A Framework for Aggregation of Heterogeneous Experts' Opinions in Construction Risk Assessment

By

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Abstract

Construction companies constantly seek to improve risk analysis techniques to determine projects' risk contingency. The construction risk assessment practice relies on heterogeneous experts' opinions in a group decision making (GDM) process to determine the risk probabilities and impacts on a project. In this research, the risk probabilities and impacts are expressed as linguistic terms represented by fuzzy sets, which better represents the uncertainty in experts' risk assessment. However, the current GDM process obtains the experts' collective risk assessment through the consensus reaching process (CRP), which has several limitations, such as being a time consuming procedure. This research improves construction risk assessment GDM by introducing a structured aggregation framework to combine heterogeneous experts' risk assessments.

During the aggregation process, the industry common practice in order to represent the heterogeneous experts' different expertise level is to assign experts' importance weights. However, previous literature methods for assigning heterogeneous experts' importance weights are subjective and biased. Therefore, there is a lack of a structured approach for assessing experts' expertise level in construction risk assessment. The aggregation framework illustrated in this thesis presents a systematic and flexible multi-step methodology to assess heterogeneous experts' expertise level and assign experts' importance weights in the construction risk assessment GDM aggregation process. The methods used in the aggregation framework advance the practical application of evaluating heterogeneous experts in construction, while the combination of experts' risk assessments through aggregation advances construction industry GDM practice. A case study with actual project data demonstrates the steps involved in the

aggregation framework, and analyzes the most suitable aggregation operator to be implemented in the context by comparing the project risk contingency results to Monte Carlo Simulation (MCS) results.

The main contributions of this paper are: introducing a clear and consistent list of criteria, metrics and scales of measure to evaluate experts' risk assessment expertise; developing a method to weight experts' importance in risk assessment according to their expertise level; and improving construction risk assessment GDM by introducing a structured framework for construction risk assessment that combines heterogeneous experts' assessments through aggregation.

Preface

This thesis is an original work by Natalie Imad Monzer. The research project, of which this dissertation is based on, received research ethics approval from the University of Alberta Research Ethics Board, Project Name “Aggregation of heterogeneous experts’ opinions in construction risk assessment”, Study ID: Pro00068837, approved on March 8, 2017.

Parts of this thesis’ chapters have been submitted for publication as Monzer, I. N., Lourenzutti, T.O.R., Fayek, A. Robinson, and Siraj, N. (2018). “A Framework for Aggregation of Heterogeneous Experts’ Opinions in Construction Risk Assessment.” in review, submitted January 31, 2018. I was responsible for the major parts of the data collection, and Lourenzutti T.O.R, Fayek, A. Robinson, and Siraj, N. were involved with concept formation, composition, editing of the manuscript, and improvement of the analysis and the composition of the manuscript.

Dedication

“Men make their own history, but they do not make it as they please” – Karl Marx

I dedicate this thesis to my extraordinary father and mother.

Through my father’s intelligence, cultural knowledge, kindness and generosity, I have learned to always see beauty in the world, even when darkness takes over.

Through my mother’s astuteness, curiosity, love, and selflessness, I have learned to always being open to new discoveries and life lessons with a best friend to support me forever.

I would also like to thank my caring sisters, who will always know me better than anyone else and can always bring the child in me back to life.

I love my family with my all my heart, and I would never be able to achieve this accomplishment without their constant support and love.

Last, but not least, I would like to show my deepest appreciation to my husband, who has supported me in every step of this tough journey in the last couple of years. Thank you for your patience, mentoring and love.

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CHAPTER 1 INTRODUCTION

1.1 Background

In most fields, a group of individuals or experts with different points of view, backgrounds, and levels of expertise participate in a group decision making (GDM) process with the purpose of achieving a common solution. Participation of several experts in a decision making process is essential when a given problem is multifaceted, ill-structured, or subject to a great deal of uncertainty and when the available alternatives and criteria are imprecise, vague, or belong to a wide range of values (Perez et al. 2011;Vanicek et al. 2009). Group decision making (GDM) is defined as a decision situation in which there is a set of feasible alternatives, $X = \{x_1, x_2, \dots, x_n\}, (n \geq 2)$, and a group of two or more experts, $E = \{e_1, e_2, \dots, e_n\}, (e \geq 2)$, characterized by their own background and knowledge, who recognizes the existence of a common problem and try to reach a collective decision (Herrera-Viedma et al. 2014; Perez et al. 2014; Herrera et al. 1996). Most GDM problems are solved by employing either one of two essential processes: a consensus process or an aggregation process (Cabrerizo et al. 2010). According to Perez et al. (2014), consensus is a dynamic and interactive process, conducted in multistage settings, where the experts discuss and change their opinion step by step with the aim of improving the level of agreement among the group of experts. An acceptable level of agreement should be reached among the experts before choosing a consensus solution. On the other hand, the aggregation process mathematically reduces a set of experts' input values or opinions into one unique representative value, without the need to adjust the experts' initial opinions or reach an agreement. The aggregation of heterogeneous experts' opinions in the field of construction risk assessment will be further studied in this research.

Construction projects involve dynamic environments and constantly changing variables, which increases the risks in the construction industry. To manage risks, construction companies rely on risk analysis techniques and contingency determination procedures. Different techniques have been proposed to analyze risks, such as the probabilistic approach (Ezell et al. 2010) and the traditional deterministic approach (Modarres et al. 2016). The probabilistic approach includes methods such as decision tree analysis (Ahmed et al. 2007), fault tree analysis (Ardeshir et al.

2014), Monte Carlo simulation (MCS) (Salah and Moselhi 2015), failure mode and effect analysis (Mohammadi and Tavakolan 2013), and system dynamics (Nasirzadeh et al. 2008). However, lack of historical data due to the uniqueness of each construction project limits the applicability of probabilistic methods, such as the ones applied in MCS, since it causes difficulties in the estimation of probability distributions for costs (Salah and Moselhi 2015).

On the other hand, the deterministic approach analyzes risk through a single point estimate of potential impacts by assessing the probability and impact of risk and opportunity events (CII 2012). The contingency determination procedure proposed by the Construction Industry Institute (CII) (2012) follows the deterministic (Level 2) approach for calculating the risk severity as the product of the probability and the impact of risk and opportunity events in order to estimate the risk contingency allocation. However, due to the uncertainty inherent in risk analysis, it is challenging to assess the degree of exposure and the appropriate contingency using a single value to determine risk probability and impact in construction projects (Mak and Picken 2000, Elbarkouky et al. 2016). Consequently, a group of experts is frequently involved in the process of risks identification, probability and impact assessment, and contingency determination.

The acquisition and representation of a domain knowledge from these experts is critical for accurately assessing project contingency. The deterministic and probabilistic risk analysis techniques have limited capacity to account for the imprecision and subjectivity present in experts' risk assessment in order to estimate the construction project's risk contingency (Ardeshir et al., 2014). Fuzzy logic (Zadeh 1965) is a valuable tool to handle subjectivity and imprecision inherent in human assessment. In order to account for subjective uncertainties from the expert assessments, Elbarkouky et al. (2016) proposed an approach based on CII (2012) that, instead of using single values for risk probabilities and impact, allows the experts to provide their assessment using linguistic terms, which are represented by fuzzy numbers. Fuzzy numbers can better handle the uncertainty and vagueness of the probability and impact assessment in risk events. Thus, the application of fuzzy logic in the aggregation of heterogeneous experts' opinions in construction risk assessment GDM is the chosen approach in this research.

1.2 Problem Statement

The common approach to address the heterogeneity of a group is by assigning qualitative or quantitative weights to every expert based on their importance degree (i.e., how relevant their expertise is in relation to the problem) (Perez et al. 2014; Herrera-Viedma et al. 2014). Thus, importance weights can be used to determine each expert's level of influence on the final construction risk decision being made (Perez et al. 2011). The first main research gap is that in most previous aggregation approaches the experts' importance weights are commonly assigned by the moderator and do not employ structured mechanisms to evaluate the experts' expertise based on relevant qualification attributes (Herrera-Viedma et al. 2005; Perez et al. 2011; Cabrerizo et al. 2010); second, aggregation approaches that do not use the moderator, usually employ a feedback mechanism for assigning experts' importance weights but these weights do not vary depending on the knowledge of the experts on the specific field (Perez et al. 2011); third, there is no clear guideline or criteria for assigning importance weights to experts based on field related qualification attributes; and fourth most qualification attributes used to assess experts' expertise level in construction risk assessment are qualitative, and thus linguistically expressed, which consequentially requires a fuzzy logic approach to be employed in the experts' model for assigning importance weights to experts.

Generally, the aggregation process is dependent on the aggregation operator, a mathematical object that combines the experts' various opinions into one collective value. The main gaps in applying the aggregation operator to combine heterogeneous experts' opinions are such as: first, there is no clear guideline for selecting a suitable aggregation operator in the field of construction risk assessment. Secondly, most aggregation operators found in literature involve very lengthy and rigorous mathematical algorithms and formulations that could impose limitations towards the ease of the application of aggregation operators in the construction industry field. Thus this research will advance the aggregation process state of art by providing a structured guideline for selecting a suitable aggregation operator in a specific field of application.

In order to develop a framework for aggregating experts' opinions based on their expertise level in construction risk assessment, it is necessary to first determine how to assess experts' expertise level in risk assessment. For this purpose, a list of relevant qualification criteria is developed specifically for construction risk assessment. However, since not all the qualification criteria have the same relevance in assessing expertise level, the FAHP is used to determine the criteria weights. Once the weights of the qualification criteria are determined, the experts involved in the decision making process have their expertise evaluated to determine their opinions' weights.

Next, the experts provide their assessment on probability and impact of risks and opportunities, which will be aggregated based on the experts' weights previously calculated. Finally, the aggregated assessment is used to obtain the final contingency value. Figure 1.1 illustrates the steps of the proposed framework.

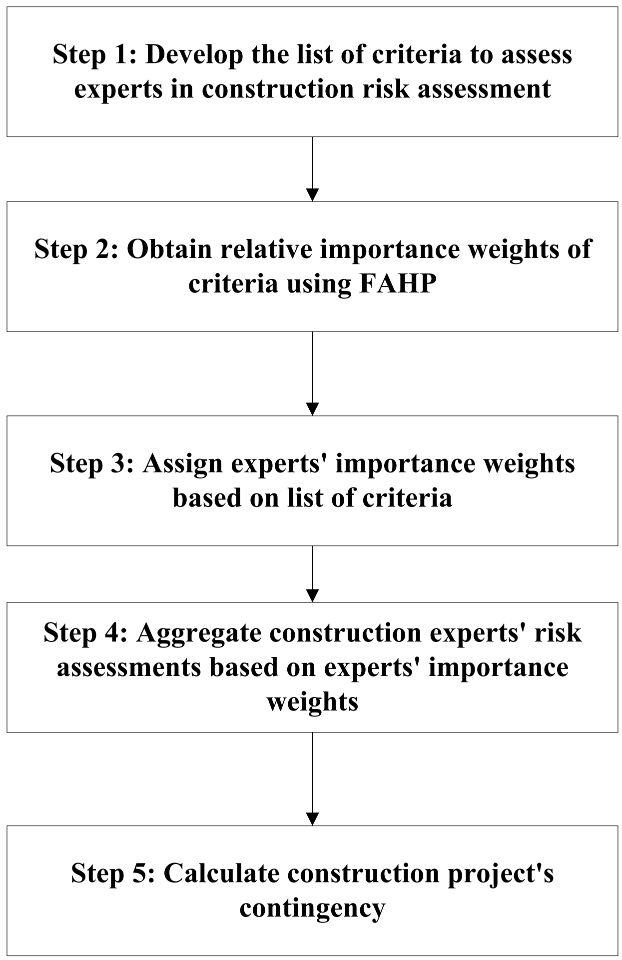

Figure 1.1 Steps in developing framework for construction risk assessment through aggregation of heterogeneous experts' opinions

The illustration of the aggregation framework in a risk assessment case study practically demonstrates the benefits of the developed research. Thus, the proposed aggregation framework will facilitate the process of combining heterogeneous experts' opinions in construction risk assessment GDM problems by implementing the aggregation process.

1.3 Research Objectives

The hypotheses of this research is that aggregating the opinions of heterogeneous experts in construction risk assessment can improve GDM in comparison to implementing a consensus reaching process for risk assessment. The goal of this research is to develop an aggregation framework for combining the opinions of heterogeneous experts in the specific field of construction risk assessment. In order to develop the aggregation framework, the main objectives are to develop (1) a model for assigning importance weights to experts based on their expertise level in construction risk assessment, and (2) to analyze the application of selected aggregation operators in a construction case study for projects' contingency estimation.

The first step of the aggregation process is improved by proposing a new model for assigning importance weights to experts based on a clear and consistent list of criteria for assessing experts' levels of expertise in construction risk assessment. Rather than assigning heterogeneous experts' importance weights arbitrarily and subjectively, the proposed model for assigning importance weights to experts assigns importance weights to experts in the aggregation process based on selected qualification attributes (i.e., knowledge, experience, reputation, performance etc.) and in relation to the specific application field of construction risk assessment. Also, the proposed model for assigning importance weights to experts provides a logical and comprehensive framework for structuring a GDM problem and quantifying its elements. Furthermore, the model addresses the subjectivity and uncertainty characteristic of the construction risk environment by allowing experts to represent their opinions and qualitative qualification attributes using fuzzy linguistic scales.

Moreover, the aggregation framework improves the second aggregation step by developing a comparative analysis of existing aggregation operators that takes into account advantages and disadvantages of each aggregation operator and situations in which each can be used. This comparative analysis assists in aligning the aggregation operators' characteristics and the research goals, thus presenting a structured approach for applying aggregation operators in different heterogeneous GDM scenarios. Furthermore, the aggregation framework is applied in comparing and selecting the most appropriate aggregation operator to incorporate in a specific case study to estimate project's risk contingency values in a construction company.

In conclusion, this research's objective is to support the selection of the appropriate type of aggregation operators based on their suitability and the nature of the GDM problem to be solved. Although in this research the field of study is construction risk assessment GDM, the rationale presented for the selection of the most suitable aggregation operator in the case study context can be transferred to other research fields as well.

The detailed objectives of this research are as follow:

1. To introduce a structured model for assigning importance weights to experts that automates the weight assigning task of the moderator in order to ensure accurate and representative importance weights for heterogeneous experts' in construction risk assessment GDM.
2. To propose a new model for assigning importance weights to experts based on the specific list of criteria for risk assessment and management expertise, while also accounting for the subjectivity and uncertainty in experts' opinions.
3. To investigate the properties, mathematical formulation, advantages, and disadvantages of different aggregation operators and the situations in which they can be applied.
4. To apply a structured framework to risk assessment GDM in order to obtain the probability and impact of risk and opportunity events in a construction project through aggregation of heterogeneous experts' opinions.
5. To compare the aggregation framework risk severity (i.e. risk probability multiplied by risk impact) results with a benchmark (i.e. MCS) in order to determine which aggregation method provides the closest results.

1.4 Expected Contributions

This research study is expected to have several contributions. Some contributions will advance the state of art for researchers and academics and thus are grouped under academic contributions. Other contributions will benefit the construction industry advancement and thus are grouped under industry contributions.

1.4.1 Academic Contributions

The proposed aggregation framework will advance the state of art with the following main academic contributions:

1. Eliminate the moderator judgement from the process of assigning weights to experts in construction risk assessment, and thus avoiding the subjectivity or bias that could possibly be introduced by the moderator assessing experts' expertise level.

2. Address previous research gap of assigning experts' importance weights arbitrarily and subjectively by developing a method to weight experts' importance in risk assessment based on a clear and consistent list of criteria, metrics and scales of measure to evaluate experts' risk assessment expertise.

3. Apply fuzzy set theory to process the subjectivity and vagueness inherent in human assessments since the experts' opinions for both the qualification criteria assessment and the risk assessment are captured by linguistic terms, which are modelled using fuzzy numbers, in the aggregation framework.

4. Propose a guideline for applying aggregation in a construction risk assessment GDM scenario by providing a systematic multi-step methodology that assesses the experts' expertise level in construction risk assessment and assigns weights to the experts according to their expertise. The aggregation framework obtains the construction project risk contingency by assessing the risk and opportunity events probability and impact.

1.4.2 Industrial Contributions

The proposed aggregation framework is expected to make the following industrial contributions:

1. Allowing construction risk assessment experts to express their opinions in comparing and ranking the list of criteria importance using linguistic terms, which better represent human thinking.

2. Offering a better performance to the construction risk assessment GDM by avoiding the consensus process and using the aggregation framework, which offers a quicker process and does not depend on the availability of historical data for probabilistic distribution estimation (such as the MCS).

3. Improving the process of heterogeneous group decision making in the construction risk assessment field by proposing a clear and consistent list of criteria to assess experts' expertise levels and assigning experts' importance weights in the aggregation framework.

4. Illustrating the aggregation framework in a construction project case study which illustrates a structured methodology to be applied in industry applications for combining heterogeneous experts' opinions in construction risk assessment.

1.5 Research Methodology

The aggregation framework in this research will be developed over three main stages:

1) Literature Review of group decision making techniques, such as consensus reaching process and the aggregation process. Also, a comprehensive review of existing aggregation operators is developed.

2) Compilation and validation of a list of criteria, corresponding metrics and scales to assess heterogeneous experts' expertise level and development of the fuzzy model for assigning importance weights to experts in the construction risk assessment field.

3) Analysis and selection of a suitable aggregation operator for the construction risk assessment case study scenario by the implementation of the aggregation framework in a risk assessment software for project's contingency estimation.

The first stage includes a broad literature review related to group decision making techniques for combining heterogeneous experts' opinions. The two techniques described are the consensus reaching process and the aggregation process. A comprehensive review of previous aggregation operators' properties and applications are presented.

In the second stage, a comprehensive review of qualification attributes to assess experts' expertise level in construction risk assessment is conducted and a clear and consistent list of criteria to evaluate experts' expertise level is proposed. Data is collected from industry experts to validate the list of criteria, scale of measure and metrics developed during group meetings and through questionnaires and surveys. Also a detailed and extensive review of previous experts' importance model for assigning importance weights to experts is conducted and the need for an innovative, clear, and structured model for assigning importance weights to experts in construction risk assessment is justified. The fuzzy model for assigning importance weights to experts is developed and validated also based on data input from industry experts in the form of questionnaires.

