2 Diversity of experience	Number of different companies you have worked for	Integer		N/A
	1.3 Relevant experience	Number of years you have been working in risk management	Integer		N/A

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
	1.4 Applied experience	Number of years you have been working in risk management	Integer		N/A
	1.5 Varied experience	Number of different functional areas or project types worked with in your entire career	Integer		N/A
2. Knowledge	2.1 Academic knowledge	Number years of study in your discipline	Integer		N/A
	2.2 Education level	Highest degree achieved to date	1–5 predetermined rating		1. High school degree 2. College degree 3. Technical degree 4. Bachelor degree 5. Master's degree
	2.3 On-the-job training	Number of courses taken in current discipline	Integer		N/A
3. Professional performance	3.1 Current occupation in the company	Your occupation in company currently working for	1–5 predetermined rating		1. Project engineer 2. Senior engineer 3. Project manager 4. Manager 5. Senior manager

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
	3.2 Years in current occupation	Number of years in your current occupation at company	Integer		N/A
	3.3 Expertise self- evaluation	Level of risk management expertise that participant expert acknowledges about himself/herself	1–5 predetermined rating		1. VERY LOW risk management expertise 2. LOW risk management expertise 3. AVERAGE risk management expertise 4. HIGH risk management expertise 5. VERY HIGH risk management expertise
4. Risk management practice	4.1 Average hours of work in risk per week	Number of hours per week working in risk management related tasks in current company	Integer		N/A
	4.2 Level of risk management training	Number of certifications you have obtained from risk management training sessions or workshops	Integer		N/A
	4.3 Risk management conferences experience	Number of risk management conferences you have attended	Integer		N/A

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
	4.4 Risk identification and planning	Experience level with proper risk identification and development of an overall risk management plan with risk response planning	1–5 predetermined rating		1. NO proper risk identification, VERY POOR development of an overall risk management plan with risk response planning 2. NO proper risk identification, POOR development of an overall risk management plan with risk response planning 3. SOME risk identification, FAIR development of an overall risk management plan with risk response planning 4. SOME risk identification, GOOD development of an overall risk management plan with risk response planning 5. DETAILED risk identification, VERY GOOD development of an overall risk management plan with risk response planning
	4.5 Risk monitoring and control	Experience level with keeping track of identified risks, monitoring residual risks and identifying new risks, ensuring the execution of risk plans, evaluating their effectiveness in reducing risk	1–5 predetermined rating		1. NOT keeping track of identified risks, VERY POOR monitoring of residual risks and identifying new risks, VERY POOR in ensuring the execution of risk plans, NO evaluation on their effectiveness in reducing risk 2. NOT keeping track of identified risks, POOR monitoring of residual risks and identifying new risks, POOR in ensuring the execution of risk plans, NO evaluation on their effectiveness in reducing risk 3. Keeping SOME track of identified risks, FAIR monitoring of residual risks and identifying new risks,

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
					FAIR in ensuring the execution of risk plans, SOME evaluation on their effectiveness in reducing risk 4. Keeping DETAILED track of identified risks, GOOD monitoring of residual risks and identifying new risks, GOOD in ensuring the execution of risk plans, DETAILED evaluation on their effectiveness in reducing risk 5. Keeping DETAILED track of identified risks, VERY GOOD monitoring of residual risks and identifying new risks, VERY GOOD in ensuring the execution of risk plans, DETAILED evaluation on their effectiveness in reducing risk
	4.6 Crisis management	Experience level in understanding the time phase of crisis (to be reactive or proactive), and having effective systems to prevent/control/manage crisis	1–5 predetermined rating		1. REACTIVE, VERY POOR systems to prevent crisis 2. REACTIVE, POOR systems to prevent crisis 3. REACTIVE, FAIR systems to prevent crisis 4. PROACTIVE, GOOD systems to prevent crisis 5. PROACTIVE, VERY GOOD systems to prevent crisis
5. Project specifics	5.1 Project size limit	Monetary value of the largest risk management project you have worked on in current company	Integer		N/A

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
	5.2 Commitment to time deadlines	Percentage of projects finished on time by all projects you have been involved in	Integer		N/A
	5.3 Commitment to cost budget	Percentage of projects finished on budget by all projects you have been involved in	Integer		N/A
	5.4 Safety adherence	Number of projects you have worked on with zero incident rates	Integer		N/A
	5.5 Geographic diversity experience	Number of different project locations that you have worked on	Integer		N/A
6. Reputation	6.2 Willingness to participate in survey	Experts' attitude and willingness towards participating in research survey	1–5 predetermined rating		1. COMPLETELY unwilling 2. SOMEWHAT NOT willing 3. SOMEWHAT willing 4. Willing 5. COMPLETELY willing
	6.4 Enthusiasm and willingness	Level of enthusiasm and willingness in performing risk management tasks in current company	1–5 predetermined rating		1. VERY POOR enthusiasm, COMPLETELY unwilling 2. POOR enthusiasm, SOMEWHAT NOT willing 3. AVERAGE enthusiasm, SOMEWHAT willing 4. GOOD enthusiasm, willing 5. VERY GOOD enthusiasm, COMPLETELY willing

Appendix C. Form 3: Expertise Level of the Experts in Risk Management (completed by supervisor)

B.2. Form 3: Supervisor evaluation form (completed by supervisor)

1. Supervisor's name: ____

2. Demographic information

Your age: ☐ 20–30 ☐ 31–40 ☐ 41–50 ☐ 51–60 ☐ Over 60

Your gender: ☐ Male ☐ Female ☐ Other / prefer not to say

4. Name of research participant to be evaluated: ____

5. Each qualitative qualification attribute is measured using the corresponding predetermined rating scales described below. Based on your own judgement **about the participant's** expertise level, please assign a data value for each qualitative qualification attribute listed.