Finally, a comparative analysis of selected aggregation operators is developed based on the specific case study in construction risk assessment GDM. The research is completed by presenting the aggregation framework results using a risk contingency software tool for an industry case study. A sensitivity analysis of the aggregation framework results and other software parameters in comparison to the benchmark MCS results is developed. The aggregation framework results in the case study are also compared to the consensus results obtained.

The flowchart below (Figure 1.2) describes the step-by-step methodology applied in this research. It is important to note that the methodology proposed in this research is specific to the construction risk assessment field, with a case study application in the risk contingency calculation GDM. However, it is possible to generalize the methodology approach discussed in this chapter to any other specific field where group decision making is being applied.

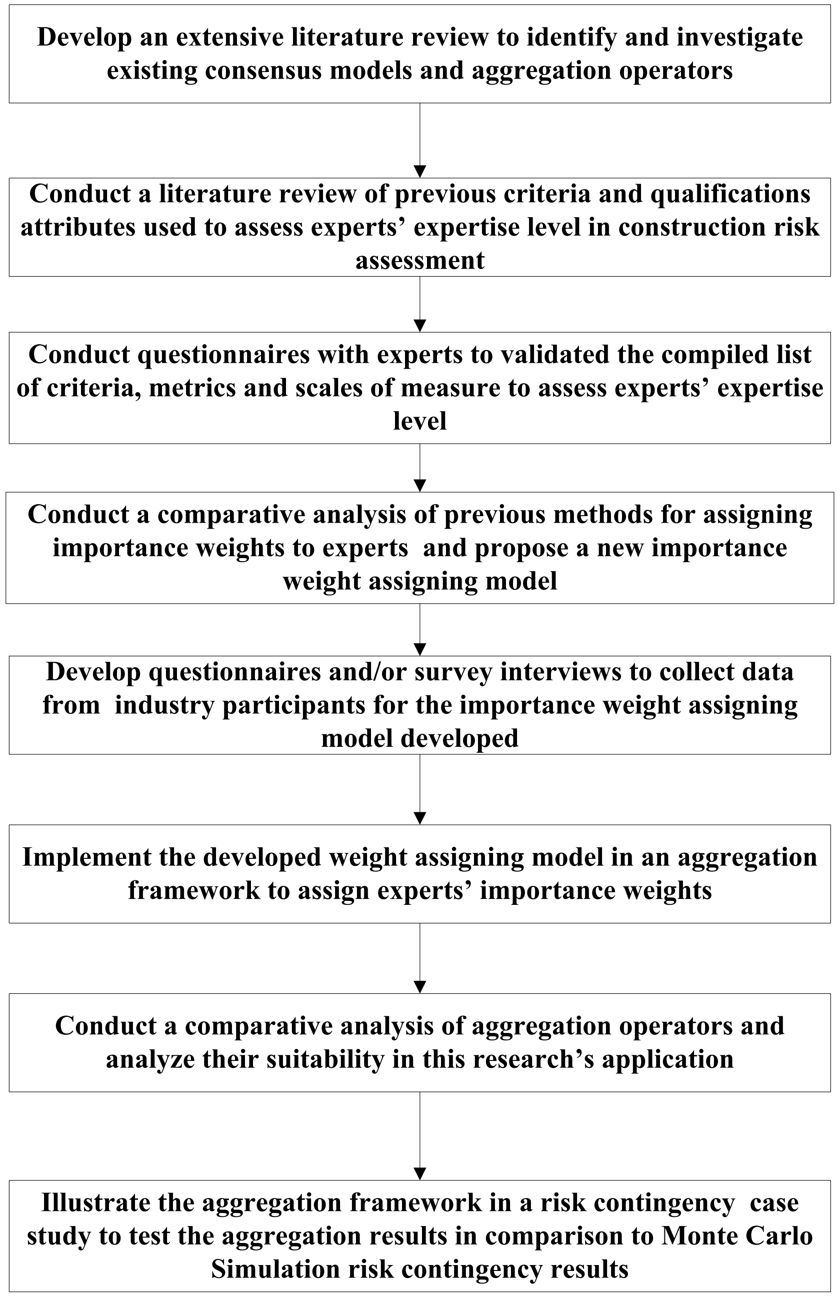

Figure 1.2 Research's step by step methodology for developing an aggregation framework

1.6 Thesis Organization

Chapter 1 presents a brief background of this research and the problem statement motivating this study. Also, the main research objectives and contributions are presented along with the research methodology.

Chapter 2 provides a literature review about group decision making techniques such as the consensus and aggregation processes. Also, a comprehensive review of previous aggregation operators' properties, mathematical formulations and applications is presented.

Chapter 3 covers the step-by-step methodology applied to compile a list of criteria for assessing experts' expertise level in construction risk assessment and to develop a new model for assigning importance weights to experts. The list of criteria and the model for assigning importance weights to experts are validated through data collected from construction risk assessment experts.

Chapter 4 describes the comparative analysis of aggregation operators, and presents the developed aggregation framework, by the implementation of the model for assigning importance weights to experts along with the aggregation operators in a case study. The aggregation framework is validated by performing a sensitivity analysis of the various parameters involved in the construction risk assessment case study.

Chapter 5 describes the conclusions, contributions and limitations of this research while also presenting recommendations for future research.

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CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

The construction risk assessment and management process often involves heterogeneous group of experts various levels of expertise who must collectively make decisions and reach a common solution. Involving a group of heterogeneous experts in GDM problems has proven to improve the set of solutions and decisions to the problem. However, real-life group decision making involves a great deal of uncertainty and subjectivity. Also, the process of combining GDM heterogeneous experts' opinions has been thoroughly studied in past decades due to its complexity and its unclear methods (Dubois and Prade 2004, Vanicek et al. 2009, Perez et al. 2011, Palomares et al. 2014). In order to address these challenges, this research explores the application of fuzzy logic in contexts involving the combination of heterogeneous experts' opinions in GDM problems.

This chapter describes the process involved in GDM scenarios and discusses the two different approaches used for combining GDM heterogeneous experts' opinions: the consensus reaching process (CRP) and the aggregation process. A brief review of previous consensus models is developed, however due to hindering CRP limitations, the GDM approach chosen for combining heterogeneous experts' opinions in this research is the aggregation process. Thus, a thorough review of the processes necessary for aggregating the opinions of GDM heterogeneous group of experts in order to achieve one unique and representative problem solution is developed. The literature review of the aggregation process consists of a detailed analysis of existing crisp and fuzzy aggregation operators by outlining the main properties and applications of each.

2.2 Literature Review of GDM

In GDM scenarios each expert may have different motivations or visions about a specific set of alternatives involved in the decision making, thus each expert may approach the GDM from a different point of view but all of the experts have the common goal of reaching a final agreement on the best set of solutions (Cholewa 1985; Herrera et al. 1996; and Perez et al. 2014). Due to the complexity of GDM, it is increasingly difficult to incorporate all experts' opinions in the solution achieved. However, GDM has several important goals such as (i) identifying and better appreciating the difference and common areas among experts, (ii) considering the relationship amongst criteria before a decision is made, (iii) expressing experts' opinions by ranking alternatives, (iv) evaluating and rating alternatives, and (v) choosing the best alternative from a final set of selected alternatives. Finally, the main goal of GDM is to (vi) narrow down a final set of alternatives for solving a problem, by adopting a participative and flexible approach, that allows the group of experts DMs to explore their different opinions (Muralidharan et al. 2002).

It is possible to separate the GDM into two different types: the heterogeneous GDM and the homogenous GDM. In a homogenous environment all experts are considered to have the same level of knowledge in the subject being analyzed, thus the experts have equal importance and add equal value to the GDM problem (Muralidharan et al. 2002; Herrera-Viedma et al. 2014). However, a more comprehensive resolution for any GDM problem should involve experts with different backgrounds and expertise levels, since this way, the experts heterogeneous backgrounds would encompass most of the possible different views for reaching a decision. Thus, the heterogeneous GDM scenarios present a richer environment for making complex decisions. Previous research has shown that heterogeneous GDM results in better group decisions than homogenous GDM decisions (Cholewa 1985; Chen and Chen 2005).

Nevertheless, regarding the process of GDM, most real-world problems being analyzed in the process do not have well defined parameters and objectives. In the past, probabilistic methods have been suggested to deal with the uncertainty in real-world GDM problems. However due to the imprecision, vagueness and subjectivity involved in most of these GDM problems, the probabilistic quantitative approaches, that account for random uncertainty, do not manage to overcome the lack of precision obstacles in order to solve these real world problems (Herrera et al. 1998; Vanicek et al. 2009; Palomares et al. 2014). In most recent years an alternative solution has been the application of fuzzy logic and fuzzy set theory (FST) to solve these real world ill-defined GDM problems. One of the advantages of using fuzzy theory when dealing with GDM problems is that some of the alternatives and criteria are better analyzed qualitatively in order to incorporate more human consistency and "Human Intelligence" to the process. In other words, by using FST, it is feasible to translate the fuzziness of human judgements to quantitative measures in GDM problems (Bardossy 1993; Hsu and Chen 1996; Lee 1999).

In conclusion, due to the complex relation between group decision making, fuzziness and aggregation the aim of this research will be to further analyze the available methods for aggregation of heterogeneous experts' opinions in order to provide a systematic and easily accessible model to perform the analysis necessary.

2.3 Literature Review on Approaches for GDM: Consensus and Aggregation

2.3.1 Consensus Background

There is a vast area of continuous research for improving the existing methods of grouping (i.e., combination) of different experts' opinions into one collective opinion. Following one of the GDM techniques, the commonly used process for the combination of experts' opinions is the consensus reaching process (CRP) (Cabrerizo et al. 2010). A consensus reaching process is a negotiation process conducted iteratively in multistage settings where the experts discuss and change their opinions or preferences in order to reach a common agreement (Herrera et al. 1996, Herrera-Viedma et al. 2014; Perez et al. 2014). It is important to point out that consensus decision making does not necessarily mean reaching a complete agreement among all experts, it simply means trying to consider all individual opinions in order to attain a collective consent of all participants and choose the most beneficial option to the whole group. The nature of the consensus reaching process is based on cooperation in contrast with other GDM settings that might involve competition (i.e., when it comes to voting or gaming) (Herrera-Viedma et al. 2014). Nevertheless, consensus should reflect the opinion of all involved experts. After the consensus reaching process (CRP) is finalized, the collective consensus opinion (i.e., social opinion from the global ranking) of experts is formed.

Previous literature by Herrera-Viedma et al. (1998) first suggested a GDM process that was subsequently used by several authors such as Herrera-Viedma et al. (2005), Perez et al. (2011), and Cabrerizo et al. (2010). The GDM process is based on the consensus reaching process having iterations rounds coordinated by a moderator. The group of heterogeneous experts selected for consensus should have an extensive knowledge in different areas in order to cover all the decision criteria. Consequently, the chosen moderator should also have a deep knowledge about the problem and all the alternatives and criteria involved in it. Also, the moderator has to be able to select a set of experts that demonstrate higher knowledge and experience in the subject in order to assign them with higher values of importance weights. Thus, the moderator's task of assigning weights to experts is a well-defined task in order to accurately manage and fairly classify experts. In order to further improve the consensus process, the moderator also has the power of assigning different importance weight values to the different criteria involved in the decision making process (Perez et al. 2011).Several researchers have attempted to automate the task of the moderator and to carry out the entire consensus reaching process automatically. For example, Perez et al. (2014) presented a new consensus model for a heterogeneous group of experts that incorporates a feedback mechanism capable of generating and customizing the recommendations to each expert depending on the importance or relevance level of the expert in the group based on his/her own knowledge about the problem under investigation.

However, due to the vague knowledge of each expert in relation to a specific criterion of evaluation or alternative during the GDM, the experts might not be able to give a numerical evaluation with exact precision for each alternative. Hence, a more representative approach to incorporate the experts' human judgments is to use linguistic assessments and natural language, instead of using exact numerical values. Fuzzy logic provides a solution to the representation and processing of imprecise information and opinions in the consensus reaching process (CRP). Furthermore, in a fuzzy environment a group decision problem is taken out as follows: there are a finite number of experts that can choose amongst a finite number of alternatives. Thus, each variable involved in the decision problem will be assessed by means of linguistic terms (Vanicek et al. 2009).Several consensus models have been proposed to deal with GDM problems in a fuzzy context (Tanino 1984, Bardossy et al. 1993, Hsu and Chen 1996, Herrera et al. 1998, Lee 1999, Muralidharan et al. 2002, Herrera-Viedma et al. 2014, Palomares et al. 2014). Consensus reaching processes being done in the fuzzy environment aim at classifying a set of alternatives from best to worst associating with them some degrees of preference expressed in the $[0,1]$ interval (Herrera-Viedma et al. 2014).

Another suggestion found in past literature (ElBarkouky et al. 2010a, ElBarkouky et al. 2010b, Awad and Fayek 2012, Marsh and Fayek 2010) to improve the consensus reaching process (CRP) is to assign weights to experts taking into consideration the level of knowledge of an expert on specific domain related criteria. This process takes into account the experts knowledge level as well as the criterion followed by experts to assess an alternative. In other words, an expert may be more experienced than another in a specific domain of study (i.e., procurement) based on certain assessment criteria while another expert may be more knowledgeable in another domain of study (i.e., risk management) decision making process based on different analysis criteria. Thus, some recent consensus models also take into consideration the importance weight of the expert before changing their input in the consensus iteration rounds. Experts with higher importance weights values do not adjust their opinions as much as experts who have lower values of importance weights and have opinions not significantly similar to the consensus (Herrera-Viedma et al. 2014). Fuzzy consensus models that combine experts' importance weights and consensus measures have been developed in the literature (Grabisch et al. 1998, Lee 1999, Peneva and Popchev 2003, Xu 2007, Xia et al 2013, Wei et al. 2013, Herrera-Viedma et al. 2014).

2.3.2 Consensus Limitations

The following gaps exist in research on heterogeneous consensus approaches:

1. In most heterogeneous consensus models, the weights of the experts are taken into consideration only when combining heterogeneous experts' opinions and are rarely considered as an input in the feedback mechanism when advising the experts to change their opinions and preferences (Herrera-Viedma et al. 2014).
2. The importance weights of the experts do not vary depending on the knowledge of the experts on the alternative and criteria; rather the weights are arbitrarily assigned and fixed throughout the consensus process regardless of what is being assessed by the experts (Perez et al. 2011).

3. In most consensus reaching models, the weights for the experts are commonly assigned by the moderator and do not employ a structured and clear model to assign importance weights to experts based on certain qualification attributes relevant to a domain of study.

One of the main disadvantages of performing a consensus process would be the time consuming administration effort necessary in order to organize the consensus sessions and coordinate all the participants. Another main disadvantage would be the influence that higher hierarchically positioned, or more experienced experts, may have in the discussion process and this might intimidate the other participants to express their opinions more freely. Actually, in previous focus groups experts have expressed disadvantages of the consensus reaching process as feeling compelled to adhere to the most assertive expert, such as the expert that first speaks or the expert that speaks the loudest. Furthermore, taking into consideration that confidence is not equivalent to competence, and assuming that the experts that easily express their opinions would be influencing experts that actually might know more about the field, criteria and alternatives being discussed in the group decision making, then the collective consensus decision being made is inaccurate, imprecise and definitely not aligned with all the experts' opinions. Thus, a discordant expert may feel obliged to change his or her preferences significantly to attain the required level of agreement among all participants.

In conclusion, the consensus reaching process may be ineffective and time consuming since it may not be representative of the group of experts' opinions; and it may be expensive since some cases can require several iteration rounds until experts' agreement is reached (Vanicek et al. 2009). Consequently, to all these drawbacks, some might opt to using another GDM technique instead of the consensus reaching. In this research, the suggested GDM technique to combine heterogeneous experts' opinions is the aggregation process. The main advantage of applying the aggregation process instead of the consensus process is the simplification of the process of combining heterogeneous experts' opinions. The application of the aggregation process does not require the experts' agreement on a collective opinion and is further detailed in the following sections.

2.3.3 Aggregation Background

In the aggregation process, the consensus process does not exist (i.e., no forming of a social opinion first), but the phases involved in the aggregation process are organized as: initial exploitation phase and aggregation phase. In the initial exploitation phase the GDM problem, alternatives and criteria are further analyzed. Also in this first phase the experts' expertise level is assessed and importance weights are assigned to experts. The aggregation process phase can be simply defined as a mathematical function that can reduce experts' preferences to one unique representative value without the need to adjust experts' opinions first (Hsu and Chen 1996). The aggregation process combines heterogeneous experts' opinions according to each expert's expertise level in the specific GDM problem domain; the heterogeneous group of experts individually assesses the problem and alternatives and provides personal opinions as solution inputs. Then, the decision maker combines the experts' opinions mathematically, through the aggregation process, and finally provides a collective solution to the problem. As previously mentioned, in this research the aggregation process is divided into two steps: (i) assessing experts' levels of expertise and assigning importance weights to experts; and (ii) subsequently applying an aggregation operator to combine the heterogeneous experts' opinions.

Moreover, there are many situations of GDM where aggregations of qualitatively and linguistically measured decisions have to be translated into numerical values in order to prioritize preferences chosen. However, this transformation can result in loss of important subjective information contained in the qualitative evaluation, thus it is suitable to use fuzzy-based aggregation methods to maintain the set of solutions' linguistic forms. Furthermore, because the aggregation of experts' decisions and choice of alternatives constitutes a major success factor in combining the opinions of heterogeneous experts, the aggregation of preferences in Fuzzy-GDM has been widely studied (Xu 2007; Xia et al 2013; Wei et al. 2013). An overall review of a few crisp and fuzzy aggregation operators, such as, ordered weight averaging (OWA), fuzzy similarity aggregation method (FSAM), linguistic ordered weight averaging (LOWA), induced ordered weight averaging (IOWA), and fuzzy number induced ordered weight averaging (FN-IOWA) will be presented in this research (Yager 1988, Hsu and Chen 1996, Herrera et al. 1998, Chen and Chen 2005, Lu et al. 2006, Elbarkouky et al. 2014).