Criteria	**Sub-criteria**	**Description**	**Scale of measure**	**Data value**	**Predetermined rating (1–5) description**
4. Risk management practice	4.4 Risk identification and planning	Experience level with proper risk identification and development of an overall risk management plan with risk response planning	1–5 predetermined rating		1. NO proper risk identification, VERY POOR development of an overall risk management plan with risk response planning 2. NO proper risk identification, POOR development of an overall risk management plan with risk response planning 3. SOME risk identification, FAIR development of an overall risk management plan with risk response planning

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
					4. SOME risk identification, GOOD development of an overall risk management plan with risk response planning 5. DETAILED risk identification, VERY GOOD development of an overall risk management plan with risk response planning
	4.5 Risk monitoring and control	Experience level with keeping track of identified risks, monitoring residual risks and identifying new risks, ensuring the execution of risk plans, evaluating their effectiveness in reducing risk	1–5 predetermined rating		1. NOT keeping track of identified risks, VERY POOR monitoring of residual risks and identifying new risks, VERY POOR in ensuring the execution of risk plans, NO evaluation on their effectiveness in reducing risk 2. NOT keeping track of identified risks, POOR monitoring of residual risks and identifying new risks, POOR in ensuring the execution of risk plans, NO evaluation on their effectiveness in reducing risk 3. Keeping SOME track of identified risks, FAIR monitoring of residual risks and identifying new risks, FAIR in ensuring the execution of risk plans, SOME evaluation on their effectiveness in reducing risk 4. Keeping DETAILED track of identified risks, GOOD monitoring of residual risks and

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
					identifying new risks, GOOD in ensuring the execution of risk plans, DETAILED evaluation on their effectiveness in reducing risk 5. Keeping DETAILED track of identified risks, VERY GOOD monitoring of residual risks and identifying new risks, VERY GOOD in ensuring the execution of risk plans, DETAILED evaluation on their effectiveness in reducing risk
	4.6 Crisis management	Experience level in understanding the time phase of crisis (to be reactive or proactive), and having effective systems to prevent/control/manage crisis	1–5 predetermined rating		1. REACTIVE,VERY POOR systems to prevent crisis 2. REACTIVE, POOR systems to prevent crisis 3. REACTIVE, FAIR systems to prevent crisis 4. PROACTIVE, GOOD systems to prevent crisis 5. PROACTIVE, VERY GOOD systems to prevent crisis
6. Reputation	6.1 Social acclimation	Level of the expert's social acclimation by others	1–5 predetermined rating		1. VERY LOW social acclimation 2. LOW social acclimation 3. AVERAGE social acclimation 4. HIGH social acclimation 5. VERY HIGH social acclimation

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
	6.2 Willingness to participate in survey	Expert's attitude and willingness towards participating in research survey	1–5 predetermined rating		1. COMPLETELY unwilling 2. SOMEWHAT NOT willing 3. SOMEWHAT willing 4. Willing 5. COMPLETELY willing
	6.3 Professional reputation	Level of credibility of expert based on consistency and reasonableness (use of engineering judgement) of previous decisions	1–5 predetermined rating		1. VERY INCONSISTENT professional decisions, VERY UNREASONABLE professional decisions 2. INCONSISTENT professional decisions, UNREASONABLE professional decisions 3. SOMEWHAT CONSISTENT professional decisions, SOMEWHAT REASONABLE professional decisions 4. CONSISTENT professional decisions, REASONABLE professional decisions 5. VERY CONSISTENT professional decisions, VERY REASONABLE professional decisions

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
	6.4 Enthusiasm and willingness	Level of enthusiasm and willingness in performing risk management tasks in current company	1–5 predetermined rating		1. VERY POOR enthusiasm, COMPLETELY unwilling 2. POOR enthusiasm, SOMEWHAT NOT Willing 3. AVERAGE enthusiasm, SOMEWHAT willing 4. GOOD enthusiasm, willling 5. VERY GOOD enthusiasm, COMPLETELY willing
	6.5 Level of risk conservativeness	Indicates the expert's level of conservativeness in risk management decisions	1–5 predetermined rating		1. VERY AGGRESSIVE risk-taking 2. AGGRESSIVE risk-taking 3. MODERATE risk-taking 4. CONSERVATIVE risk-taking 5. VERY CONSERVATIVE risk-taking
7. Personal attributes and skills	7.1 Level of communication skills	Indicates the expert's level of communication skills with other team members and peers including maintaining interpersonal skills with team (eloquent); clearly expressing their point of view; and ability to communicate with others who are at different levels (technical/language/knowledge)	1–5 predetermined rating		1. VERY POOR interpersonal skills, NO eloquence, VERY POOR vertical communication 2. POOR interpersonal skills, NO eloquence, POOR vertical communication 3. AVERAGE interpersonal skills, SOME eloquence, AVERAGE vertical communication 4. GOOD interpersonal skills, CLEAR eloquence, GOOD vertical communication

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
					5. VERY GOOD interpersonal skills, CLEAR eloquence, VERY GOOD vertical communication
	7.2 Level of teamwork skills	Indicates the expert's level of teamwork skills within the current company, such as participating as an active and contributing member to achieve the team's goals	1–5 predetermined rating		1. VERY INACTIVE team member, NO contribution to team's goals 2. INACTIVE team member, NO contribution to team's goals 3. AVERAGE ACTIVE team member, SOME contribution to team's goals 4. ACTIVE team member, FAIR contribution to team's goals 5. VERY ACTIVE team member, FAIR contribution to team's goals
	7.3 Level of leadership skills	Indicates the expert's level of leadership skills within the current company, such as finding resources and training team members; offering tools to support team members; communicating project objectives and progress; and willingness to coach or mentor others			1. VERY POOR training, NO support tools to team members, VERY POOR communication of objectives and progress, COMPLETELY unwilling to mentor 2. POOR training, NO support tools to team members, POOR communication of objectives and progress, SOMEWHAT NOT willing to mentor

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
					3. AVERAGE training, SOME support tools to team members, AVERAGE communication of objectives and progress, SOMEWHAT willing to mentor 4. GOOD trainings, FAIR support tools to team members, GOOD communication of objectives and progress, willing to mentor 5. VERY GOOD training, FAIR support tools to team members, VERY GOOD communication of objectives and progress, COMPLETELY willing to mentor
	7.4 Level of analytical skills	Expert's level of anticipating and identifying problems in daily tasks while accounting for any missing data	1–5 predetermined rating		1. VERY POOR anticipation, VERY POOR identification of problems 2. POOR anticipation, POOR identification of problems 3. AVERAGE anticipation, AVERAGE identification of problems 4. GOOD anticipation, GOOD identification of problems 5. VERY GOOD anticipation, VERY GOOD identification of problem

Criteria	Sub-criteria	Description	Scale of measure	Data value	Predetermined rating (1–5) description
	7.5 Level of ethics	Expert's level of conforming to any legal or regulatory framework enforced by company, and expert's level of morality	1–5 predetermined rating		1. VERY POOR compliance to legal and regulatory framework, VERY POOR level of morality 2. POOR compliance to legal and regulatory framework, POOR level of morality 3. AVERAGE compliance to legal and regulatory framework, AVERAGE level of morality 4. GOOD compliance to legal and regulatory framework, GOOD level of morality 5. VERY GOOD compliance to legal and regulatory framework, VERY GOOD level of morality

Appendix D. Form 4: Membership Functions of Linguistic Terms

				Expert 1				Expert 2				Expert 3			
				Lower bound	Lower modal	Upper modal	Upper bound	Lower bound	Lower modal	Upper modal	Upper bound	Lower bound	Lower modal	Upper modal	Upper bound
Risk events	Negative risk events (threats)	Probability	Very low												
			Low												
			Medium												
			High												
			Very high												
		Impact	Very low												
			Low												
			Medium												
			High												
			Very high												
	Positive risk events (opportunities)	Probability	Very low												
			Low												
			Medium												
			High												
			Very high												
		Impact	Very low												
			Low												
			Medium												
			High												
			Very high												

				Expert 1				Expert 2				Expert 3			
				Lower bound	Lower modal	Upper modal	Upper bound	Lower bound	Lower modal	Upper modal	Upper bound	Lower bound	Lower modal	Upper modal	Upper bound
Risk response actions	Effectiveness	Affordability	Very low												
			Low												
			Medium												
			High												
			Very high												
		Achievability	Very low												
			Low												
			Medium												
			High												
			Very high												
		controllability	Very low												
			Low												
			Medium												
			High												
			Very high												

			Expert 1				Expert 2				Expert 3			
			Lower bound	Lower modal	Upper modal	Upper bound	Lower bound	Lower modal	Upper modal	Upper bound	Lower bound	Lower modal	Upper modal	Upper bound
Causal relationships	Degree of causality of soft relationships	Very low												
		Low												
		Medium												
		High												
		Very high												

Appendix E. Forms 5 and 7: Identification and Assessment of Both Positive and Negative Risk Events Before and After Implementing Risk Responses

Project name: ____

Work package name: __________________________________

Percentage completion of the work package: ________________

Please assess the probability of occurrence of the following risks/opportunities and their respective impact on the selected work package on a scale of 1–5, where 1 = “Very Low,” 2 = “Low,” 3 = “Medium,” 4 = “High,” and 5 = “Very High.” If the risk event does not affect the work package, please assign “N/A” (“Not applicable”). Please also determine the percentage of the work package cost that may be affected by each risk/opportunity. Blank rows are left intentionally for participants to add additional risks.

1. Management Risks/Opportunities

No.	Management Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
1.1	Lack of experience and project management skills of the project team	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.2	Poor coordination and communication among various parties involved in the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Management Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
1.3	Inadequate project organization structure	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.4	Poor relationship among various parties involved in the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.5	Unavailability of sufficient professionals and managers	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.6	Inadequate or poor project planning and budgeting	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.7	Interdependencies with other projects (consistency and complementarities with other projects)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.8	Poor site management and supervision by the contractor	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.9	Poor project quality management including inadequate quality planning, quality assurance, and quality control	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Management Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
1.10	Poor or incomplete definition of project scope	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.11	Loss of productivity due to inadequate site facilities planning or inability to manage labour	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.12	Poor capability of owner in project management	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.13	Low management competency of subcontractors	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.14	Lack of proper training program to new and existing staff in the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.15	Poor project monitoring and auditing	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.16	Low level motivation and efficiency of existing manpower	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.17	Frequent replacement of project managers and key personnel	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.18	Poor project cost management and control	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Management Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
1.19	Inefficiency of owner's supervisors	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.20	Unexpected change in owner's staff/organization	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.21	Inadequate experience of consultant with regard to type of work package/project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.22	Low project team cohesion (poor interpersonal relations between project team members)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.23	High staff turnover in the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.24	Poor time management due to change of manager or management strategies of the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.25	Consultant lacks adequate number of staff (inspector) during construction phase of the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
1.26	Inadequate project complexity analysis	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Management Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