2.4 Literature Review on Aggregation Operators

The main feature of the any aggregation process is to use aggregation operators. There are two main categories of aggregation operators: 1) crisp aggregation operators used to combine experts' preferences represented as crisp numbers, and 2) fuzzy aggregation operators that are used to combine experts' preferences represented as linguistic terms (which can be transformed to interval numbers, or fuzzy numbers) (Omar and Fayek 2016). Whenever group decision making involves solution alternatives and options that cannot be estimated with an exact numerical value, a more significant representation of experts' opinions is provided through linguistic assessment and natural language. Fuzzy aggregation operators are used to combine the different experts' linguistic preferences in a group decision making scenario. More specifically, in construction group decision making processes, there are many applications that require fuzzy aggregation, such as the evaluation of contractors bidding for a construction project. The criteria to evaluate the contractor includes qualitative qualification attributes, such as bonding capacity, budget and track record of previous projects, that are better expressed linguistically instead of numerically (such as in crisp aggregation operators) (Siraj et al. 2016).

Previous literature (Peneva and Popchev 2003; Herrera-Viedma et al. 2014; Palomares et al. 2014) developed fuzzy aggregation operators to combine experts' linguistic preferences represented by fuzzy numbers and produce a single representative fuzzy number or crisp value. The individual fuzzy sets (or fuzzy number) of experts' evaluations can be aggregated point by point into the aggregation function and only then the aggregation operators can be applied. Considering a group $E = \{e_1, \ldots, e_m\}$ of experts and each of them has an opinion represented by a fuzzy membership function (Vanicek et al. 2009). The aggregation mapping is done point by point by using an aggregation operator λ according to four main properties and to the formula:

$$\lambda(f_1, f_2, \ldots f_m) = h\big(f_1(x), f_2(x), \ldots f_m(x)\big) \qquad (2.1)$$

Where $h: [0,1]^m \rightarrow [0,1]$ is a function defined in an m-dimensional universe that satisfies the four main properties (Vanicek et al. 2009):

1) $h(0,0, \ldots ,0) = 0$ …Boundary Conditions;

2) $h(1,1,\ldots,1) = 1$ …Boundary Conditions;

3) h is monotonic: $\forall_j = 1, \ldots, m: p_j \leq q_j \rightarrow h(p_1, p_2, \ldots, p_m) \leq h(q_1, q_2, \ldots, q_m)$;and

4) h Is continuous.

Thus, it can be concluded that these considerations allow the functions to be investigated separately on the points of universe instead of operators defined on the function spaces (Detyniecki 2001 and Vanicek et al. 2009).

There are several properties for aggregation operators (Detyniecki 2001, Calvo et al. 2012, and Omar and Fayek 2016). The most relevant properties to this research are discussed below:

1. Boundary Condition: Constrains the results of the aggregation function to the minimal and maximal boundaries. $f(x)$is the aggregation function with $f(0, \ldots, 0) = 0$ and $f(1, \ldots, 1) = 1$ where $x \in [0,1]$and x represents the expert' s opinions.

2. Monotonicity (non-decreasing): Functions have a non-decreasing relationship between the criteria and the output of the aggregation. $x_i' > x_i$ then $f(x_i') \geq f(x_i)$ where $x \in S$ and x represents the expert^' s opinions and $f(x)$is the aggregation function.

3. Continuity: There is no chaotic reaction in the outputs due to a small error in the inputs, which ensures the robustness of the aggregation operator. $U_{x \in S}[0,1]^x \rightarrow [0,1]$ is a continuous aggregation function if $f(x)$ $[0,1]^x \rightarrow [0,1]$.

4. Associativity: The choice of the group should not influence the overall result of the aggregation. The formula that represents the associativity property is: $f(x)$ is the aggregation function with $f((x_1, x_2, \ldots, x_n) = f(f(x_1, x_2, \ldots), x_n)$ and x represents the experts' opinions.

5. Symmetry: The order of the arguments has no influence on the result. This property is compulsory when the aggregation is made of arguments having the same importance or arises from anonymous experts or sources.

6. Commutativity Condition: Considered when there is equal importance between criteria, the ordering or ranking of arguments is irrelevant such as, $f(x)$is the aggregation function with $f(x_1, x_2, \dots, x_n) = f(x_2, x_1, \dots, x_n) = f(x_n, x_1, x_2 \dots)$ and x represents the expert' s opinion.

7. Idempotence: Strongest form of unanimity or agreement. By aggregating the same initial value n times, the result is the initial value such as, $f(x, x, x, \dots, x) = x$.

Furthermore, an operator is considered invariant if it does not depend on any given scale. An operator is considered shift-invariant if it depends on a fixed unit of measurement but the beginning of the scale is not fixed (i.e., “zero” is free). An operator is considered homogenous if the beginning of the scale is fixed but the unit of measurement is not. Comonotone additive operators can be represented as increasing functions of a single random variable. Additive operators assume that all attributes are independent (Calvo et al. 2012). Additive aggregation operators are related to the weighted means and comonotone additive operators are not. Note that if an operator is comonotone additive it is not necessarily additive, however if it is additive the operator is ensured to be comonotone additive as well (Calvo et al. 2012).

In previous literature the aggregation operators have been divided into Function Classes (Omar and Fayek 2016). Table 2.1 displays the categorization given to existing aggregation operators. The following sections will provide an overview of some relevant operators that are classified in Table 2.1 with a specific focus on the future application of these aggregation operators in the construction risk management field.

Table 2.1 Aggregation functions classes (adapted from Omar and Fayek (2016))

Aggregation Function Class	Aggregation Function Class Description	Aggregation Function Example
1. Conjunctive functions	This class of functions considers criteria that have a logical union “or” relationship.	t-conorm

Aggregation Function Class	Aggregation Function Class Description	Aggregation Function Example
2. Disjunctive Functions	This class of functions considers criteria that have a logical intersection “and” relationship.	t-norm
3. Compensative/compromise functions	This class of functions considers operators that are comprised between the union “or” and “and” relationship. They are neither conjunctive nor disjunctive.	Arithmetic mean, median, and order statistic
4. Non-compensative functions	This class of functions encompasses the compensative class, but extends beyond the minimum and maximum functions.	Symmetric sums, combined t-norm, and t-conorm
5. Weighted functions	This class is considered an extension to the compensative functions. The weighted functions class aims to eliminate the neutrality of the criteria being aggregated.	Ordered weighted arithmetic, weighted sum, ordered weighted average

2.4.1 Disjunctive Minimum and Conjunctive Maximum Aggregation Operators

The aggregation operators initially developed were basically dependent on general concepts of logical mathematical functions, such as minimum and maximum operators, to aggregate the experts’ preferences. The minimum and maximum operators represent respectively disjunction or conjunctions of fuzzy sets. These operators have also been classified as non-additive aggregation operators (Siraj et al. 2016). The minimum and maximum operators can be linguistically represented as "and" and "or” respectively. In previous literature (Chiclana et al. 2007, and Yager 2004a) the minimum operator has been defined as having the lower experts’ importance weights to play a more significant role, and this was proposed to limit the power of veto (further explained in section 2.5.2.1). The minimum operator has a t-norm (triangular norm) as a transformation function. On the other hand, the transformation function that represents the maximum operator is the t-conorms function (triangular conorm) (Chiclana et al. 2007). Transformation functions are used to change the preference representation of an expert’s opinion, for example to change a linguistic preference to a numerical value. The minimum and maximum operators can be used in mixed environments (i.e., crisp and fuzzy) where experts' preferences can be expressed as numeric or linguistic variables. For instance, if the expert presented his opinion as a linguistic value, Herrera-Viedma et al. (2005) presented a transformation function $T_{(S_i\, S(T))}$ to transform it into a fuzzy set (Herrera-Viedma et al. 2005). Naturally, the transformation function depends on the characteristic of the aggregation operator.

The application of maximum and minimum operators is represented by (Xu and Da 2003):

$$f(a_1, a_2, \dots, a_n) = max\,\{a_i\} \qquad (2.2)$$

$$f(a_1, a_2, \dots, a_n) = min\,\{a_i\} \qquad (2.3)$$

Where $(a_1, a_2, \dots, a_n)$ represent the collection of alternatives and f is the maximum or minimum aggregation operator respectively. The minimum and maximum operators are monotone, symmetric, associative and idempotent.

However, it has been shown in previous literature that the disjunctive and conjunctive operators do not always match the decision maker's attitudes when aggregating linguistic categories (Dubois and Prade 1985). In conclusion, due to the minimum and maximum operators not having the additive property, not being compensatory (not able to obtain an aggregated value "in the middle"), and only being able to aggregate numerical variables (unless using transformation functions), they have been considered inferior to other proposed operators that are described in the following sections.Several operators have been introduced to the literature to address the gaps found in the disjunctive and conjunctive operators. These aggregation operators can be found below and they addressed gaps of the minimum and maximum operator such as the linear property that makes these operators shift-invariant and homogenous, comonotone additive but not additive (Calvo et al. 2012).

2.4.2 Average Functions Aggregation Operators

2.4.2.1 Crisp Average Aggregation Operators

The functions that use average or mean as aggregation operators are also called compensative or compromise functions, which represent the union of the "or" and "and" relationships. The compensative aggregation operators are neither static conjunctive nor disjunctive (Omar and

Fayek 2015). Averaging aggregation operators (arithmetic average or fuzzy means) satisfy the idempotent condition and are invariant with respect to permutation of indices.

2.4.2.1.1 Arithmetic Averaging (AA) Aggregation Operator

The first relevant and most basic aggregation operator used to combine experts' crisp opinions is the arithmetic averaging operator (AA) (Cholewa 1985; Detyniecki 2001; Xu and Da 2003, Calvo et al. 2012). The arithmetic averaging operator (also called the arithmetic mean), provides an aggregated value that is smaller than the greatest argument and bigger than the smallest argument (Xu and Da 2003and Calvo et. 2012). Let $\{a_1, a_2, \dots, a_n\}$ be a collection of arguments and let $f: R^n \rightarrow R$, the AA operator is represented as (Equation 2.4):

$$f(a_1, a_2, \dots, a_n) = \frac{1}{n}\sum_{i=1}^{n} a_i \qquad (2.4)$$

The resulting aggregation is the "middle value", reinforcing the compensation property of the AA operator. Thus, the AA operator is used since it is simple and satisfies the properties of monotonicity, continuity, symmetry, associativity, idempotence and stability for linear transformations. However, the AA operator is nonabsorbent (Equation 2.5) and has no behavioral properties, such disjunctive and conjunctive behaviors (Detyniecki 2001 and Calvo et al. 2012).

If the aggregation operator has an absorbent element b then it can be used like an eliminating score or like a veto (or it can also be considered as a qualifying score) (Detyniecki 2001):

$$f(x_1, \dots, a, \dots, x_n) = b \qquad (2.5)$$

Where, f is the aggregation operator function and $(x_1, x_2, \dots, x_n)$ are the arguments.

2.4.2.1.2 Weighted Arithmetic Average (WAA) Aggregation Operator

An extension of the AA is the weighted arithmetic average (WAA) operator (Cholewa 1985; Detyniecki 2001; Calvo et al. 2012). The weighted arithmetic average (also called the weighted mean) is used when there are $n \geq 2$ experts in the group decision making, with specific experts' importance weights of $w = (w_1, w_2, \ldots, w_n) \in (0,1)^n$ satisfying the condition $\sum_{j=1}^{n} w_j = 1$ (Beliakov and Warren 2001; Detyniecki 2001). Considering the same collection of arguments and function domain as presented for the AA, the WAA is defined as (Equation 2.6):

$$f(a_1, a_2, \ldots, a_n) = \sum_{i=1}^{n} w_i a_i \qquad (2.6)$$

Note that if $w = \left(\frac{1}{n}, \frac{1}{n}, \ldots, \frac{1}{n}\right)$ then f is reduced to the AA operator. The WAA operator satisfies the idempotency condition but does not satisfy the symmetry condition (Detyniecki 2001 and Vanicek et al. 2009). Thus, the result of the aggregation can depend on the order of inputs.

A few more extended examples of averaging operators are the generalized means, the quasi-arithmetic means, h_α, defined for the real number α Equation 2.7 (Detyniecki 2001 and Vanicek et al. 2009):

$$h_\alpha(a_1, a_2, \ldots, a_n) = \left(\frac{1}{n}\sum_{i=1}^{n} a_i^\alpha\right)^{\frac{1}{\alpha}} \qquad (2.7)$$

For the special choices of parameters we obtain:

- $\alpha = 1$ ….. arithmetic mean
- $\alpha = 2$ ….. quadratic mean
- $\alpha = -1$ ….. harmonic mean
- When α tends to $-\infty$, the Equation 2.7 tends to the maximum operator.
- When α tends to $+\infty$, the Equation 2.7 tends to the minimum operator.
- When α tends to 0, the Equation 2.7 tends to the geometric mean (Section 2.5.4).

2.4.2.2 Fuzzy Average Aggregation Operators

2.4.2.2.1 Fuzzy Weighted Average (FWA) Aggregation Operator

The fuzzy weighted average (FWA) operator is part of the additive class of operators (Siraj et al. 2016). The additive class of aggregation operators consists of operators that additively combine each expert's preferences into one collective value representing the experts' overall evaluation of a give group decision making problem.

Several studies have discussed the FWA operator (Dong and Wong 1987, Bardossy et al. 1992,, Liou and Wang 1992, Xu and Da 2003, Chen and Hwang 2012, Liu et al. 2013, Siraj et al. 2016). Let $f: \Theta^n \rightarrow \Theta$ where Θ is the set of all fuzzy numbers. The general formula for the FWA operator is given in Equation 2.8 (Dong and Wong 1987 and Xu and Da 2003):

$$f(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \sum_{i=1}^{n} w_i \tilde{a}_i \Big/ \sum_{i=1}^{n} w_i \qquad (2.8)$$

Where $w = (w_1, w_2, \dots, w_3)$ is the weighting vector and $\tilde{a}_i \in \Theta$.

If the weights in w are already normalized then $w \in (0,1)$ and $\sum_{j=1}^{n} w = 1$ then a simplified application of the FWA operator is given by Equation 2.9 (Siraj et al. 2016):

$$f(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \sum_{i=1}^{n} w_i \tilde{a}_i \qquad (2.9)$$

An extension of the averaging aggregation operators is the weighted functions operators presented in the next section. The weighted function operators aim at eliminating the neutrality (or absorbent) property of the averaging aggregation operators (Omar and Fayek 2016).

2.4.3 Ordered Weighted Functions Aggregation Operators

2.4.3.1 Crisp Ordered Weighted Aggregation Operators

2.4.3.1.1 Ordered Weighted Averaging (OWA) Aggregation Operator

A landmark for the study of aggregation operators was through the research of Yager (1988) that introduced a new type of operator called the ordered weighted averaging (OWA) operator. This operator has the properties of lying between the "and" and "or" operators by providing the lower and upper bounds as the largest "and" operator (i.e., min) and the smallest "or" operator (i.e., max) respectively. In other words, the OWA operator requires satisfaction of all the criteria but it also requires the satisfaction of at least one of the criteria. This method is useful to weight each answer according to the qualification or the competence of the participants, and the weights depend on the order of preference instead of depending on the source of information. In other words, the weight assigned is not dependent on the expert that provided the input opinion; the weight is dependent on the ordered evaluation values being organized in ascending or descending order. Thus, the input information first has to be ordered and then the weights are determined in this exact same order

The weights associated with the OWA operator are defined as $w = (w_1, w_2, \dots, w_n)^T$ such that $w_j \in [0,1]$ and $\sum_{j=1}^{n} w_j = 1$ (Yager 1988, and Xu and Da 2003). The OWA operator is defined mathematically as (Yager 1992, 1998):

$$f(a_1, a_2, \dots, a_n) = \sum_{j=1}^{n} w_j b_j \qquad (2.10)$$

where b_j is the j^{th} largest element of the a_i.

The mathematical formulas for computing the weights of the OWA operator using linguistic quantifiers are based on the non-decreasing quantifier Q which is given by this expression (Yager 1993, , Herrera et al. 1996):

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right) \quad i = 1, \dots, n \qquad (2.11)$$

where n is the dimension of the OWA operator (the number of experts that the weights w_i will be applied to).

2.4.3.2 Fuzzy Ordered Weighted Aggregation Operators

2.4.3.2.1 Fuzzy Ordered Weighted Averaging (FOWA) Aggregation Operator

The simplest form of weighted aggregation operator applied in combining heterogeneous experts' linguistic opinions would be the fuzzy ordered weighted averaging (FOWA) aggregation operator (Yager 1985; Merigo and Casanovas 2008; Merigo 2011). The FOWA aggregation operator is simply an extension of the OWA operator for uncertain situations where the available data input and knowledge source can be assessed using fuzzy numbers. The FOWA aggregation operator is capable of parameterize a family of aggregation operators such as the fuzzy maximum, fuzzy minimum, and the fuzzy average criteria. Also, the FOWA aggregation operator has similar properties as the OWA aggregation operator. The FOWA aggregation operator is commutative, monotonic, bounded and idempotent. The weighting vector w_j can be altered in order to obtain different types of FOWA operators, such as the step-FOWA operator the window FOWA operator and the FOWA median operator (Merigo and Casanova 2008, Merigo 2010, Merigo 2011).

Let $f: \Theta^n \rightarrow \Theta$ where Θ is the set of all fuzzy numbers. The formula for applying the FOWA aggregation is (Equation 2.12):

$$f(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \sum_{j=1}^{n} w_j \tilde{b}_j \qquad (2.12)$$

Where $w = (w_1, w_2, \dots, w_n)$ is the weighting vector and of the $\tilde{a}_i \in \Theta$, which means $\tilde{a}_i$ are fuzzy number representing the experts' opinions in GDM. Also, $w \in (0,1)$ and $\sum_{j=1}^{n} w_j = 1$, and $\tilde{b}_j$ is the largest jth of the $\tilde{a}_i$.

2.4.3.2.2 Induced Ordered Weighted Averaging (IOWA) Aggregation Operator

Another highly significant aggregation operator in the literature is a variant of the OWA aggregator, the induced ordered weighted averaging (IOWA) operator (Yager and Filev 1999, and Yager 2003). In this case the importance degrees are used to induce the ordering of the preference values before aggregation. The input arguments, representing the experts' opinions are not rearranged based on their values but rather using a function of arguments as further shown in this section. There are three main types of IOWA operators found in the literature: the Importance IOWA (I-IOWA), the Consistency IOWA (C-IOWA) and the Preference IOWA (P-IOWA) (Yager and Filev 1999, Yager 2003, Chiclana 2007).

The I-IOWA operator may only be used when the group of experts solving the problem is classified as heterogeneous because the ordering of the preferences is based on the importance weights of the experts providing the information source. The importance weights are assigned to the experts according to the linguistic quantifier being used and the ordering of the preference values is induced from most to least important ones. In other words, the induced ordering obtained using the IOWA operator allow researchers to take control of the aggregation stage in GDM problems, in the sense that the reordering related to each value can be given according to any criteria specified by the researcher.