2. *Technical Risks/Opportunities*

No.	Technical Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
2.1	Inappropriate design and poor engineering	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.2	Unanticipated engineering and design changes	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.3	Delay in design (design process takes longer than anticipated)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.4	Delay in issuing construction drawing due to late approval	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.5	Unclear and inadequate details in design drawings and specifications	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.6	Unpredicted technical problems in construction	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.7	Unproven engineering techniques (the techniques adopted are immature and cannot fulfill the standards and requirements as expected)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.8	Inadequate study and insufficient data before	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Technical Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
	design (errors in feasibility studies)																									
2.9	Incomplete design	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.10	Complexity of design	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.11	Problems in technology transfer and implementation	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.12	Rapidly changing technologies	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.13	Low constructability	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.14	Inefficiency in decision making on key design issues	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.15	Using inadequate software for design	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.16	Gaps between implementation and specifications; incompatibility between construction drawings and methods	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.17	Lack of proper design review and checking by consultant	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
2.18	Lack of skilled designers in the project region	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Technical Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
2.19	Non-familiarity of the project team with a certain technology	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

3. Construction Risks/Opportunities

No.	Construction Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
3.1	Delays and interruptions causing cost increase to the work package/project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.2	Poor workmanship and construction errors leading to rework	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.3	Unreasonably tight project schedule causing cost increase to the work package/project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.4	Complexity of proposed construction methods/techniques	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.5	Contractor's incompetence in executing the work package/project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.6	Change in construction methods/techniques	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.7	Adoption of improper, poor, or unproven construction methods/techniques	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.8	Conflicting interfaces of work items	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Construction Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
3.9	Pressure to deliver project on accelerated schedule (pressure to crash project duration)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.10	Strict quality requirements	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.11	Contractor’s lack of experience in similar projects	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.12	Owner's improper intervention in construction phase	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.13	Delay in approving the contractor work by consultant or owner of the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.14	Failure to identify construction defects	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.15	Vagueness of construction methods/techniques	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
3.16	Technical mistakes during construction stage by contractor	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Construction Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

4. Resources Related Risks/Opportunities

No.	Resources Related Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
4.1	**Labour related**																									
4.1.1	Unavailability of sufficient amount of skilled labour in project region	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.1.2	Low labour productivity of local workforce	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.1.3	Untrained and inexperienced labour force	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.1.4	Strikes and labor disputes	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Resources Related Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
4.1.5	Higher workforce attrition rates	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.1.6	Workforce absenteeism	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.2	**Material related**																									
4.2.1	Unavailability or shortage of expected material	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.2.2	Delay in materials delivery	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.2.3	Defective or non-conforming materials that do not meet the standard	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.2.4	Material wastage and damage due to poor construction methods, working habit, or improper storage	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.2.5	Import restrictions on materials needed in construction	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Resources Related Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
4.2.6	Changes in material types and specifications during construction	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.2.7	Delay in material approval	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.2.8	Limited capability and service quality of material suppliers and logistic service	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.2.9	Incorrect definition of type and quantity of needed materials by designer(s)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.3	**Equipment related**																									
4.3.1	Unavailability or shortage of expected equipment	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.3.2	Equipment breakdown	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.3.3	Low productivity and efficiency of equipment	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.3.4	Delay in equipment delivery to the project site	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Resources Related Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
4.3.5	Quality problem of construction equipment	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.3.6	Improper selection of construction equipment by contractor or subcontractor	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.3.7	Unavailability of spare parts and high maintenance cost of equipment	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.3.8	Equipment import restriction	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.3.9	Type and number of needed equipment are not compatible with work package/project scale	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.4	**Subcontractor related**																									
4.4.1	Unavailability of qualified subcontractors	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.4.2	Subcontractors’ failure; default of subcontractors	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Resources Related Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
4.4.3	Poor performance of subcontractors	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.4.4	Subcontractor lack of required technical skill	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.4.5	Subcontractor lack of adequate number of staff and equipment	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
4.4.6	Delay in appointing subcontractor	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

5. Site Conditions Risks/Opportunities

No.	Site Conditions Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
5.1	Unpredicted adverse engineering geology (subsurface conditions)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.2	Differing and unforeseen site conditions	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.3	Difficulties of access and work on site due to specific geographical constraint of region	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.4	Lack of readily available utilities on site (e.g., water, electricity) and supporting infrastructure unavailability	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.5	Late construction site possession	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.6	Inadequate site investigations (soil tests and site survey)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.7	Improper selection of project location	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.8	Security problems at project site	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Site Conditions Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
5.9	Land acquisition and compensation problem (the cost and time for land acquisition exceeds the original plans)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.10	Delays in right of way process	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.11	Finding historical objects during excavation process	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.12	Ineffective control and management of traffic	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.13	Limited construction area (on-site congestion)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.14	Unexpected underground utilities encounter	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.15	Ground water seepage which can damage underground construction work	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.16	Poor preliminary assessment and evaluation of ground movement and settlements	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Site Conditions Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
5.17	Distance from primary sources, materials, and manufacturers	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
5.18	Obstruction to surrounding business or others	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

6. *Contractual and Legal Risks/Opportunities*

No.	Contractual and Legal Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
6.1	Contradictions and vagueness in the contract documents	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.2	Frequent change orders	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.3	Delays in resolving contractual disputes and litigations	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.4	Change in codes and regulations	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.5	Possibility of contractual disputes and claims	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.6	Immaturity and/or unreliability of legal system	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.7	Change in project scope	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.8	Unclear roles and responsibilities of project stakeholders	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.9	Intense competition at tender stage	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.10	Breach of contract by owner, contractor, or subcontractors	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.11	Rigidity of contract provision	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Contractual and Legal Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
6.12	Lack of integrity in the tendering process (unfairness in tendering)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.13	Contract strategy changes from plan	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.14	Inadequate claim administration	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.15	Excessive contract variation	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.16	Contract and specification interpretation disagreement	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.17	Extent of work differs from contract	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.18	Errors or omissions in BOQ	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.19	Intensity of contract (the ratio of contract value and contract period)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.20	Inappropriate form or type of contract	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
6.21	Lack of legal judgement reinforcement	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Contractual and Legal Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

7. *Economic and Financial Risks/Opportunities*

No.	Economic and Financial Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
7.1	Unpredicted change of inflation rate	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.2	Fluctuation in currency exchange and/or difficulty of convertibility	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.3	Escalation of material prices	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.4	Unpredicted change of interest rate	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.5	Delay in payments	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.6	Project funding problems	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.7	Change in tax regulation	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.8	Poor financial market or unavailability of financial instrument resulting difficulty of financing	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.9	Economic recession or instability of economic condition	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.10	Financial failure of the owner or contractor	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.11	Change in government funding policy	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Economic and Financial Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
7.12	Lack of insurance (insufficient insurance)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.13	Market demand change	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.14	Wage inflation (increase in labors and employee salaries)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.15	Inaccurate assessment or forecast of market demand	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.16	Enactment of a new bylaw leading to cost changes	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.17	Energy price changes	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.18	Tight fiscal and monetary policies	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.19	Change in banker’s policy for loans	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
7.20	Conflict between project financiers	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Economic and Financial Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

8. *Social Risks/Opportunities*

No.	Social Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
8.1	Differences in social, cultural, and religious background	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.2	Unfavorable social environment	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.3	Public opposition to the project (public objections)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.4	Societal conflict and/or public unrest	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.5	Insecurity and crime (theft, vandalism, and/or fraudulent practices)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.6	Land acquisition and compensation problems (the cost and time for land acquisition exceeds the original plans)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.7	Poor public relations with local contacts	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.8	Social grievances (local communities pose objections)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.9	Substance abuse	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Social Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
8.10	Unexpected aboriginal claims or protests leading to cost increase	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.11	Disturbances to public activities	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
8.12	Loss of public trust/goodwill	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

9. *Political Risks/Opportunities*

No.	Political Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
9.1	Changes in government laws, regulations, or policies affecting the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.2	Outbreak of hostilities (wars, revolution, civil disorder/riots, terrorism)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.3	Political instability of the government (unfavorable political environment)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.4	Delay or refusal of project approval and permit by government departments	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.5	Corrupt local government officials demand bribes or unjust rewards	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.6	High level of bureaucracy of the authority	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.7	Poor relations with related government departments	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.8	Government's improper intervention during construction	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Political Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
9.9	Poor international relations; instability of international relation	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.10	Government restrictions on foreign companies (mandatory technology transfer, differential taxation of foreign firms, etc.)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.11	Multinational sanctions (embargos)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.12	Change of government (government discontinuity)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.13	Out-of-date labor, tax, insurance, trade, and/or environmental laws	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
9.14	Lack of support from government	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

10. Environmental Risks/Opportunities

No.	Environmental Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
10.1	Adverse weather conditions (continuous rainfall, snow, temperature, wind)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
10.2	Force majeure (natural and man-made disasters that are beyond the firm's control, such as floods, thunder and lightning, landslide, earthquake, hurricane, etc.)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
10.3	Adverse environmental impacts of the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
10.4	Pollution associated with construction activities (dust, harmful gases, noise, solid and liquid wastes, etc.)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
10.5	Strict environmental regulations and requirements	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
10.6	Changes in environmental permitting	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
10.7	Poor preliminary assessment and evaluation of	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Environmental Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
	environmental impacts of the project																									
10.8	Poor environmental regulations and control	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
10.9	Prosecution due to unlawful disposal of construction waste	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

11. Health and Safety Risks/Opportunities

No.	Health and Safety Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
11.1	Accidents occurring during construction	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.2	Inadequate safety measures or unsafe operations	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.3	Poor construction safety management	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.4	Damage to persons or property or materials due to poor health and safety management of the project	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.5	Changed labour safety laws or regulations	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.6	Lack of safety insurance	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.7	Ineffective protection of surrounding environment (e.g., adjacent buildings and facilities)	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.8	Failure to comply with HS&E standards or security plan	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.9	Accidents caused by or to resident communities or third parties	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

No.	Health and Safety Risks/Opportunities	Risk probability of occurrence						Risk impact on work package cost						Opportunity probability of occurrence						Opportunity impact on work package cost						Cost of work package affected (%)
		N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	N/A	Very Low	Low	Medium	High	Very High	
11.10	Epidemic illness	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.11	Poor safety and environmental regulations	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.12	Strict health and safety regulations	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.13	Poor performance of contractor in health and safety of work	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.14	Public concerns related to health and safety of the project due to poor communication	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
11.15	Poor planning of contractor for emergency measures	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5	

Appendix F. Form 6: Identifying Risk Response Actions and Assessing their Effectiveness

Project name: ____
Work package name: __________________________________
Percentage completion of the work package: ________________

Please identify and evaluate the effectiveness of several risk response actions for each identified risk event on a scale of 1–5, where 1 = "Very Low," 2 = "Low," 3 = "Medium," 4 = "High," and 5 = "Very High." Blank rows are left intentionally for participants to add additional risk response actions.