Previously some ties have occurred among alternatives when applying the IOWA operator. In order to break the ties Chiclana et al. (2007) suggested to apply repeatedly the application of the three IOWA operators mentioned above. The mathematical expressions for the IOWA operator involve the order induced variables represented by the set $\{u_1, \dots, u_n\}$ based on the magnitude of the argument variables such as a_i from the OWA operator, forming the two-tuple OWA pairs (u_i, a_i) for $(i \in N)$ (Xu and Da 2003). The main formula of the IOWA operator is (Yager and Filev 1999, Yager 2003).:

$$f((u_1, a_1), \dots, (u_n, a_n)) = \sum_{j=1}^{n} w_j b_j \qquad (2.13)$$

where the weights are defined as $w = (w_1, w_2, \dots, w_n)^T$ such that $w_j \in [0,1]$ and $\sum_{j=1}^{n} w_j = 1$ and b_j is the a_i.value which has associated with it j[th] largest element of u_i.

The IOWA aggregation operator can be applied to linguistic and non-linguistic information provided by the experts. A significant aggregation operator found in the literature that introduced the concept of a linguistic operator is the linguistic ordered weighted averaging (LOWA) aggregation operator (Herrera et al. 1996).

2.4.3.2.3 Linguistic Ordered Weighted Average (LOWA) Aggregation Operator

Delgado et al. (1993) suggested using a symbolic method that involves direct computations on linguistic labels taking into consideration the meaning and properties of such linguistic assessments (i.e., linguistic labels given) (Pei et al. 2009). The LOWA aggregation model makes use of the linguistic quantifiers for representing the concept of fuzzy majority in order to determine the weights of the GDM experts. The author proposed the LOWA operator to be applied in order to combine the individual linguistic preferences by the direct approach. Fuzzy majority can be defined as a soft majority concept. In other words, instead of having a strict threshold number representing the majority of experts, one would using linguistic quantifiers fuzzy membership functions in order to define fuzzy majority, which results in having "most" of the relevant experts agreeing on "almost all" the alternatives (Herrera et al. 1996, and Kacprzyk et al. 2010).

Two concepts of choice degrees of alternatives that were used in this literature to apply the LOWA operator are: fuzzy majority of dominance and fuzzy majority of experts. Fuzzy majority of dominance (of alternatives) is defined as a measure that quantifies the dominance of one alternative over all the others of one expert's opinion (i.e., level of preference of individual). Fuzzy majority of experts is used to quantify the dominance that one alternative has over all the other according to all the experts' opinions as a whole (i.e., level of preference of the group) (Herrera et al. 1996). By using these concepts and the properties of the LOWA operator the authors justified the rationality behind this operator and showed the operator usefulness in the fuzzy linguistic GDM environment.

For a set of linguistic labels $A = \{a_1, a_2, \dots, a_n\}$ to be aggregated, the LOWA operator is defined as (Delgado et al. 1993):

$$f(a_1, a_2, \dots, a_n) = w \cdot B^T = \varphi^n\{w_k, b_k, k = 1, 2, \dots, n\} = w_1 \otimes b_1 \oplus (1 - w_1) \otimes \varphi^{n-1}\{\beta_h, b_h, h = 2,3, \dots, n\} \qquad (2.14)$$

where $w = [w_1, w_2, \dots, w_n]$ is a weighting vector such that $w_i \in [0,1]$ and $\sum_i w_i = 1$; $\beta_h = \frac{w_h}{\sum_{k=2}^{n} w_k}$, $h = 2,3, \dots, n$; and $B^T = (b_1, b_2, \dots, b_n)^T$ is the associated ordered label vector. Each element $b_i \in B$ is the ith largest label in the collection $x_1, x_2, \dots, x_n$. C^n is the convex combination of n labels and if $n = 2$, it is defined as: $C^2\{w_i, b_i, i = 1,2\} = w_1 \otimes s_j \oplus (1 -$

$w_1) \otimes s_j = s_k,\ s_j, s_i \in S = \{s_0, \dots, s_T\}, (j \geq i)$, where $k = min\{T, i + round(w_1 \times (j - i))\}$, where *round* is the usual round operation, and $b_1 = s_j$, $b_2 = s_i$.

Nevertheless, since the LOWA operator deals with non-weighted linguistic information, an expansion of the LOWA operator application was studied by Herrera et al. (1998) in order to avoid issues related to weighted aggregation operators by using two different aggregation operators: linguistic weighted aggregation disjunction (LWD) and linguistic weighted conjunction (LWC) (Herrera et al. 1998). The LWD aggregates a set of individual weighted opinions according to the mathematical formula:

$$(c_E, a_E) = LWD[(c_1, a_1), \dots, (c_m, a_m)]\,;\, a_E = \max_{i=1,\dots,m} \min(c_i, a_i) \tag{2.15}$$

Where$c_E = \varphi_Q(c_1, \dots, c_m)$ represents the selected linguistic quantifier.

The LWC operator follows the same mathematical formula in (2.15) presented for the LWD (i.e., substituting the LWD by LWC) but the a_E is obtained as $a_E = MIN\ MAX_{i=1,..,m}(Neg(c_i), a_i)$ and the c_E mathematical formula is maintained the same as well.

2.4.3.2.4 Fuzzy Number Induced Ordered Weighted Averaging (FN-IOWA) Aggregation Operator

Another aggregation operator used to represent linguistic terms is the Fuzzy Number Induced Ordered Weighted averaging (FN-IOWA) operator introduced by Chen and Chen (2005). The FN-IOWA operator uses fuzzy numbers to represent human's linguistic opinions and it is considered to be more useful when dealing with human thinking linguistically expressed opinions in GDM.

The main advantages of the FN-IOWA are that it can flexibly determine the weight of each expert's opinion based on linguistic quantifiers. However, the expert's opinions do need to have a common intersection such as previous operators such as the ones used in Hsu and Chen (1996) literature (Section 2.5.5) and it does need to use Delphi method to adjust fuzzy numbers given by experts (Chen and Chen 2005). Similarly, to the IOWA operator formula the FN-IOWA operator formula is (Chen and Chen 2005):

$$f((u_1, \tilde{a}_1), ((u_1, \tilde{a}_2), \dots, (u_n, \tilde{a}_n)) = W^T B = \begin{pmatrix} \widetilde{b_1} \\ \vdots \\ \widetilde{b_n} \end{pmatrix} \begin{pmatrix} \widetilde{w_1} \\ \vdots \\ \widetilde{w_n} \end{pmatrix} \qquad (2.16)$$

Where the $\widetilde{w_j}$ is the weighting factor represented by a fuzzy number and $\widetilde{b_j}$ is an argument value of the OWA pair represented by a fuzzy number (Chen and Chen 2005).

Another alternative of aggregation operators, which also originate as an extension of the averaging operators, involves the geometric aggregation operators. In the following section the details about the geometric aggregation operators will be further described.

2.4.4 Geometric Aggregation Operators

2.4.4.1 Crisp Geometric Aggregation Operators

2.4.4.1.1 Geometric Average (GA) Aggregation Operator

As previously mentioned the generalized format for the quasi-arithmetic means, h_α defined for the real number α in Equation 2.7 (Detyniecki 2001, Xu and Da 2003, Vanicek et al. 2009, Calvo et al. 2012). When α tends to $0,$ the Equation 2.7 tends to the geometric mean. The geometric mean is also called the geometric average (GA). Let $f: R^n \rightarrow R$, the formula for the geometric mean when applied to crisp numbers can be defined as (Equation 2.17):

$$f(a_1, a_2, \dots, a_n) = \left(\prod_{i=1}^{n} a_i \right)^{1/n} \qquad (2.17)$$

Where n is the total number of arguments that will be aggregated.

2.4.4.1.2 Geometric Weighted Average (GWA) Aggregation Operator

Considering the weighted geometric average (GWA) aggregation operator, as an alternative of the geometric average (GA) aggregation operator, it is necessary to take into the weights of each of the alternatives as well (Xu and Yager 2006, Dong et al. 2010, Calvo et al. 2012). Let $f: R^n \to R$, the formula for the weighted geometric average when applied to crisp numbers can be defined as (Equation 2.18):

$$f(a_1, a_2, \dots, a_n) = \prod_{i=1}^{n} {a_i}^{w_i} \qquad (2.18)$$

Where the exponential weighting vector of the a_i $(i \in N)$ is $w = (w_1, w_2, \dots, w_n) \in (0,1)^m$ satisfying the condition $\sum_{j=1}^{n} w_j = 1$. Note that if $w = \left(\frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n}\right)$ then f is reduced to the GA operator (Xu and Da 2003).

Since these two operators (GA and GWA) can only be applied where the arguments are exact numerical variables, in the next section we present the operators that the arguments to be inexact numerical or linguistic variables (represented by fuzzy numbers).

2.4.4.2 Fuzzy Geometric Aggregation Operator

2.4.4.2.1 Fuzzy Geometric Average (FGA) Aggregation Operator

Similarly to the GA, the fuzzy geometric average (FGA) operator is applied to fuzzy numbers or intervals to combine the linguistic term opinions of experts in group decision making. The FGA has a simplicity and ease in its application to fuzzy numbers (Chen et al. 1992). Previous literatures have surveyed the application of the geometric aggregation operator in the fuzzy environment (Buckley 1985; Buckley 2001; Hsieh et al. 2004,;Wang et al. 2009; Ramik and Korviny 2009).

Let $f: \Theta^n \to \Theta$ where Θ is the set of fuzzy numbers. The general formula for the FGA operator is given in Equation 2.19:

$$f(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \left(\prod_{i=1}^{n} \tilde{a}_i\right)^{1/n} \qquad (2.19)$$

Where n is the total number of arguments that will be aggregated. The FGA specific aggregation operator is applied when no weight differentiation is necessary in the group decision making scenario. Usually the FGA is used to combine opinions of experts' in a homogenous group, where all experts are considered to have a similar level of expertise. In other words, $w = \left(\frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n}\right)$ then f is the FGA operator (Xu and Da 2003; Dong et al. 2010; Tian and Yan 2013).

2.4.4.2.2 Fuzzy Weighted Geometric (FWG) Aggregation Operator

However, if the arguments input are being differentiated through assigning importance weights the aggregation operator used is the fuzzy weighted geometric (FWG) aggregation operator. Let $f: \Theta^n \rightarrow \Theta$ where Θ is the set of fuzzy numbers. The formula to represent the FWG is given by Equation 2.20:

$$f(a_1, a_2, \dots, a_n) = \prod_{i=1}^{n} \tilde{a}_i^{\,w_i} \qquad (2.20)$$

Where the exponential weighting vector of the is $w = (w_1, w_2, \dots, w_n) \in (0,1)^m$ satisfying the condition $\sum_{j=1}^{n} w_j = 1$.

The following two sections of this chapter will present additional aggregation operators that can be used in the crisp (exact numeric) or fuzzy (interval values, fuzzy values or linguistic values represented as fuzzy numbers) environments.

2.4.5 Similarity Aggregation Operators

2.4.5.1 Similarity Aggregation Method (SAM)

Another relevant aggregation operator presented by Hsu and Chen (1996) is not based on fuzzy preference relations like the previous one. The authors introduce the similarity aggregation method (SAM) used to combine individual subjective opinions of experts. The SAM method is based on defining the index of consensus of each expert to the other experts using a similarity measure. Then, the aggregation procedure uses the index of consensus and the importance of each expert in order to combine different experts' opinions. The experts' opinions are represented by positive trapezoidal fuzzy numbers (PTFNs). The PTFNs are generated by the Delphi method from expert's opinion and are assumed to have a common intersection at some α-level cut, $\alpha \in (0,1]$.

A similarity measure is introduced to measure the degree of agreement between experts and accordingly an agreement matrix is constructed to analyze the agreement degrees between experts' opinions. Finally based on the importance weight of each expert the opinions are combined by the SAM. The similarity measure proposed by Hsu and Chen (1996) is given by the formula:

$$S(\tilde{A}_i, \tilde{A}_j) = \frac{\int_x \left(\min\{\tilde{a}_i(x), \tilde{a}_j(x)\}\right) dx}{\int_x \left(\max\{\tilde{a}_i(x), \tilde{a}_j(x)\}\right) dx} \qquad (2.21)$$

Where $\tilde{A}_i$ and $\tilde{A}_j$ represent two experts' value opinions and $\int_x \left(\min\{\tilde{a}_i(x), \tilde{a}_j(x)\}\right) dx$ represent the area of intersection (consistent opinions) and $\int_x \left(\max\{\tilde{a}_i(x), \tilde{a}_j(x)\}\right) dx$ represents the area of union of opinions (total area).

If two experts have the same exact value opinion then $\tilde{A}_i = \tilde{A}_j$ and thus $S(\tilde{A}_i, \tilde{A}_j) = 1$ the two experts opinions are considered consistent, and the agreement degree is one. In other words, in the SAM method, the higher the intersection values between the experts' opinions, the higher the agreement degree (i.e., similarity measure in Equation 2.22) (Hsu and Chen 1996). After obtaining all experts' agreement degrees, the relative agreement degree (RAD) of each expert is calculated as a factor of the ith expert agreement degree over the sum of all experts' agreement degrees. Furthermore, in the SAM method, experts' importance weights (w) are assigned to each expert based on their relative importance with respect to the moderator's chosen most important expert. Finally, a consensus degree coefficient (CDC) is defined by a fuzzy multiplication equation such as:

$$CDC_i = \beta \cdot w_i + (1 - \beta) \cdot RAD_i \qquad (2.22)$$

Where β represents the experts' importance degree such as $0 \leq \beta \leq 1$ .Thus, in the SAM method by Hsu and Chen (1996), the (CDC) of each expert evaluates the worthiness of each expert's opinion and the aggregated result ($\tilde{R}$) is:

$$\tilde{R} = \sum_{i=1}^{n}(CDC_i \cdot \tilde{R_i}) \qquad (2.23)$$

2.4.5.2 Consistency Aggregation Method (CAM)

An advancement of the SAM was proposed by Lu et al. (2006) and it is called consistency aggregation method (CAM). A few of the problems encountered in the work of Hsu and Chen (1996) are that the opinions of the experts represented by fuzzy numbers should have a common intersection at some level α- level cut, α ∈ (0,1], otherwise it will not work. It was found that using the Delphi method to modify the experts' opinions can distort these opinions to some extents. Furthermore, if the supports of the fuzzy number do not intersect it cannot be concluded that the opinions do not intersect. Also, the final problem in the SAM is that the similarity measure used is a proportion of the consistent are to the total area only. However, the supports of the consistent area and the total area were not considered and this leads to loss of information.

The new proposed CAM is based on similarity and distance since they are considered to be equally important indices for experts' fuzzy opinions. The adjusted similarity measure (CAM) takes into consideration an innovative method to calculate the distance between the experts' opinions (represented by fuzzy numbers) and then assigns importance weight for each expert's opinion. Although the criteria or algorithm for assigning weights to experts is not demonstrated, it is implied that a moderator decides on the most important expert and then the other experts' importance weights are assigned relatively to that higher importance expert (similarly to the SAM importance weight assigning method presented above). Also, the CAM has proven to give more fair and reasonable results according to the supports of the consistent area and the total area. Therefore, the similarity measure (CAM) presented by Lu et al. (2006) solves the problems in Hsu and Chen (1996) presented above by suggesting a distance measure to calculate the consistency between the experts' opinions. .

The new similarity measure (CAM) is given as (Lu et al. 2006):

$$S(\tilde{A}_i, \tilde{A}_j) = \frac{\int_x (\min\{\widetilde{a_i}(x), \widetilde{a_j}(x)\})^2 dx}{\int_x (\max\{\widetilde{a_i}(x), \widetilde{a_j}(x)\})^2 dx} \qquad (2.24)$$

The distance measure proposed is calculated based on the Hamming distance:

$$d_H(\tilde{A}_i, \tilde{A}_j) = \int_x \left|\tilde{a}_i(x) - \tilde{a}_j(x)\right| dx \qquad (2.25)$$

Where $\tilde{A}$ and $\tilde{B}$ are fuzzy number and $\mu_{\tilde{A}}(x)$ and $\mu_{\tilde{B}}(x)$ are their respective membership functions. After further mathematical calculations the distance between the experts' opinions is presented and the aggregation method uses a new consistency measure such as:

$$r(\tilde{A}_i, \tilde{A}_j) = \beta S(\tilde{A}_i, \tilde{A}_j) + (1-\beta)(1 - d_h(\tilde{A}_i, \tilde{A}_j)) \qquad (2.26)$$

Where $\tilde{A}_i$ and $\tilde{A}_j$ represent two experts' value opinions (fuzzy numbers) and $\beta \in [0,1]$ is the weight of $S(\tilde{A}_i, \tilde{A}_j)$, which reflects the relative importance between the similarity and the distance with respect to each expert. The basic idea of this consistency measure is that, the larger the similarity measure $S(\tilde{A}_i, \tilde{A}_j)$ and the smaller the distance measure $d(\tilde{A}_i, \tilde{A}_j)$, the larger the consistency degree $r(\tilde{A}_i, \tilde{A}_j)$ between two experts' opinions (fuzzy numbers $\tilde{A}_i$ and $\tilde{A}_j$). Then the importance weight for each expert is assigned as w_i where E_i is the ith expert, and finally the aggregation result is given by the fuzzy multiplication operation ($\odot$):

$$\tilde{A} = F(\tilde{A}_1, \tilde{A}_2, \dots, \tilde{A}_n) = \sum_{i=1}^{n} w_i \odot \tilde{A}_i \qquad (2.27)$$

2.4.5.3 Fuzzy Optimal Aggregation Method (FOAM)

The last relevant aggregation method in this paper will be the one introduced by Lee (1999) and it's called the fuzzy optimal aggregation method (FOAM). The procedure to aggregate the experts' opinions is based on the principal of optimality in consensus (i.e., R which represents agreement amongst experts (i)) and the generalized optimal consensus of opinions formula is presented as:

$$\tilde{R}_i^{(I+1)} = \sum_{i=1}^{n} ({Z_i}^I)^m \tilde{R}_i / \sum_{i=1}^{n} ({Z_i}^I)^m \qquad (2.28)$$

Where $Z_i = \frac{s(\widetilde{A}_i, \tilde{R})}{\sum_{i=1}^{n} s(\widetilde{A}_i, \tilde{R})}$ and m is called the exponential weight, which reduces the influence of the opinions further away (small W_i) from consensus opinions (R) compared to opinions close (large W_i) to consensus (R). The weights are adjusted through iterations (I) until the difference between the initial weights W_i and the iterated weights is close to zero. Then the aggregation coefficient of every expert (ACI_i) is determined by combining the final aggregation weights of experts. Also the importance weights of the expert $w(E_i)$ are assigned relative to the moderator choice of highest importance expert as in previous methods. The ACI formula is:

$$ACI_i = \frac{\beta (Z_i)^m}{\sum_{i=1}^{n} (Z_i)^m} + (1-\beta) w_i \qquad (2.29)$$

Where β is a variable such as $0 \leq \beta \leq 1$ and if $\beta = 1$ then the importance weight assigned to experts is not considered in the aggregation process. If $= 0$, then only the importance weights assigned to experts is reflected in the consensus. Finally, the aggregated fuzzy number is the sum of the ACI multiplied by each fuzzy number representing each expert's opinion.

2.4.6 Prioritized Aggregation Operator (TOPSIS)

In many multi-criteria group decision making (MCGDM) problems, the process of decision requires an evaluation between competitive alternatives, determining the performance of each alternative with respect to each criterion, in order to reach a decision (Shih et al. 2007 and Mahdavi et al. 2008). Alternative solutions to a MCGDM problem are possible course of action or options that can best resolve the issues being analyzed. For example, in a risk management environment there may be several alternatives to mitigate the risk of delayed delivery of materials and equipment. Two possible solutions would be preordering materials and equipment in advance or adding a buffer time in the construction schedule. In many situations, while evaluating these alternatives for MCGDM the satisfaction of the higher priority criterion affects the overall evaluation of the entire set of criteria (Omar and Fayek 2016). Therefore, in prioritized aggregation it is essential to know the importance of each criterion relative to other criteria with respect to the overall objective (Mahdavi et al. 2008, and Omar and Fayek 2016). Prioritized aggregation provides the fundamental advantage of combining criteria while considering the tradeoffs (i.e., prioritized relationship) between the respective satisfaction of the different criteria (Yager 2004b, Wei and Tang 2012, and Omar and Fayek 2016).

TOPSIS requires defining a positive ideal solution (PIS) and a negative ideal solution (NIS) to the MCGDM. The positive ideal solution maximizes the benefit criteria and minimizes the cost criteria. On the other hand, the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Wang and Lee 2007). In other words, the PIS consists of all of the best values attainable of criteria (most favorable) and the NIS is based on all worst values attainable of criteria (least favorable) (Wang and Lee 2007, and Omar and Fayek 2016). Another possible analysis of the PIS and NIS is based on the theoretical maximum and theoretical minimum variable for the solution alternatives. In other words, instead of considering the best (PIS) or worst (NIS) value attained in a criterion, it considers the best possible solution (or worst possible solution) independent if any alternative reaches these values or not. Furthermore, TOPSIS originates from the concept of geometrically displacing the ideal solution from which the compromise solution has the shortest distance (Shih et al. 2007, and Omar and Fayek 2016). Each alternative being analyzed is assigned an index (defined as the relative closeness index) that represents how close it is to the PIS and how far it is from the NIS (Yager 2004b, and Chu 2002). A preference order of alternatives will be ranked according to this index (Yager 1980). Furthermore, Shih et al. (2007) previously defined TOPSIS as “a utility based method that compares each alternative directly depending on the data in the evaluation matrices and weights”.

One of the major weaknesses of TOPSIS is not providing for weight elicitation and consistency checking for judgment (Shih et al. 2007). A suggestive way to address these shortcomings would be to introduce fuzziness to the TOPSIS process, which would develop a Fuzzy TOPSIS process. Since DMs are required to evaluate the criteria linguistically while considering the interrelationships between these criteria, fuzzy set theory has been used to better account for the imprecision and complexity in these environments (Hsu and Chen 1996). Thus, Fuzzy TOPSIS is also used in previous literature (Chen 2000, Wang and Elhag 2006, Wang and Lee 2009). Due to the fuzziness in the decision data, linguistic variables are used to assess the ranking of each alternative with respect to each criterion and the weight of each criterion (Mahdavi et al. 2008).

Advantages of TOPSIS include 1) applying a sound logic to represent the satisfaction level of criteria according to their proximity to their most favorable satisfaction, 2) employing a simple and effective computational process by calculating a scalar value for both the best and worst alternatives, and 3) analyzing the alternatives of the MCGDM problem on at least two dimensions (Yager 2004a, Shih et al. 2007, and Omar and Fayek 2016). As a conclusion, TOPSIS application provides means for the development of a systematic prioritized scoring operator dependent on both the relative importance of criteria and the satisfaction of these criteria (Omar and Fayek 2016).

2.5 Concluding Remarks

The literature review presented an overall analysis of heterogeneous group decision making scenarios in construction risk assessment and management, where groups of experts with different levels of expertise are involved at various stages of the project lifecycle to make decisions and reach a common solution. The GDM techniques for combining heterogeneous experts' opinions were surveyed: consensus reaching process and aggregation process. The most suitable technique has been concluded to be the aggregation approach. The aggregation process combines heterogeneous experts' opinions according to each expert's expertise level in the specific GDM problem domain. Mainly the aggregation process can be divided into two steps: (i) assessing experts' levels of expertise and assigning importance weights to experts; and (ii) subsequently applying an aggregation operator to combine the heterogeneous experts' opinions.

The outcome of this chapter is an investigation of different aggregation operators' features, properties, mathematical formulation, and the situations in which each can be applied. The next chapter will address the first step of the aggregation process and further explain the methodology for assessing the experts' expertise level and assigning importance weights to experts, according to a new proposed model for assigning importance weights to experts.

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CHAPTER 3 Development of the Model for Assigning Importance Weights to Experts

3.1 Introduction

In order to assign importance weights to heterogeneous experts' in construction risk assessment, an extensive literature review to explore a variety of construction risk assessment expertise criteria was develop. Thus, a comprehensive list of criteria for assessing experts' expertise levels was developed to assign construction risk assessment experts' importance weights. The process of combining all these criteria into one single assessment tool is challenging and complex. In order to model the uncertainty and subjectivity present in the assessment of experts' expertise level, an efficient approach is using fuzzy logic in the experts' importance model for assigning importance weights to experts. Thus, the ability to apply fuzzy logic to include experts' knowledge and subjective judgment into the GDM importance weight assigning process advances the state of art in the construction risk assessment field.

The comparative analysis presented in this Chapter compares the existing importance weight assigning methods found in literature. There are 5 main models for assigning importance weights to experts found in literature are thoroughly described in Section 3.2.2: moderator, consistency measures, FES, MAUF and AHP. None of these methods are suitable for this research's application and thus there is a need of a new model for assigning importance weights to experts that accounts for the experts' expertise level in construction risk assessment. This Chapter presents the detailed methodology and data analysis used to develop a model for assigning importance weights to experts according to the expert's expertise level in construction risk assessment. The expert's expertise level is assessed through a clear, consistent and validated list of criteria relevant to the construction risk assessment field.

In the following sections the final list of criteria, a comparative analysis of models for assigning importance weights to experts, and the FAHP model for assigning importance weights to experts are presented in detail. Also, the application of the Fuzzy Analytical Hierarchy Process (FAHP) as a model for assigning importance weights to experts will be extensively described, with all the detailed mathematical formulas applied.

3.2 Comparative Analysis of Existing Models for Assigning Importance Weights to Experts

Previous models for assigning importance weights to experts applied in literature are: (1) a moderator or manager subjectively assigns the weights directly to the experts (Perez et al. 2011); (2) the weights are determined by comparing the consistency of the experts in making the preferences (Herrera-Viedma et al. 2014, Palomares et al. 2014); (3) a fuzzy expert system is adopted to determine the weights based on essential qualification attributes (Elbarouky et al. 2014); (4) a multi-attribute utility function is used to determine the consensus weight factor (CWF) for each expert based on the expert utility values and relative weight of experience measures (Awad and Fayek 2012a); and (5) the Analytical Hierarchy Process (AHP) that can be used to derive weights by considering the set of attributes related to decision makers' level of expertise (Omar and Fayek 2016). Table 3.1 below further presents the general drawbacks and benefits of each weight assigning method found in literature.

Table 3.1 Comparative Analysis of Previous Weight Assigning Methods

Weight Assigning Methods	Advantages	Disadvantages
1.Moderator	• Fast and easy weight assignment process due its straightforwardness. • Easy to change and adjust model since it depends on human judgement and can be combined with a feedback technique to adjust experts' weights.	Since it depends on human judgement, this method is: • Highly Subjective model • Prone to individual bias • Prone to human error
2.Consistency Measures	• Validation of model based on data collection results which ensure higher accuracy of the model. • Easy to manage and adjust since it is based on data input provided by experts.	• Consensus process is time consuming and complex because many group sessions can be required. • Model could be misleading of actual expert's weight since different experts could be better in one criteria than the other (comparison of data does not

Weight Assigning Methods	Advantages	Disadvantages
		account for this limitation).
3.FES	• Easy access to knowledge by using linguistic terms as descriptors to input and output values of the system. • Based on experts' qualification attributes as input variables to determine the experts' weights as output variables.	• May require several consensus sessions for reaching an agreement on the development of membership functions. • Dimensionality issue due to the large number of input data, which requires more computational effort. • Complex if-then rule base model due to the large number of input data.
4.MAUF	• Easy and efficient GDM approach since it is based on integrating individual utility functions according to the importance of experts' experience measures. • Depending on a number of different experience measures an overall importance weight to each expert is determined.	• May require several consensus sessions for reaching an agreement on the development of utility functions. • Dimensionality issue due to the large number of input data which requires more computational effort.
5.AHP	• Widely used method for GDM problems due to the easiness that it handles multiple criteria. • Based on experts' qualification attributes. • Structured yet flexible approach that can be easily updated or adjusted. • Powerful and straightforward methodology that can be integrated to almost any GDM system.	• The pairwise comparison might lead to a dimensionality issue due to large number of variables being compared. • Inadequate for dealing with the imprecise or vague nature of linguistic assessment.

There are several methods proposed in the literature for assigning importance weights to experts. For instance, a moderator or manager subjectively assigns the weights directly to the experts

(Perez et al. 2011). Although this is a commonly used approach, this approach is highly biased towards the opinion of the moderator. Other methods are consistency methods, where the weights are determined according to the consistency of the experts' preferences (Perez et al., 2014). However, these methods use the experts' assessment to determine their own weights, disregarding the experts' expertise level. In other words, the experts are evaluated according to their opinions and not according to their expertise.

In order to assess the expertise level of experts based on their knowledge, qualifications, and experience, multiple criteria need to be considered. Different methods have been applied for this purpose in construction. For instance, Elbarkouky and Fayek (2011a, 2011b) used fuzzy expert systems (FES) to determine the experts' weights based on their qualification attributes to aggregate experts' opinions on roles and responsibilities in project delivery systems. Awad and Fayek (2012a, 2012b) used a multi-attribute utility function (MAUF) to determine the consensus weight factor for each expert based on the expert utility values and relative weight of experience measures for contractor prequalification for surety bonding. However, both these approaches, FES and MAUF, have limitations when dealing with a large number of criteria.

In order to propose a method that assigns weights to experts based on their expertise level and which is also able to handle a large number of criteria, this work proposes a two-step approach: first, a generalization of the Analytic Hierarchy Process (AHP) (Saaty 1987), the FAHP, is used to determine the weight of each qualification criterion used to assess the experts; and then, the assessment of the experts according to these qualification criteria is used to derive the experts' relative importance weight according to the criteria weights provided by the FAHP.

The AHP, is a logical and clear theory of measurement (Saaty 1987) and it has been successfully applied in construction (Askari et al. 2014). The AHP is able to handle a large number of criteria, by hierarchically reducing the number of necessary comparisons. However, the standard AHP is unable to handle the uncertainties associated with expert's assessment. To address this limitation, Buckley (1985) first proposed the FAHP, a generalized version of AHP that allows the experts to provide their assessment using linguistic terms, which are represented by fuzzy numbers.

However the AHP has disadvantages as listed on Table 3.1. One of the disadvantages is the dimensionality issue that can be easily addressed by dividing the model into sub-models. The other disadvantage of the classical AHP model would be its inability to resolve the uncertainty and imprecision associated with the mapping of the decision maker's perception into one crisp number (Li and Zou 2011). In order to simulate the actual human judgement process, Buckley (1985) extended the Saaty's importance rating scale so that the experts are allowed to use linguistic terms, represented as fuzzy numbers ratios, in the pairwise comparison matrices in place of the classical AHP crisp ratios (Li and Zou 2011). Thus, the fuzzy pairwise comparison matrices were developed to approach the vague and uncertain value of human opinion (Li and Zou 2011).

Since we are dealing with construction methods that are complicated and usually involve massive uncertainties and subjectivities, instead of using the AHP definite scales, the FAHP linguistic scales are proposed to be used in the model for assigning importance weights to experts to better capture the expert's opinions (Chen and Wang 2009). Furthermore, the FAHP model provides the advantages of allowing overlapping linguistic terms which better represent human opinions, and thus the change among different opinions is considered smoother than the crisp number representations of experts' opinions. In conclusion, a more suitable model for determining the importance weights of experts is the Fuzzy Analytical Hierarchy Process (FAHP).

3.3 List of Criteria for Assessing Experts' Expertise Level

Experts have a large store of background knowledge and a cultivated sensitivity to its relevance, which refines their intuitive insight (Brown 1968 and Cooke and Goosens 2004). Thus, experts are able to provide a quick access to information in order for researchers to form an opinion on the events being analyzed (Herrera-Viedma et al. 2005). For instance, in the construction field the risk assessment of events is usually analyzed by experts due to the high uncertainty and vagueness in the events being studied. However, at the bottom of this discussion is the actual definition of an expert. The definition of who is an expert influences the selection of individuals to participate in researches. Previous literature has presented a limited consensus as to what an expert is. An expert has been simply defined as "informed individual", "specialist in field" or "someone who has knowledge about a specific subject" (Farrignton-Darby and Wilson 2006; Baker et al. 2006). Even though, there is a limited consensus towards what an expert is, it should be emphasized that an expert is not about whom each person is, it is about what attributes they possess (Shanteau et al. 2002 and Sun et al 2008). Based on a comprehensive review of previous qualifications attributes used to assess experts' expertise level in risk construction management, a preliminary list of criteria has been compiled and it is displayed in the Appendix as Table A.1.

The process of preparing the construction risk assessment list of criteria to evaluate experts' expertise level was performed in two main steps. The first step was to develop an initial list (Table A.1 in the Appendix) that included all the criteria previously found in the literature review (Brown 1968, Muralidharan et al. 2002, Cornelissen et al. 2003, Cooke and Goosens 2004, Baker et al. 2006, Hoffmann et al. 2007, Wang and Yuan 2011) and obtained through researchers' inputs. The second step was to refine the initial preliminary list of criteria to include only the most important evaluation criteria in the specific field of construction risk assessment. Thus, after group meetings with eight experts that have been working in the field for more than 10 years, the list of criteria has been refined and validated as displayed in Table A.2 in the Appendix.

The developed list of criteria contained quantitative and qualitative criteria. Quantitative criteria are measured using numerical scales, while qualitative criteria are measured using predetermined rating scales. A predetermined rating scale 1-5 was created for all qualitative criteria. The Likert scale includes an odd number of values in order to allow decision makers to select a neutral rating (Hartley 2014, Johnson and Morgan 2016). The process for developing the predetermined scales is intended to decrease the subjectivity of qualitative criteria analysis. During experts' group surveys, in order to reduce the subjective interpretation during the rating of qualitative criteria, the participants agreed on a set of reference variables to quantify the qualitative criteria. Using rating scales to quantify criteria does not reduce the subjectivity inherit of these criteria, unless the scales are predefined and relative bases for the decision are provided (Marsh 2008). Therefore, by creating these predetermined rating scale based on reference variables (i.e. reference points) it is possible to objectively quantify a qualitative Sub-Criterion and model the decision process more accurately (Awad and Fayek 2012a).

The assessment list of criteria is summarized in Figure 3.1 and it is organized into 7 criteria categories that each contains between 3 to 7 sub-criteria attributes. In total there are 32 criteria used to assess experts' expertise level in construction risk assessment GDM. For example, the

“Experience” quantitative criterion in the list of criteria, is used to assess level of expertise and contains of the following five Sub-Criteria: (1) “total years of experience” (i.e., the number of years the expert has been working in his/her discipline); (2) “diversity of experience” (i.e., the number of different companies the expert worked for); (3) “relevant experience” (i.e., the number of years the expert has been working in risk management); (4) “applied experience” (i.e., the number of projects in which the expert performed risk management tasks); and (5) “varied experience” (i.e., the number of different functional areas or project types worked with in the entire expert's career). An example of a qualitative criterion among the list provided in Figure 3.1 is “Reputation”. The “Reputation” criterion includes the following five Sub-Criteria: (1) “social acclamation” (i.e., the a number of participants that indicate one specific participant expert as being the most relevant expert in risk management); (2) “willingness to participate in the survey” (i.e., the quality of responses provided by a participating expert); (3) “professional reputation” (i.e., the expert’s level of credibility, based on consistency and reasonableness (i.e., use of engineering judgement in previous decisions); (4) “enthusiasm and willingness” (i.e., the expert’s level of enthusiasm and willingness in performing risk management tasks in his/her current company); and (5) “level of risk conservativeness”, (i.e., an expert’s tendency to be conservative in their risk assessment practices).