Risk category	Risk ID.	Name of risk event	Response strategy ID	Risk response actions/measures to be implemented	Implementation cost (CAD)	Effectiveness of risk response actions														
						Achievability of risk response action					Affordability of risk response action					Controllability of related risk event				
						Very Low	Low	Medium	High	Very High	Very Low	Low	Medium	High	Very High	Very Low	Low	Medium	High	Very High

Appendix G. Form 8: Determining Causal Relationships and their Degree of Causality among Project Components

Project name: ____

Work package name: __________________________________

Percentage completion of the work package: ________________

Since the table must be formed based on identified risk events, please refer to the Excel format of this form. Keep only identified risk events and add risk response actions. Then, evaluate the degree of causality between each pair of horizontal and vertical cell on a scale of 1–5, where 1 = "Very Low," 2 = "Low," 3 = "Medium," 4 = "High," and 5 = "Very high." Please list the all risk events and risk response actions that have occurred and indicate their causal relationship. The following table shows the assessment form for causality degree among management risks.

	Management Risk Events	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10	1.11	1.12	1.13	1.14	1.15	1.16	1.17	1.18	1.19	1.20	1.21	1.22	1.23	1.24	1.25	1.26
1.1	Lack of experience and project management skills of the project team																										
1.2	Poor coordination and communication among various parties involved in the project																										
1.3	Inadequate project organization structure																										
1.4	Poor relationship among various parties involved in the project																										
1.5	Unavailability of sufficient professionals and managers																										
1.6	Inadequate or poor project planning and budgeting																										
1.7	Interdependencies with other projects (consistency and complementarities with other projects)																										
1.8	Poor site management and supervision by the contractor																										

1.9	Poor project quality management including inadequate quality planning, quality assurance, and quality control																										
1.10	Poor or incomplete definition of project scope																										
1.11	Loss of productivity due to inadequate site facilities planning or inability to manage labor																										
1.12	Poor capability of owner in project management																										
1.13	Low management competency of subcontractors																										
1.14	Lack of proper training program to new and existing staff in the project																										
1.15	Poor project monitoring and auditing																										
1.16	Low level motivation and efficiency of existing manpower																										
1.17	Frequent replacement of project managers and key personnel																										
1.18	Poor project cost management and control																										
1.19	Inefficiency of owner’s supervisors																										
1.20	Unexpected change in owner’s staff/organization																										
1.21	Inadequate experience of consultant with regard to type of work package/project																										
1.22	Low project team cohesion (poor interpersonal relations between project team members)																										
1.23	High staff turnover in the project																										
1.24	Poor time management due to change of manager or management strategies of the project																										
1.25	Consultant lacks adequate number of staff (inspector) during construction phase of the project																										
1.26	Inadequate project complexity analysis																										

	Technical Risk Events	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	2.10	2.11	2.12	2.13	2.14	2.15	2.16	2.17	2.18	2.19
2.1	Inappropriate design and poor engineering																			
2.2	Unanticipated engineering and design changes																			
2.3	Delay in design (design process takes longer than anticipated)																			
2.4	Delay in issuing construction drawing due to late approval																			
2.5	Unclear and inadequate details in design drawings and specifications																			
2.6	Unpredicted technical problems in construction																			
2.7	Unproven engineering techniques (the techniques adopted are immature and cannot fulfill the standards and requirements as expected)																			
2.8	Inadequate study and insufficient data before design (errors in feasibility studies)																			
2.9	Incomplete design																			
2.10	Complexity of design																			
2.11	Problems in technology transfer and implementation																			
2.12	Rapidly changing technologies																			
2.13	Low constructability																			
2.14	Inefficiency in decision making on key design issues																			
2.15	Using inadequate software for design																			
2.16	Gaps between implementation and specifications; incompatibility between construction drawings and methods																			
2.17	Lack of proper design review and checking by consultant																			
2.18	Lack of skilled designers in the project region																			
2.19	Non-familiarity of the project team with a certain technology																			

	Construction Risk Events	3.1	3.2	3.3	3.4	3.5	3.6	3.7	3.8	3.9	3.10	3.11	3.12	3.13	3.14	3.15	3.16
3.1	Delays and interruptions causing cost increase to the work package/project																
3.2	Poor workmanship and construction errors leading to rework																
3.3	Unreasonably tight project schedule causing cost increase to the work package/project																
3.4	Complexity of proposed construction methods/techniques																
3.5	Contractor’s incompetence in executing the work package/project																
3.6	Change in construction methods/techniques																
3.7	Adoption of improper, poor, or unproven construction methods/techniques																
3.8	Conflicting interfaces of work items																
3.9	Pressure to deliver project on accelerated schedule (pressure to crash project duration)																
3.10	Strict quality requirements																
3.11	Contractor’s lack of experience in similar projects																
3.12	Owner's improper intervention in construction phase																
3.13	Delay in approving the contractor work by consultant or owner of the project																
3.14	Failure to identify construction defects																
3.15	Vagueness of construction methods/techniques																
3.16	Technical mistakes during construction stage by contractor																