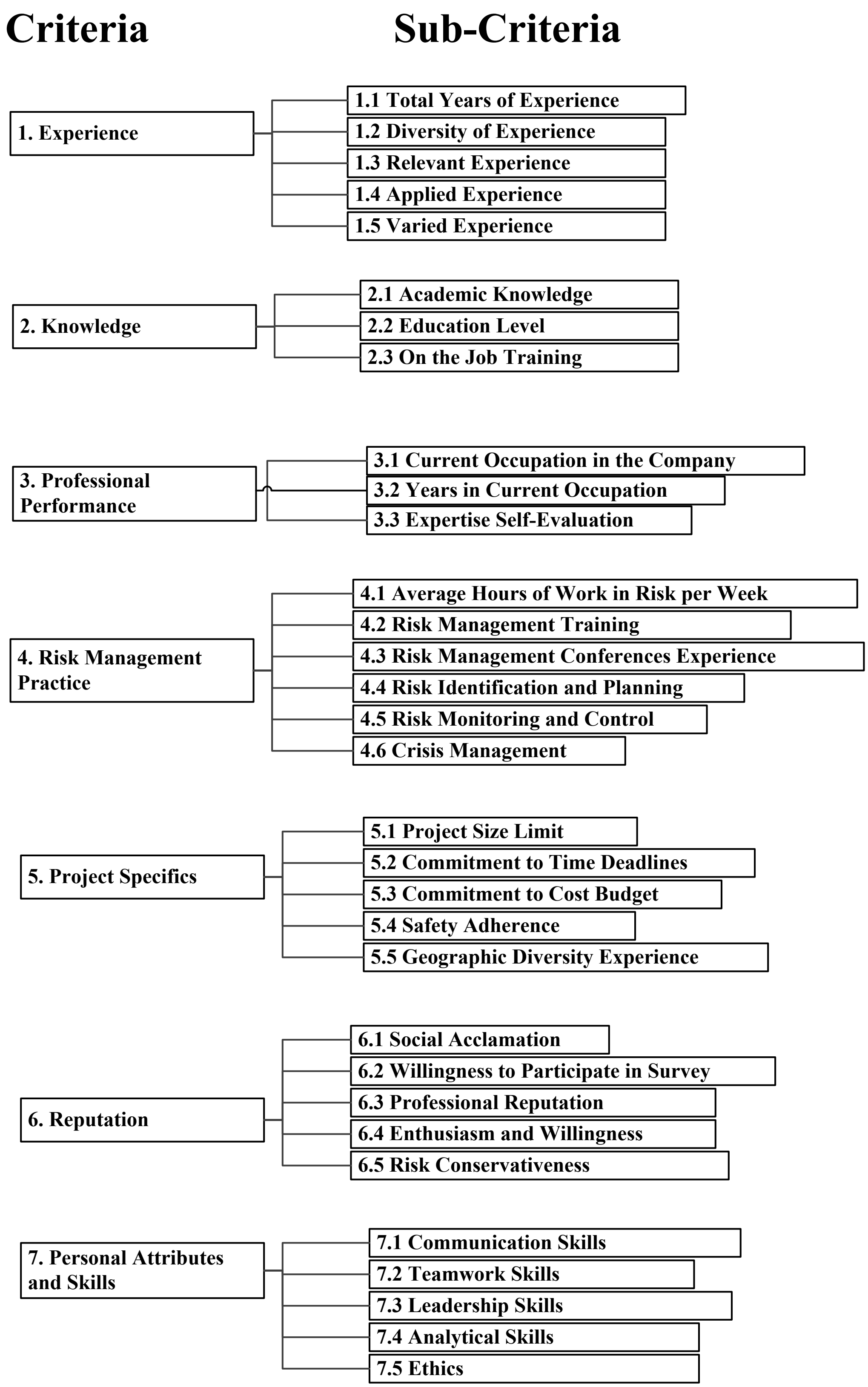

Figure 3.1 List of Criteria for assessing experts' expertise in construction risk management

All qualitative sub-criteria in Figure 3.1 are measured using the predetermined rating scales similarly to the one shown in Table 3.2 below. All predetermined scales are further explained in Table A.2 in the Appendix.

Table 3.2 Predetermined rating scale for experts' Sub-Criterion "Professional Reputation"

Predetermined Rating Scale	Description of References Variables of Predetermined Rating Scale
1	*Very inconsistent* and *very unreasonable* professional decisions
2	*Inconsistent* and *unreasonable* professional decisions
3	*Somewhat consistent* and *somewhat reasonable* professional decisions
4	*Consistent* and *reasonable* professional decisions
5	*Very consistent* and *very reasonable* professional decisions

3.4 The FAHP Model for Assigning Importance Weights to Experts

Once the list of qualification criteria is determined, it is necessary to evaluate the relative importance of each criterion to assess expertise level in construction risk assessment. In this study, the FAHP is applied to derive the qualification criteria weights.

The FAHP presents a clear format for information elicitation in the form of pairwise comparison matrices where each entry a_{ij} of a pairwise comparison matrix represents how much more the element i is preferred over element j with respect to the parent criteria in the level above. In the FAHP, the entries of the pairwise comparison matrices are fuzzy numbers, commonly triangular fuzzy numbers (Van Laarhoven and Predrycz 1983, Chang 1996). Triangular fuzzy number (TFN) is a special case of trapezoidal fuzzy number. A fuzzy number $\tilde{a}$ is said to be a trapezoidal fuzzy numbers, if its membership function is given by Equation 3.1:

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{(x-l)}{m_1-l}, \text{when } l \leq x \leq m_1 \\ 1 \quad , \text{when } m_1 < x \leq m_2 \\ \frac{(u-x)}{u-m_2}, \text{when } m_1 < x \leq u \\ 0, \qquad \text{otherwise} \end{cases} \tag{3.1}$$

for some $l, m_1, m_2, u \in \mathbb{R}$: $l \leq m_1 \leq m_2 \leq u$. Hereafter, a trapezoidal fuzzy number is represented by the tuple (l, m_1, m_2, u) of its parameters. If $m_1 = m_2 = m$, the fuzzy number is said to be triangular fuzzy number, and it is represented by the tuple (l, m, u) of its parameters.

Consequently, a fuzzy scale, based on triangular fuzzy number, is required. Table 3.3 displays a fuzzy linguistic scale for the pairwise comparisons (Demirel et al. 2008). In addition, for the reciprocity of the pairwise comparison matrices, the fuzzy inverse formula (Equation 3.2) is applied to represent the reciprocal TFNs.

$$(l, m, u)^{-1} = \left({}^{1}/_{u}, {}^{1}/_{m}, {}^{1}/_{l}\right) \tag{3.2}$$

Table 3.3 Linguistic scales for the pairwise comparison in FAHP (adapted from Demirel et al. 2008)

Linguistic Scale for Relative Importance	Triangular Fuzzy Scale	Reciprocal of Triangular Fuzzy Scale
Exactly the same	(1,1,1)	(1,1,1)
Approximately the same importance	(1/2,1,3/2)	(2/3,1,2)
Weakly more important	(1,3/2,2)	(1/2,2/3,1)
More important	(3/2,2,5/2)	(2/5,1/2,2/3)
Strongly more important	(2,5/2,3)	(1/3,2/5,1/2)
Absolutely more important	(5/2,3,7/2)	(2/7,1/3,2/5)

The fuzzy pairwise comparison matrices are developed based on the expert's input. In cases that more than one expert is involved, say d experts, it is necessary to aggregate their fuzzy pairwise comparison matrices for each one of the hierarchical position. Let $\tilde{A}_m$ be the pairwise comparison matrix from the mth expert in a specific hierarchical position, as shown in Equation 3.3.

$$\tilde{A}_m = \left[\tilde{a}_{ij}^{(m)}\right] = \begin{bmatrix} (1,1,1) & \tilde{a}_{12}^{(m)} & \cdots & \tilde{a}_{1n}^{(m)} \\ 1/\tilde{a}_{12}^{(m)} & (1,1,1) & \dots & \tilde{a}_{2n}^{(m)} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{a}_{1n}^{(m)} & 1/\tilde{a}_{2n}^{(m)} & \cdots & (1,1,1) \end{bmatrix}, m = 1, \dots, d \tag{3.3}$$

Then, the aggregated fuzzy pairwise comparison matrix $\tilde{A}$, is obtained by aggregating the respective entries of the experts' fuzzy pairwise comparison matrices, as shown in Equation 3.4.

$$\tilde{A} = \begin{bmatrix} (1,1,1) & f\left(\tilde{a}_{12}^{(1)}, \dots, \tilde{a}_{12}^{(d)}\right) & \cdots & f\left(\tilde{a}_{1n}^{(1)}, \dots, \tilde{a}_{1n}^{(d)}\right) \\ f\left(1/\tilde{a}_{12}^{(1)}, \dots, 1/\tilde{a}_{12}^{(d)}\right) & (1,1,1) & \dots & f\left(\tilde{a}_{2n}^{(1)}, \dots, \tilde{a}_{2n}^{(d)}\right) \\ \vdots & \vdots & \ddots & \vdots \\ f\left(1/\tilde{a}_{1n}^{(1)}, \dots, 1/\tilde{a}_{1n}^{(d)}\right) & f\left(1/\tilde{a}_{2n}^{(1)}, \dots, 1/\tilde{a}_{2n}^{(d)}\right) & \cdots & (1,1,1) \end{bmatrix} \tag{3.4}$$

where f stands for the aggregation operator. One of the most commonly used aggregation operator to combine fuzzy pairwise comparison matrices is the fuzzy weighted geometric operator (FWG). In this work, the FWG operator, shown in Equation 2.20, is applied considering all experts that participated in the data collection with similar expertise levels (i.e. homogeneous), and thus all the experts are assigned equal weights.

3.4.1 Assigning Importance Weights to the Criteria and Sub-Criteria

Once the aggregated fuzzy pairwise comparison matrices are obtained for all hierarchical position, the FAHP is applied to determine the relative importance weights for each criterion and sub-criterion. There are several FAHP calculation approaches (e.g., Van Laarhoven and Predrycz (1983), Buckley (1985) and Chang (1996))Chang (1996) is a commonly used approach, since it involves considerably simpler computational efforts than the other methods, and it has been successfully applied in many fields (Ding et al. 2008). Following Chang (1996), there are three main steps to obtain the criteria and sub-criteria relative importance weights in FAHP, which must be performed for each fuzzy pairwise comparison matrix. The steps are as follows:

1. For each element (in this case, criteria or sub-criteria) i, $i = 1, \dots, n$, considered by the fuzzy pairwise comparison matrix, compute the value of the fuzzy synthetic extent $\widetilde{S_i}$ by applying the algebraic operations of multiplication and summation to the TFNs as follows (Equation 3.5):

$$\tilde{S} = \begin{bmatrix} \tilde{S}_1 \\ \vdots \\ \tilde{S}_n \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{n} \tilde{a}_{1j} \otimes \left(\sum_{k=1}^{n} \sum_{j=1}^{n} \tilde{a}_{kj} \right)^{-1} \\ \vdots \\ \sum_{j=1}^{n} \tilde{a}_{nj} \otimes \left(\sum_{k=1}^{n} \sum_{j=1}^{n} \tilde{a}_{kj} \right)^{-1} \end{bmatrix} =$$

$$\begin{bmatrix} \left(\sum_{j=1}^{n} l_{1j}, \sum_{j=1}^{n} m_{1j}, \sum_{j=1}^{n} u_{1j} \right) \otimes \left(\frac{1}{\sum_{k=1}^{n} \sum_{j=1}^{n} u_{kj}}, \frac{1}{\sum_{k=1}^{n} \sum_{j=1}^{n} m_{kj}}, \frac{1}{\sum_{k=1}^{n} \sum_{j=1}^{n} l_{kj}} \right) \\ \vdots \\ \left(\sum_{j=1}^{n} l_{n\ j}, \sum_{j=1}^{n} m_{n\ j}, \sum_{j=1}^{n} u_{n\ j} \right) \otimes \left(\frac{1}{\sum_{k=1}^{n} \sum_{j=1}^{n} u_{kj}}, \frac{1}{\sum_{k=1}^{n} \sum_{j=1}^{n} m_{kj}}, \frac{1}{\sum_{k=1}^{n} \sum_{j=1}^{n} l_{kj}} \right) \end{bmatrix} \tag{3.5}$$

where $\otimes$ represents the fuzzy arithmetic multiplication of TFNs.

2. The non-fuzzy values that represent the relative preference of one element over the others are calculated based on the fuzzy synthetic extent values. Therefore, in order to approximate the fuzzy priorities in the pairwise comparison matrices it is necessary to compute the degree of possibility of $\tilde{S}_{\mathrm{i}} = (l_i, m_{\mathrm{i}}, u_i) \geq \tilde{S}_{\mathrm{j}} = (l_{\mathrm{j}}, m_{\mathrm{j}}, u_{\mathrm{j}})$ as shown in Equation 3.6.

$$V(\tilde{S}_i \geq \tilde{S}_j) = \begin{cases} 1, & if\ m_j \geq m_i \\ 0, & if\ l_i \geq u_j \\ \frac{l_i - u_j}{(m_j - u_j) - (m_i - l_i)}, & otherwise \end{cases}, \quad i, j = 1, \dots, n_c \tag{3.6}$$

Next, the degree of possibility for a TFN $\widetilde{S_i}$ to be greater than all the n TFNs in $\{\tilde{S}_1, \dots, \tilde{S}_{n_c}\}$, is given by:

$$V = \begin{bmatrix} v_1 \\ \vdots \\ v_{n_c} \end{bmatrix} = \begin{bmatrix} \min_{k \in \{1,2,\dots,n_c\}} V(\tilde{S}_1 \geq \tilde{S}_k) \\ \vdots \\ \min_{k \in \{1,2,\dots,n_c\}} V(\tilde{S}_{n_c} \geq \tilde{S}_k) \end{bmatrix} \tag{3.7}$$

Each component v_i of V represents the relative non-fuzzy weight of the i^{th} element over the other ones under consideration by the fuzzy pairwise comparison matrix. However, these weights have to be normalized in order to be analogous to the classical AHP criteria weights.

3. Normalize the vector V to get the final non-fuzzy normalized weight vector W according to Equation 3.8.

$$W = \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} v_1 / \sum_{i=1}^{n} v_i \\ \vdots \\ v_n / \sum_{i=1}^{n} v_i \end{bmatrix} \tag{3.8}$$

The vector W is the weight vector, with respect to the immediate parent element, of the elements of the fuzzy pairwise comparison matrix under consideration. Let $w_{C_1}, w_{C_2}, \dots, w_{C_7}$ denote the weights of the seven criteria in Figure 3.2 and $w_{S_{ij}}$, $i = 1, \dots, 7$ and $j = 1, \dots, n_{C_i}$, be the weight of sub-criterion j with respect to criterion i, where n_{C_i} is the number of sub-criterion under criterion i.

3.4.2 Assigning Heterogeneous Experts' Importance Weights

Once the qualification criteria and their relative importance weights are obtained, it is possible to determine the experts' weights based on their expertise level. First, each expert involved in the decision making process is evaluated according to each sub-criterion in the list of criteria (Figure 3.2). Then, the evaluation data is normalized to the interval [0,1]. Next, the weights obtained in Step 2 for the criteria and sub-criteria are applied to calculate each expert's score (ES_j) using Equation 3.9.

$$ES_j = \sum_{i=1}^{n} \sum_{k=1}^{n_{C_i}} w_{C_i} w_{S_{ik}} I_{S_{ik}}^{(j)}, \; j = 1, \dots, d \tag{3.9}$$

where $I_{S_{ik}}^{(j)}$ represents the normalized evaluation of the j^{th} expert according to the k^{th} sub-criterion of criterion C_i, w_{C_i} is the weight of criterion C_i and $w_{S_{ik}}$ is the weight of k^{th} sub-criterion of criterion C_i, as defined in Step 2. Also, d is the number of experts, n represent the number of criteria, and n_{C_i} the number of sub-criteria under criterion C_i.

However, the experts' scores cannot be directly used as weights since they are not normalized. Therefore, after the individual ES_j is calculated for all experts in the group, the importance weight (IW) of each expert is calculated using Equation 3.10.

$$IW_j = {ES_j}\Big/{\sum_{p=1}^{d} ES_p}, \quad j = 1,\ldots,d \tag{3.10}$$

The importance weight IW of the experts is based on the experts' expertise level and will be used next to weight the experts' risk assessments. The higher is the expertise level of an expert, the higher his/her importance weight will be, and consequently, more impact his/her assessment will have in the risk analysis.

3.5 Validation of the Developed List of Criteria, Metrics and Scales

As previously mentioned, the list of criteria to evaluate experts' expertise level in construction risk assessment was developed in two steps. The first step of conducting a thorough literature review in order to develop a preliminary list of criteria (Table A.1), which is further explained in Chapter 2. In this section we will discuss the second step of validating the list of criteria previously developed in order to obtain the list of criteria displayed in Table A.2.

The process of validation of the list of criteria was developed through a group meeting where the 8 participants were asked to complete a survey. The survey contained 6 different sections and was completed within a time frame of 45 to 60 minutes by each participant. The survey is assigned for each participant to respond independently and individually. The survey first section is designed to collect general information about the organization the participant work for and their position in this organization. Thus, demographic and general information about the participants are used to differentiate their answers.

The second and third sections of the survey collect the agreement level of the experts with the sub-criteria and criteria category. The second section includes the validation of a list of sub-criteria in relation to the criteria categories to evaluate experts' expertise level in the area of risk assessment in construction projects. The third section includes the validation of a list of qualification criteria categories in relation to experts' expertise level in the area of risk assessment in construction projects. The participants were required to assign a rating in the agreement scale for each sub-criteria and criteria category. The opportunity to add any missing criteria or sub-criteria was given to the experts as well. Examples of the designed sub-criteria and criteria validation questions can be found in the Appendix in Table A.3 to A.10.

The fourth section is an assessment of who should be the source of data collection for the complete sub-criteria list. An example of the designed questions to assess the sub-criteria data source is shown in Table A.11. The list of criteria used to evaluate experts' expertise level can be obtained from four different sources: Expert (self), Expert's Supervisor, Expert's Peers or Expert's Subordinates. The fifth and the sixth sections of the survey aim at validating the scales of measure used for each sub-criterion. The fifth section is designed to collect the ranges for each quantitative (i.e. numeric) criterion. The sixth section is designed to assess the agreement of each participant with the reference variables used to quantify values on the predetermined rating scales for the qualitative (i.e. linguistic) criteria. In the fifth section, the participants were asked if they agree or disagree with the scales of measure for quantitative sub-criteria. If they disagree with the scales of measure, the participants were asked to provide a suggestive description for the sub-criteria scale of measure. Examples of the designed questions to assess the participant agreement with the quantitative sub-criteria scale of measure developed are shown in Table A.12. In the sixth section, a sample of the designed questions to assess the participant agreement with the qualitative sub-criteria scale of measure developed are shown in Table A.13. It is important to note that for the quantitative criteria the scales of measure used are all numeric, varying from integer to real numbers, whereas for the qualitative criteria the scales of measure are linguistic based on predetermined rating scales as described in Section 3.2.1 and shown in Appendix Table A.2.

After collecting data from the participants in the first group meeting (i.e. 8 participants), the results of the data collection were compiled and analyzed. The data collection aimed at validating the preliminary list of criteria (Table A.1) to assess experts' expertise level, validating the metrics and scales used to measure each qualification attribute in the list of criteria, and incorporating the experts' opinions in who should be the data source for obtaining each qualification attribute in the list of criteria. The participants' opinions were initially considered to have the same weight since the 8 experts have considerably similar expertise level and substantial experience in the construction risk assessment field. Thus, when analyzing the data results the experts were considered to be homogenous, and the combined majority of the experts' opinions prevailed in decision making.

A general analysis of the data results demonstrates that the list of criteria, developed to assess experts' expertise level in construction risk assessment, has decreased from containing 36 sub-criteria to containing 32 sub-criteria. The sub-criteria that did not have the participants' agreement and endorsement with being part of the list of criteria were removed. The 4 sub-criterion removed are under the "Professional Performance" Category as: (1) "Years since Professional Engineer (P.Eng.) Certification", (2) "Previous Key Employee Commitment", (3) "Current Key Employee Commitment", and (4) "Level of Construction Training". The final conclusion of the criteria and sub-criteria participants' agreement level is that 2 Sub-Criteria were substituted by new ones, in the "Experience" and "Knowledge" Criteria Categories, and 4 Sub-Criteria were completely removed from the "Professional Performance" Criteria Category. Table A.2 in the Appendix displays the final validated list of criteria to assess experts' expertise level in construction risk assessment.

Furthermore, the 8 participants were asked to assess who should be the source of data collection for the complete sub-criteria list. The results of the data collection show that the majority of the participants believe that each sub-criteria data input should be obtained from the Expert (self) and/or the Expert's Supervisor. In other words, when collecting data input about each qualification attribute used to assess an expert's expertise level, the participants considered the Expert (himself/herself) to be a trustworthy and unbiased data source for most of the list of criteria. However, the few qualitative qualification attributes present in the list of criteria should have the Expert's Supervisor as the main data source to obtain a more accurate evaluation. The list of sub-criteria that should be obtained from the Expert (self) and the Expert's Supervisor data source is shown in Table 4.2 (Chapter 4).

Finally, the 8 participants were asked their agreement level with the scales of measure used for the quantitative and qualitative sub-criteria. Only 1 quantitative sub-criteria scale of measure adjustment was done. On the other hand, since the qualitative sub-criteria are measured using predetermined rating scales that are based on reference variables, the participants were asked their level of agreement with the reference variables being used and to add any reference variable they may consider significant to measuring a specific qualitative sub-criteria. The results show that the participants added 1 or two reference variables to better measure the 3 qualitative sub-criteria: Communication skills, Leadership skills, Ethics.

3.6 Validation of the FAHP Model for Assigning Importance Weights to Experts

In order to develop the FAHP model for assigning importance weights to experts, each expert's individual input is obtained for ranking the criteria and sub-criteria hierarchy levels of the FAHP structure. In order to rank the importance of these sub-criteria and criteria, each expert's assessment is represented in fuzzy pairwise comparison matrices, which are developed for each hierarchical level in the FAHP. The next step is to aggregate each of the expert's fuzzy pairwise comparison matrices by applying the fuzzy weighted geometric (FWG) aggregation operator. In this work, the FWG operator, shown in Equation 2.20, is applied considering all experts that participated in the data collection with similar expertise levels (i.e., homogeneous), and thus all the experts are assigned equal weights. The results of these pairwise comparison matrices are input into the FAHP model for assigning importance weights to experts to provide the sub-criteria and criteria relative importance weights.

The pairwise comparison questionnaires for the sub-criteria and for the criteria were developed based on previous literature review (Hsieh et al. 2004, Chen and Wang 2009, Askari et al. 2014, Srichetta Nguyen et al. 2016). The questionnaires used to collect the fuzzy pairwise comparison matrices required in the FAHP model for assigning importance weights to experts can be found in the Appendix in Table A.14 and A.15. The sub-criteria pairwise comparison matrices are developed by ranking the importance of each sub-criterion in comparison to another sub-criterion in relation to main criteria category. In other words, the participants are asked to individually rank the relative importance of the sub-criteria relative to the criteria. A sample of the sub-criteria pairwise comparison questionnaire distributed to the participants is shown in Figure 3.2.

The sub-criteria questionnaire pairwise comparison questions take the form: "How important is Sub-Criterion 1 when compared to Sub-Criterion 2 with respect to the higher level Criterion Category for evaluating expert's risk assessment expertise?" For example, as it can be seen in

Figure 3.2, the participant is asked to compare the importance of the Sub-Criterion 1 “Total Years of Experience” and Sub-Criterion 2“Diversity of Experience” in relation to “Experience” Criteria category. The participant is asked to provide the following responses in linguistic fashion, as shown in Figure 3.2, by putting an X in the chosen rating box. All the pairwise comparison questionnaires required linguistic data input from experts which makes it easier to capture variations in experts’ opinions. Fuzzy sets make it possible to represent these linguistic terms as fuzzy numbers and address the subjectivity and uncertainty in human judgement. As previously shown in Table 3.2, the linguistic scale can be represented through Triangular Fuzzy Numbers (TFNs).

Importance of sub-criteria with respect to the ***EXPERIENCE higher level category*** **Importance of Sub-Criterion 1 over Sub-Criterion 2**											
Question	Sub-Criterion 1	Absolutely more important	Strongly more important	More important	Weakly more important	Approximately the same importance	Weakly less important	Less important	Strongly less important	Absolutely less important	Sub-Criterion 2
Q1	Total Years of Experience										Diversity of Experience
Q2	Total Years of Experience										Relevant Experience
Q3	Total Years of Experience										Applied Experience
Q4	Total Years of Experience										Supervisory Experience
Q5	Diversity of Experience										Relevant Experience
Q6	Diversity of Experience										Applied Experience
Q7	Diversity of Experience										Supervisory Experience
Q8	Relevant Experience										Applied Experience
Q9	Relevant Experience										Supervisory Experience
Q10	Applied Experience										Supervisory Experience

Figure 3.2 Sub-Criteria pairwise comparison questionnaire in relation to criteria category

A sample of the criteria pairwise comparison questionnaire distribute to the participants is shown in Figure 3.3. The criteria questionnaire pairwise comparison questions take the form: “How important is Criterion 1 when compared to Criterion 2 in evaluating expert's risk assessment expertise?" For example, as it can be seen in Figure 3.3, the participant is asked to compare the importance of the Criterion 1 "Experience" and Criterion 2 "Knowledge" in relation to assessing experts' expertise level in construction risk assessment.

Importance of criteria with respect to ***EXPERTISE LEVEL in construction risk management***											
		Importance of Criterion 1 over Criterion 2									
Question	Criterion 1	Absolutely more important	Strongly more important	More important	Weakly more important	Approximately the same importance	Weakly less important	Less important	Strongly less important	Absolutely less important	Criterion 2
Q1	Experience										Knowledge
Q2	Experience										Professional Performance
Q3	Experience										Risk Management Practice
Q4	Experience										Project Specifics
Q5	Experience										Reputation
Q6	Experience										Personal Attributes and Skills
Q7	Knowledge										Professional Performance
Q8	Knowledge										Risk Management Practice
Q9	Knowledge										Project Specifics
Q10	Knowledge										Reputation
Q11	Knowledge										Personal Attributes and Skills
Q12	Professional Performance										Risk Management Practice

Figure 3.3 Criteria pairwise comparison questionnaire in relation to experts' expertise level in construction risk management

The results of each expert's pairwise comparison questionnaire were organized in fuzzy pairwise comparison matrices (FPCM). The fuzzy pairwise comparison matrices are considered reciprocal, which means the values across the matrix diagonal are obtained applying the reciprocity in Equation 3.2. In order to input the FPCMs in the FAHP model, it is necessary to combine all experts' fuzzy pairwise comparison matrices into one aggregated FPCM.

In order to combine the 8 experts' opinions the Fuzzy Geometric Average (FGA) aggregation operator (Section 2.5.4.2.1) was applied. This choice was made assuming that the 8 experts in the group meeting have a similar expertise level in construction risk assessment. The obstacle of including the experts' expertise importance weights at this stage is due to the lack of data, since in order to obtain the importance weight of each expert we first need the FAHP criteria and sub-criteria weights. Thus, to address the model circular reference limitation, we obtained data from experts with similar expertise level and considered them as a homogenous group. The FGA formula is applied as in Equation 2.19, for each triangular fuzzy number in each expert's FPCM. The final sub-criteria aggregated FPCM and the final criteria aggregated FPCM are input into the FAHP model for assigning importance weights to experts in order to obtain the criteria and sub-criteria importance weights.

In the FAHP model for assigning importance weights to experts, the aggregated FCPM for all the sub-criteria were used to obtain the sub-criteria importance weights as described in Section 3.2.2. A similar process is followed to obtain the 7 criteria categories importance weights. The final sub-criteria and criteria weights obtained from the FCPMs in the FAHP model for assigning importance weights to experts are shown in Table 3.4. The results show that some criteria have a higher relative importance than others. For example, "Knowledge" has a higher importance weight (0.17) than "Experience" (importance weight of 0.11).

Table 3.4 Hypothetical examples of sub-criteria and criteria weights obtained from the fuzzy analytic hierarchy process (FAHP) model

CRITERIA	WEIGHTS	SUBCRITERIA	WEIGHTS
1.Experience	0.11	1.1 Total years of experience	0.34
		1.2 Diversity of experience	0.22
		1.3 Relevant experience	0.28
		1.4 Applied experience	0.05
		1.5 Varied experience	0.11
2.Knowledge	0.17	2.1 Academic knowledge	0.25
		2.2 Education level	0.23
		2.3 On-the-job training	0.52
3.Professional performance	0.14	3.1 Current occupation in the company	0.27
		3.2 Years in current occupation	0.32
		3.3 Self-evaluation of expertise	0.41

CRITERIA	WEIGHTS	SUBCRITERIA	WEIGHTS
4.Risk management practices	0.23	4.1 Average hours of work in risk per week	0.11
		4.2 Level of risk management training	0.30
		4.3 Risk management conferences experience	0.13
		4.4 Risk identification and planning	0.07
		4.5 Risk monitoring and control	0.15
		4.6 Crisis management	0.24
5.Project Specifics	0.09	5.1 Project size limit	0.30
		5.2 Commitment to time deadlines	0.27
		5.3 Commitment to cost budget	0.19
		5.4 Safety adherence	0.13
		5.5 Geographic diversity experience	0.11
6.Reputation	0.09	6.1 Social Acclamation	0.31
		6.2 Willingness to participate in survey	0.31
		6.3 Professional reputation	0.17
		6.4 Enthusiasm and willingness	0.12
		6.5 Risk conservativeness	0.09
7.Personal attributes and skills	0.17	7.1 Communication skills	0.09
		7.2 Teamwork skills	0.17
		7.3 Leadership skills	0.40
		7.4 Analytical skills	0.10
		7.5 Ethics	0.24

After this process is completed, the FAHP model for assigning importance weights to experts requires collecting experts' qualification attributes for each sub-criteria in order to apply the model and obtain the final experts' importance weight. This process is further explained in Chapter 4 for the implementation of the model for assigning importance weights to experts in the aggregation framework.

3.7 Concluding Remarks

For construction risk assessment GDM problems, the process of aggregating the opinions of experts in a heterogeneous group involves the two steps of assessing experts' levels of expertise and assigning importance weights to experts, then subsequently selecting an aggregation operator to combine heterogeneous experts' opinions and preferences. The main gaps in previous research are the lack of a clear and consistent set of criteria to assess experts' levels of expertise, as well as the lack of a structured model for assigning importance weights to experts that is based on selected qualification attributes (i.e. knowledge, experience, reputation, performance, etc.) according to the field of study relevant to the problem (i.e. construction risk assessment).

In this chapter, a list of criteria composed of the relevant qualification attributes to evaluate an expert in construction risk assessment, metrics and scales were developed. Group meetings with experts in the construction risk assessment industry contributed to developing a more accurate and representative importance model for assigning importance weights to experts by improving and validating the list of criteria, metrics and scales. The data collection results also obtained data input for the FAHP fuzzy pairwise comparison matrices and thus the criteria and sub-criteria weights were calculated.

The main contribution of this chapter is in addressing literature gaps by proposing a model for assigning importance weights to experts based on a clear and consistent list of criteria for assessing experts' levels of expertise in construction risk assessment. The FAHP model for assigning importance weights to experts provides a logical and comprehensive framework for structuring a GDM problem and quantifying its elements. It also addresses the subjectivity and uncertainty characteristic of the construction risk environment by allowing decision makers to represent pairwise comparison matrices using fuzzy linguistic scales. Finally, the FAHP model for assigning importance weights to experts involves considerable simple implementation and requires little and straightforward computational efforts in execution which improves its significance and practicality in the GDM construction risk assessment field.

In the next chapter the FAHP model for assigning importance weights to experts data results will be implemented in the aggregation framework to obtain the experts' final importance weights. Also, a comparative analysis of fuzzy weighted aggregation operators will be developed to analyze the aggregation framework application in a construction risk assessment case study.

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CHAPTER 4 Development of the Aggregation Framework

4.1 Introduction

The objective of implementing an aggregation framework into a real life application (i.e. a construction company case study) is to validate the FAHP model for assigning importance weights to experts and to analyze the performance of different aggregation operators in the specific case study constraints. In this chapter, the methodology applied for the selection of a suitable aggregation operator in a specific risk contingency estimation case study will be further explicated. This chapter's main contributions are: (1) illustrating the aggregation framework, composed of the FAHP model for assigning importance weights to experts and the fuzzy aggregation operators, in a risk contingency case study; (2) validating the risk contingency case study results through a sensitivity analysis with the benchmark contingency results obtained from MCS; and (3) providing a structured approach for selecting a suitable aggregation operator in a specific context in the construction risk assessment field.

This chapter is organized as follows: Section 4.2 presents a comparative analysis of fuzzy aggregation operators; Section 4.3 describes in detail the illustration of the aggregation framework (i.e., assigning importance weights to experts and application of selected aggregation operators); Section 4.4 analyzes the results obtained from the application of the aggregation framework in the case study; and the final Section 4.5 discusses the findings of the aggregation framework application in a case study.

4.2 Comparative Analysis of Aggregation Operators

It is important to emphasize that the existence of several aggregation operators has originated according to the necessity for different aggregation properties, applications and results. Actually, the most appropriate approach for investigating the application of different aggregation operators in construction risk assessment accounts for the project context, project performance, and preference of the user as parameters in the aggregation process. In other words, the selection of a generalized aggregation operator that can be applied in any situation or scenario is not achievable and the choice of aggregation method should always be application-specific (Smolikova and Wachowiak 2002). Thus, the goal of this chapter is to outline the advantages and disadvantages of each aggregation operator in relation to the specific field of construction risk assessment GDM and analyze the application of different aggregation operators to a case study in the construction industry. As previously mentioned, this research's objective is to support the selection of the appropriate type of aggregation operators based on their suitability and the nature of the GDM problem to be solved. Although in this research the field of study is construction risk assessment GDM, the rationale presented for the selection of the most suitable aggregation operator in the case study context can be transferred to other research fields as well. As previously mentioned (Section 1.1), the application of fuzzy logic enables the modeling of subjective uncertainty present in construction risk assessment. The fuzzy weighted aggregation operators selected from literature for combining heterogeneous experts' opinions in construction risk assessment GDM are: (i) Fuzzy Weighted Average (FWA) aggregation Operator (Chen and Klein 1996; Sadiq et al. 2004), (ii) Fuzzy Ordered Weighted Averaging (FOWA) aggregation Operator (Merigo and Casanova 2008; Merigo 2010; Merigo 2011), and (iii) Fuzzy Weighted Geometric (FWG) aggregation Operator (Hsieh et al. 2004; Gohar et al. 2012; Dong et al. 2010; Wang et al. 2009).

One of the most significant characteristics for aggregation operators is robustness. Robustness is simply defined as a restricted version of the invariance property, which means that a class of mathematical objects remains unchanged when transformations of a certain type are applied to the objects (Bouchon-Meunier 2013). We can observe in Table 4.1 that the FOWA aggregation operator includes the robustness characteristic, which is mainly due to the measurements being part of the ordinal scale. Previous literature (Smolikova and Wachowiak 2002) have used different aggregation operators as parameters to analyze a case study and the results indicated that the FWG and the FOWA operators offer more flexibility in satisfying criteria of analysis than does the FWA. The most common aggregation operator used in construction risk assessment is the FOWA aggregation operator. When dealing with fuzzy numbers, the mathematical operations are important because in fuzzy arithmetic the fuzzy number format is not necessarily maintained (e.g. multiplication of triangular fuzzy numbers). The FOWA aggregation operator provides a straightforward solution to obtaining the product of Fuzzy numbers without changing the TFN format. Furthermore, in the construction risk assessment field, AHP (or FAHP) is usually employed to assess and rank risk events according to their importance level. In FAHP when analyzing reciprocal fuzzy pairwise comparison matrices, the FOWA aggregation operator shows to be extremely efficient and advantageous. Thus, the FOWA has several advantages relevant to this research context and goals.