	Resources Related Risks	4.1	4.1.1	4.1.2	4.1.3	4.1.4	4.1.5	4.1.6	4.2	4.2.1	4.2.2	4.2.3	4.2.4	4.2.5	4.2.6	4.2.7	4.2.8	4.2.9	4.3	4.3.1	4.3.2	4.3.3	4.3.4	4.3.5	4.3.6	4.3.7	4.3.8	4.3.9	4.4	4.4.1	4.4.2	4.4.3	4.4.4	4.4.5	4.4.6
4.1	***Labour related***																																		
4.1.1	Unavailability of sufficient amount of skilled labour in project region																																		
4.1.2	Low labour productivity of local workforce																																		
4.1.3	Untrained and inexperienced labour force																																		
4.1.4	Strikes and labor disputes																																		
4.1.5	Higher workforce attrition rates																																		
4.1.6	Workforce absenteeism																																		
4.2	***Material related***																																		
4.2.1	Unavailability or shortage of expected material																																		

4.2.2	Delay in materials delivery																																		
4.2.3	Defective or non-conforming materials that do not meet the standard																																		
4.2.4	Material wastage and damage due to poor construction methods, working habit, or improper storage																																		
4.2.5	Import restrictions on materials needed in construction																																		
4.2.6	Changes in material types and specifications during construction																																		

4.2.7	Delay in material approval																																		
4.2.8	Limited capability and service quality of material suppliers and logistic service																																		
4.2.9	Incorrect definition of type and quantity of needed materials by designer(s)																																		
4.3	***Equipment related***																																		
4.3.1	Unavailability or shortage of expected Equipment																																		
4.3.2	Equipment breakdown																																		
4.3.3	Low productivity and efficiency of equipment																																		

4.3.4	Delay in equipment delivery to the project site																																		
4.3.5	Quality problem of construction equipment																																		
4.3.6	Improper selection of construction equipment by contractor or subcontractor																																		
4.3.7	Unavailability of spare parts and high maintenance cost of equipment																																		
4.3.8	Equipment import restriction																																		
4.3.9	Type and number of needed equipment are not compatible with work																																		

	package/project scale																																		
4.4	***Subcontractor related***																																		
4.4.1	Unavailability of qualified subcontractors																																		
4.4.2	Subcontractors' failure; default of subcontractors																																		
4.4.3	Poor performance of subcontractors																																		
4.4.4	Subcontractor lack of required technical skill																																		
4.4.5	Subcontractor lack of adequate number of staff and equipment																																		
4.4.6	Delay in appointing subcontractor																																		

	Site Conditions Risks	5	5.1	5.2	5.3	5.4	5.5	5.6	5.7	5.8	5.9	5.10	5.11	5.12	5.13	5.14	5.15	5.16	5.17	5.18
5.1	Unpredicted adverse engineering geology (subsurface conditions)																			
5.2	Differing and unforeseen site conditions																			
5.3	Difficulties of access and work on site due to specific geographical constraint of region																			
5.4	Lack of readily available utilities on site (e.g., water, electricity) and supporting infrastructure unavailability																			
5.5	Late construction site possession																			
5.6	Inadequate site investigations (soil tests and site survey)																			
5.7	Improper selection of project location																			
5.8	Security problems at project site																			
5.9	Land acquisition and compensation problem (the cost and time for land acquisition exceeds the original plans)																			
5.10	Delays in right of way process																			
5.11	Finding historical objects during excavation process																			
5.12	Ineffective control and management of traffic																			
5.13	Limited construction area (on-site congestion)																			
5.14	Unexpected underground utilities encounter																			
5.15	Ground water seepage which can damage underground construction work																			
5.16	Poor preliminary assessment and evaluation of ground movement and settlements																			
5.17	Distance from primary sources, materials, and manufacturers																			
5.18	Obstruction to surrounding business or others																			

	Contractual and Legal Risks	6	6.1	6.2	6.3	6.4	6.5	6.6	6.7	6.8	6.9	6.10	6.11	6.12	6.13	6.14	6.15	6.16	6.17	6.18	6.19	6.20	6.21
6.1	Contradictions and vagueness in the contract documents																						
6.2	Frequent change orders																						
6.3	Delays in resolving contractual disputes and litigations																						
6.4	Change in codes and regulations																						
6.5	Possibility of contractual disputes and claims																						
6.6	Immaturity and/or unreliability of legal system																						
6.7	Change in project scope																						
6.8	Unclear roles and responsibilities of project stakeholders																						
6.9	Intense competition at tender stage																						
6.10	Breach of contract by owner, contractor, or subcontractors																						
6.11	Rigidity of contract provision																						
6.12	Lack of integrity in the tendering process (unfairness in tendering)																						
6.13	Contract strategy changes from plan																						
6.14	Inadequate claim administration																						
6.15	Excessive contract variation																						
6.16	Contract and specification interpretation disagreement																						
6.17	Extent of work differs from contract																						
6.18	Errors or omissions in BOQ																						
6.19	Intensity of contract (the ratio of contract value and contract period)																						
6.20	Inappropriate form or type of contract																						
6.21	Lack of legal judgement reinforcement																						

	Economic and Financial Risks	7.1	7.2	7.3	7.4	7.5	7.6	7.7	7.8	7.9	7.10	7.11	7.12	7.13	7.14	7.15	7.16	7.17	7.18	7.19	7.20
7.1	Unpredicted change of inflation rate																				
7.2	Fluctuation in currency exchange and/or difficulty of convertibility																				
7.3	Escalation of material prices																				
7.4	Unpredicted change of interest rate																				
7.5	Delay in payments																				
7.6	Project funding problems																				
7.7	Change in tax regulation																				
7.8	Poor financial market or unavailability of financial instrument resulting difficulty of financing																				
7.9	Economic recession or instability of economic condition																				
7.10	Financial failure of the owner or contractor																				
7.11	Change in government funding policy																				
7.12	Lack of insurance (insufficient insurance)																				
7.13	Market demand change																				
7.14	Wage inflation (increase in labors and employee salaries)																				
7.15	Inaccurate assessment or forecast of market demand																				
7.16	Enactment of a new bylaw leading to cost changes																				
7.17	Energy price changes																				
7.18	Tight fiscal and monetary policies																				
7.19	Change in banker’s policy for loans																				
7.20	Conflict between project financiers																				

	Social Risks	8.1	8.2	8.3	8.4	8.5	8.6	8.7	8.8	8.9	8.10	8.11	8.12
8.1	Differences in social, cultural and religious background												
8.2	Unfavorable social environment												
8.3	Public opposition to the project (public objections)												
8.4	Societal conflict and/or public unrest												
8.5	Insecurity and crime (theft, vandalism and fraudulent practices)												
8.6	Land acquisition and compensation problems; the cost and time for land acquisition exceeds the original plans												
8.7	Poor public relations with local contacts												
8.8	Social grievances; local communities pose objections												
8.9	Substance abuse												
8.10	Unexpected aboriginal claims or protests leading to cost increase												
8.11	Disturbances to public activities												
8.12	Loss of public trust/goodwill												

	Political Risks	9.1	9.2	9.3	9.4	9.5	9.6	9.7	9.8	9.9	9.10	9.11	9.12	9.13	9.14
9.1	Changes in government laws, regulations, and policies affecting the project														
9.2	Outbreak of hostilities (wars, revolution, civil disorder/riots, and terrorism)														
9.3	Political instability of the government (unfavorable political environment)														
9.4	Delay or refusal of project approval and permit by government departments														
9.5	Corrupt local government officials demand bribes or unjust rewards														
9.6	High level of bureaucracy of the authority														
9.7	Poor relations with related government departments														
9.8	Government's improper intervention during construction														
9.9	Poor international relations; instability of international relation														
9.10	Government restrictions on foreign companies (mandatory technology transfer, differential taxation of foreign firms, etc.)														
9.11	Multinational sanctions (embargos)														
9.12	Change of government (government discontinuity)														
9.13	Out-of-date labor, tax, insurance, trade, and environmental laws														
9.14	Lack of support from government														

	Environmental Risks	10.1	10.2	10.3	10.4	10.5	10.6	10.7	10.8	10.9
10.1	Adverse weather conditions (continuous rainfall, snow, temperature, wind)									
10.2	Force majeure (natural and man-made disasters that are beyond the firm's control, such as floods, thunder and lightning, landslide, earthquake, hurricane, etc.)									
10.3	Adverse environmental impacts of the project									
10.4	Pollution associated with construction activities (dust, harmful gases, noise, solid and liquid wastes, etc.)									
10.5	Strict environmental regulations and requirements									
10.6	Changes in environmental permitting									
10.7	Poor preliminary assessment and evaluation of environmental impacts of the project									
10.8	Poor environmental regulations and control									
10.9	Prosecution due to unlawful disposal of construction waste									

	Health and Safety Risks	11.1	11.2	11.3	11.4	11.5	11.6	11.7	11.8	11.9	11.10	11.11	11.12	11.13	11.14	11.15
11.1	Accidents occurring during construction															
11.2	Inadequate safety measures or unsafe operations															
11.3	Poor construction safety management															
11.4	Damage to persons or property or materials due to poor health and safety management of the project															
11.5	Changed labour safety laws or regulations															
11.6	Lack of safety insurance															
11.7	Ineffective protection of surrounding environment (e.g., adjacent buildings and facilities)															
11.8	Failure to comply with HS&E standards or security plan															
11.9	Accidents caused by or to resident communities or third parties															
11.10	Epidemic illness															
11.11	Poor safety and environmental regulations															
11.12	Strict health and safety regulations															
11.13	Poor performance of contractor in health and safety of work															
11.14	Public concerns related to health and safety of the project due to poor communication															
11.15	Poor planning of contractor for emergency measures															

Appendix H. Form 9: Work Package Contingency Reserve Status and Cost Performance Assessment

Project name: ____

Work package name: __________________________________

Percentage completion of the work package: ________________

1. Work package contingency reserve status

No.	Description	Unit	Value
1.1	Total work package estimated cost at tender stage	Canadian dollars (CAD)	
1.2	Total contingency allocated for the work package at tender stage	Canadian dollars (CAD)	
1.3	Estimated work package contingency to be expended (to the specified completion stage)	Canadian dollars (CAD)	
1.4	Actual work package contingency expended (to the specified completion stage)	Canadian dollars (CAD)	

2. Work package cost performance measures

No.	Performance Measures	Unit	Value
2.1	Actual total work package cost (to the specified completion stage)	Canadian dollars (CAD)	
2.2	Total work package estimated cost (to the specified completion stage)	Canadian dollars (CAD)	
2.3	Actual work package indirect cost (to the specified completion stage)	Canadian dollars (CAD)	
2.4	Actual work package direct cost (to the specified completion stage)	Canadian dollars (CAD)	
2.5	Cost of approved changes to work package (to the specified completion stage)	Canadian dollars (CAD)	

2.6	Total value of variations in work package cost (to the specified completion stage)	Canadian dollars (CAD)	
2.7	Construction cost of rectifying all work package defects (to the specified completion stage)	Canadian dollars (CAD)	
2.8	Quantity of completed work in work package (to the specified completion stage)	QTY (Number / real number)	