Table 4.1 Comparative Analysis of Fuzzy Weighted aggregation Operators (adapted from Smolikova and Wachowiak 2002, Sadiq et al. 2004, Vanicek 2009, Calvo et al. 2012)

Aggregation Operator	Advantages	Disadvantages
Fuzzy Weighted Average (FWA)	• Continuous, idempotent, monotonic, additive and commutative • Beneficial when accounting for heterogeneous levels of expertise represented as importance weights since it is a non- symmetric aggregation operator • Compensation property gives the aggregation result as the "middle value" • Previously used in fuzzy weighted aggregation due to simplicity and computational ease • Aggregated value lying between "and" and "or" operators • Commonly applied with AHP in construction risk analysis	• Not agreement preserving and order independent • Algorithm becomes very complicated and cumbersome as *n* increases

Aggregation Operator	Advantages	Disadvantages
Fuzzy Ordered Weighted Averaging (FOWA)	• Commutative, monotonic, bounded and idempotent • Includes parameterized families of fuzzy aggregation operators: fuzzy maximum, fuzzy minimum, fuzzy average criteria among others • Ability to realize trade-offs between conflicting goals • Aggregated value lying between “and” and “or” operators • Usually tend to robustly satisfy criteria and can be computed relatively easily	• Requires the adherence of a ranking method for fuzzy numbers
Fuzzy Weighted Geometric(FWG)	• Commutative, idempotent and increasing monotonous • Aggregated value lying between “and” and “or” operators • Preservation of ordinal consistency • Can be easily applied to fuzzy reciprocal matrices • Suitable to be used in heterogeneous GDM scenarios • Commonly applied with AHP in construction risk analysis	• Based on reciprocal fuzzy pairwise comparison matrices that are perfectly consistent • Extension principle for TFN not applicable in fuzzy arithmetic multiplication operation – only approximation of TFNs

Since different aggregation operators display significantly different behavior, it is not appropriate to use any particular aggregation operator to provide generic representations for the aggregation of heterogeneous experts’ opinions (Beliakov and Warren 2001). In fact, in heterogeneous GDM problems), different aggregation operators can be used in different contexts. Therefore, the three aggregation operators presented in this section (i.e. FWA, FOWA, FWG) are analyzed based on their empirical results. This analysis indicates which aggregation operator obtains better results when compared to the benchmark results obtained through probabilistic software, the MCS. In conclusion, the selection of an aggregation operator should not be performed ad hoc and it should be based on which aggregation operators better satisfy the global goals (Smolikova and Wachowiak 2002) and the characteristics outlined in the comparative analysis (Table 4.1) of the aggregation operators.

In the next section, the aggregation operators are treated as parameters in the aggregation framework and the results obtained from the different aggregation operators will be compared to benchmark results. Also, the construction case study participants follow the consensus reaching process in order to reach an agreement and provide consensus data input. Thus, the consensus approach is also analyzed as another GDM approach in the construction case study application.

4.3 Illustrating the Aggregation Framework: Case Study

4.3.1 Illustrating the Model for Assigning Experts' Importance Weights

The proposed aggregation framework is applied in a case study to conduct the risk assessment of a wind farm power generation construction project in Kansas, USA. The risk assessment was based on the Balance of Plant (BOP) construction work packages (CWP) and it is valued at approximately $65 million. The CWP consists of eight work breakdown structure (WBS) ranging in cost from approximately $800 thousand to $16 million. The risk assessment involved a group of four experts, having more than 20 years of experience and holding managerial positions in a Canadian construction company located in Alberta. The step by step process followed to illustrate the aggregation framework in a case study is demonstrated in Figure 4.1.

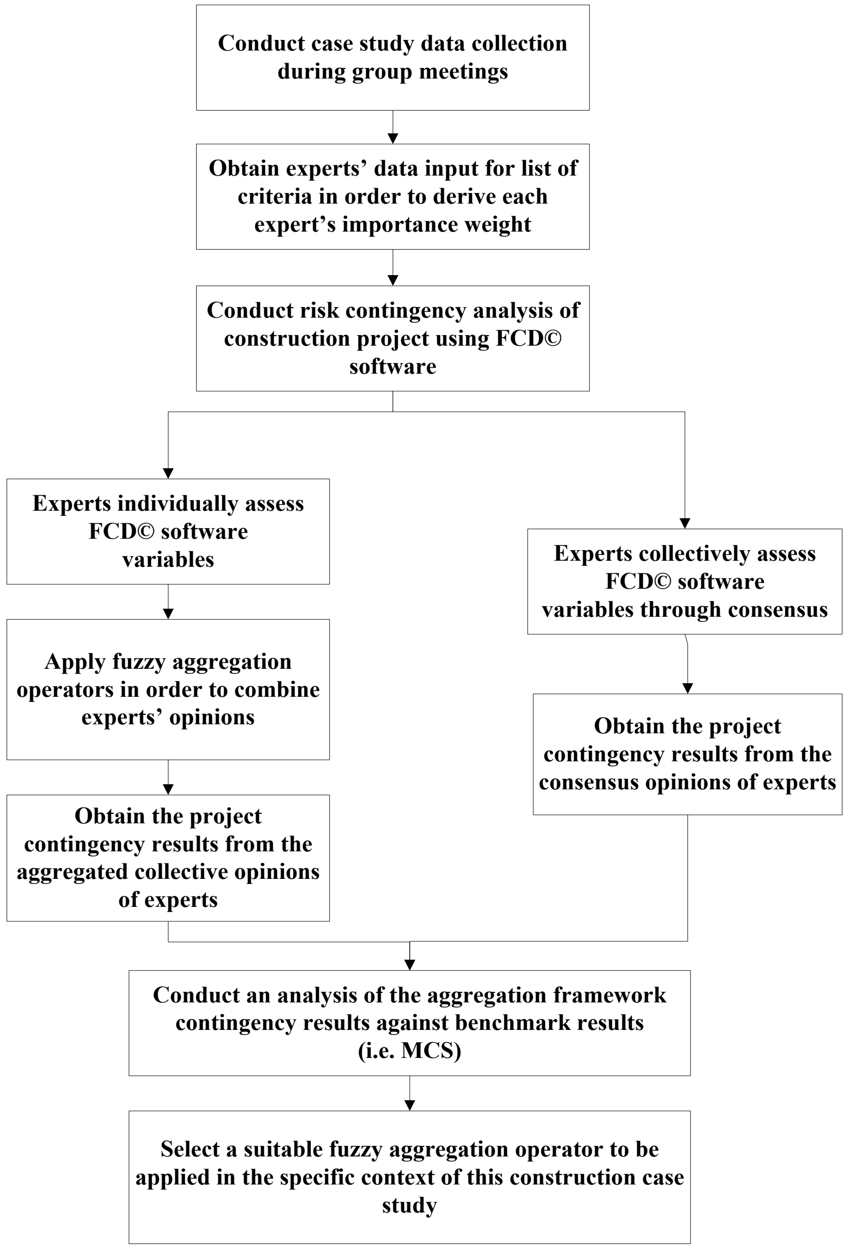

Figure 4.1 Aggregation framework illustrated application in a construction company case study

In order to assess the case study participants' expertise level in construction risk assessment and assign participants' importance weights, the FAHP model for assigning importance weights to experts was applied in the case study. The participants were asked to complete a questionnaire independently and individually. The two questionnaires used to collect personal input of the list of criteria from each participant can be found in Appendix in Table A.16 to Table A.22. The first questionnaire was the experts' questionnaire that collected each participant personal qualification attributes contained in the list of criteria for assessing experts' expertise level in construction risk assessment (Table A.1). Each participant was required to fill out this questionnaire individually. Figure 4.2 shows a sample of the experts' questionnaire distributed to the four participants in the group meeting to obtain each of their quantitative qualification attributes data.

SECTION 1: QUANTITATIVE QUALIFICATION CRITERIA FOR EXPERTS' RISK MANAGEMENT EXPERTISE ASSESSMENT

NAME:

SUPERVISOR'S NAME:

Please enter each numerical data value for the quantitative list of qualification attributes below according to each of your own personal attributes (self-evaluation).

Criteria	*Criterion*	*Description*	*Data Value*
1. Experience	1.1 Total Years of Experience	Number of years you have been working in this discipline	
	1.2 Diversity of Experience	Number of different companies you have worked for	
	1.3 Relevant Experience	Number of years you have been working in risk management	
	1.4 Applied Experience	Number of projects in which you performed risk management tasks	
	1.5 Varied Experience	Number of different functional areas or project types worked with in your entire career	
2. Knowledge	2.1 Academic Knowledge	Number years of study in your discipline	
	2.3 On the Job Training	Number of courses taken in current discipline	
3. Professional Performance	3.2 Years in current occupation	Number of years in your current occupation at company	
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	
	4.2 Level of Risk Management training	Number of certifications you have obtained from risk management training sessions or workshops	
	4.3 Risk Management conferences experience	Number of risk management conferences you have attended	
5. Project Specifics	5.1 Project Size Limit	Monetary value of the largest risk management project you have worked on in current company	
	5.2 Commitment to time deadlines	Percentage of projects finished on time by all projects you have been involved in	

Figure 4.2 Example of quantitative questions from expert's questionnaire

The first section of the expert's questionnaire consists of 16 questions and requires a short time to complete since the quantitative criteria data input is straightforward. However, the expert's questionnaire contained qualitative qualification attributes data input in the second section. Figure 4.3 shows a sample of one of the qualitative criteria and the predetermined rating scales that the participants were required to input in the data collection.

6. Crisis management

"Crisis management" indicates the level of the expert's crisis management skills. There are several points related to this issue, such as;

1. Understanding possible crises (Crises Type)
2. Understanding the time phase of crises (To be Reactive or Proactive)

Using 1-5 rating scales evaluate your risk management expertise as:

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

Criteria	***Criterion***	***Description***	***Data Value***
Risk Management Practice	Crisis management	Experience level with understanding the time phase of crisis (to be reactive or proactive), and having effective systems to prevent/control/manage crisis	

Figure 4.3 Example of qualitative questions from expert's questionnaire

The second questionnaire collected each participant's supervisor input about the participant's personal qualification attributes contained in the list of criteria. All the questions in the second questionnaire were completed solely by the participant's supervisor. All the questions in the supervisor questionnaire verified qualitative criteria for each participant. Some of the qualitative questions asked for each participant about their personal qualification attributes (self-evaluation) can also be found in the supervisor's questionnaire.

Figure 4.4 shows a sample of the second questionnaire questions that the participants' supervisor had to fill for each participant. All questions in the Supervisor's questionnaire require qualitative data input which is measured through predetermined rating scales, such as "Professional Reputation" criterion in Table 3.1.

SUPERVISOR VALIDATION OF QUALITATIVE QUALIFICATION CRITERIA FOR EXPERTS' RISK MANAGEMENT EXPERTISE ASSESSMENT

Each qualitative qualification criteria is measured using predetermined rating scales described below. Based on your own judgement **about the participant** _______ expertise level, please assign a data value for each of the qualitative qualification attributes listed.

1. **Risk identification and planning**

"Risk identification and planning" indicates the experts' experience level with risk identification and planning. There are several points related to this issue, such as;

1. Proper risk identification.
2. Development of an overall risk management plan with risk response planning.

Using 1-5 rating scales evaluate the expert's risk management expertise as:

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

Criteria	*Criterion*	*Description*	*Data Value*
Risk Management Practice	Risk identification and planning	Experience level with proper risk identification and development of an overall risk management plan with risk response planning	

Figure 4.4 Example of qualitative questions from Supervisor's questionnaire

In the previous data collection results (Chapter 3) most experts indicated that 5 qualification attributes should be obtained from both Experts' and Supervisors' Questionnaires: (1) Risk identification and planning, (2) Risk monitoring and control, (3) Crisis management, (4) Willingness to participate in the survey, and (5) Enthusiasm and Willingness. Since, for these 5 sub-criteria there would be two results, the average of the two values is used in the FAHP model for assigning importance weights to experts. All the data sources selected are supported with previous data collection results (Section 3.3).

Thus, the FAHP model contained information from the expert's and supervisor's questionnaires as data input for the list of criteria (Table A.1) to assess experts' expertise level in construction risk assessment. The results for the expert's and the supervisor's questionnaires were analyzed and inputted into the FAHP model for assigning importance weights to experts. The participants qualification attributes determined the maximum and the minimum range values as the largest and smallest data input numbers respectively. Thus, it is possible to normalize each participant data input in order to use the FAHP model for assigning importance weights to experts.

After each of the four participants completed all list of criteria data input (from the self-evaluation and supervisor questionnaires), then the FAHP weight assigning model is applied as explained in Section 3.4.2. The product of the participant's normalized data input by the criteria and sub-criteria weights would finally add up to the Expert Score (ES) and the normalized values of the Expert Scores (Equation 3.9) represent the final expert importance weight (Equation 3.10). The final expert importance weights obtained represent each of the four experts' influence on the risk contingency calculation when aggregating all the experts' opinions. Table 4.2 shows each of the four experts' Expert Scores (Equation 3.9) and Final Expert Importance Weights (Equation 3.10). It is important to note that the participants Final Importance Weights sum up to 1.0. The four Experts' Importance Weights values will be applied in the following sections in order to demonstrate the application of the fuzzy weighted aggregation operators in the construction company case study.

Table 4.2 Case Study Experts' Final Importance Weights

Expert	Expert Score	Final Expert Importance Weight (Normalized)
1	0.87	0.26
2	1.07	0.32
3	0.79	0.23
4	0.66	0.20

4.3.2 Illustrating the Construction Risk Assessment GDM

In order to calculate the contingency of a construction project, the risk and opportunity events must first be identified. The experts' assessments for both, probability and impact, are provided by means of linguistic terms, which are represented by trapezoidal fuzzy numbers. Once all the experts' assessments of each risk or opportunity event are provided, they need to be aggregated into a unique value that reflects the group's opinion. The experts' importance weights obtained in Section 4.3, $\mathrm{IW} = (\mathrm{IW}_1, \dots, \mathrm{IW}_d)$, are used as the weight vector of the experts' assessments to represent the expert's expertise level, and a fuzzy weighted aggregation operator is applied.

More precisely, let $\mathrm{E} = \{\mathrm{E}_1, \dots, \mathrm{E}_h\}$ be h risk or opportunity events identified across all work packages of a construction project. For each $\mathrm{E}_j, j = 1, \dots, h$, the experts must provide a linguistic assessment of probability and impact of such event. Let $\widetilde{\mathrm{P}}_i^{(j)}$ and $\tilde{\mathrm{I}}_i^{(j)}$, $i = 1, \dots, d$, be, respectively, the probability and impact assessments of event E_j provided by the i^{th} expert. Then, the aggregated probability value, $\widetilde{\mathrm{P}}^{(j)}$, and the aggregated impact value, $\tilde{\mathrm{I}}^{(j)}$, that represent the group's opinion on the probability and impact of the event E_j are given by $f_{\mathrm{IW}}\left(\widetilde{\mathrm{P}}_1^{(j)}, \dots, \widetilde{\mathrm{P}}_d^{(j)}\right)$ and $f_{\mathrm{IW}}\left(\tilde{\mathrm{I}}_1^{(j)}, \dots, \tilde{\mathrm{I}}_d^{(j)}\right)$, respectively, where f_{IW} stands for the fuzzy aggregation operator f, using IW as weighting vector. For instance if the FWA operator, presented in Equation 2.19, is used, then $\widetilde{\mathrm{P}}^{(j)} = \mathrm{FWA}_{\mathrm{IW}}\left(\widetilde{\mathrm{P}}_1^{(j)}, \widetilde{\mathrm{P}}_2^{(j)}, \dots, \widetilde{\mathrm{P}}_d^{(j)}\right) = \sum_{i=1}^{d} \mathrm{IW}_i \widetilde{\mathrm{P}}_i^{(j)}$ and $\tilde{\mathrm{I}}^{(j)} = \mathrm{FWA}_{\mathrm{IW}}\left(\tilde{\mathrm{I}}_1^{(j)}, \tilde{\mathrm{I}}_2^{(j)}, \dots, \tilde{\mathrm{I}}_d^{(j)}\right) = \sum_{i=1}^{d} \mathrm{IW}_i \tilde{\mathrm{I}}_i^{(j)}$. The aggregated probabilities, $\left\{\widetilde{\mathrm{P}}^{(1)}, \dots, \widetilde{\mathrm{P}}^{(h)}\right\}$, and impacts, $\left\{\tilde{\mathrm{I}}^{(1)}, \dots, \tilde{\mathrm{I}}^{(h)}\right\}$, of all events, are used to obtain the project's contingency in the next step of the framework.

Then, in order to determine the construction project's contingency, the severity of each event identified in Step 4, $E_1, \dots, E_h$, must be determined as a percentage value. The severity of a risk or opportunity event is given by Equation 4.1.

$$\widetilde{R}_j = \widetilde{P}^{(j)} \times \tilde{I}^{(j)} \ , j = 1, \dots, h \qquad (4.1)$$

where $\widetilde{R}_j$ denotes the severity of event E_j and $\widetilde{P}^{(j)}$ and $\tilde{I}^{(j)}$ are the aggregated probability and impact of event E_j obtained in Step 4. Once the severity of each event is obtained, the net severity, $\widetilde{O}$, is calculated as shown in Equation 4.2.

$$\widetilde{O}_j = \widetilde{R}_j \times U^{(j)}, \ j = 1, \dots, h \qquad (4.2)$$

where $U^{(j)}$ is the c cost of the work package indicated as dollar value ($) associated with event E_j. Finally, the project's contingency value, $\widetilde{V}$, is given by Equation 4.3.

$$\widetilde{V} = \sum_{i \in H_R} \widetilde{O}_i - \sum_{i \in H_O} \widetilde{O}_i \qquad (4.3)$$

where $H_R = \{i: E_i \text{ is a risk event}\}$ and $H_O = \{i: E_i \text{ is an opportunity event}\}$.

Since the aggregated probability and impact, $\widetilde{P}^{(j)}$ and $\tilde{I}^{(j)}$, are fuzzy numbers, Equations 4.1 to 4.3 involve fuzzy arithmetic. There are two methods to perform fuzzy arithmetic calculations: the α-cut method, and the extension principle. In the α-cut method, interval arithmetic is performed at each α-level cut of the fuzzy numbers to obtain the α-cut of the output. On the other hand, the extension principle generalizes functions from the crisp domain to the fuzzy domain, allowing the generalization of conventional mathematical operators to be applied in the fuzzy domain. For more information on fuzzy arithmetic, the reader is referred to Hanss (2005).

Considering that the project's contingency obtained in Equation 4.3, $\widetilde{V}$, is a fuzzy number, it is possible to obtain interval ranges for the contingency with different levels of confidence, by means of α-cut. Specifically, the α-cut, V_α, of $\widetilde{V}$, is the confidence interval of the contingency values at a confidence level of $1 - \alpha$. If a single crisp value for project contingency is desired, instead of obtaining the project contingency as a fuzzy number, defuzzification operators such as, Center of Area (COA), Smallest of Maxima (SOM), Middle of Maxima (MOM) or Largest of Maxima (LOM), can be applied. Generally, COA represents the output shape as a the "center of gravity", whereas SOM and LOM represent, respectively, the smallest and the largest values of the project contingency when $\alpha = 1$; MOM is the middle value of the range of contingencies when $\alpha = 1$.

In order to calculate the project's risk contingency, a software tool will be used in this case study. The FCD© software provides a tool that automates the fuzzy arithmetic procedure to determine construction projects' risk contingency based on the linguistic assessment of the probability and impact of risk and opportunity events (ElBarkouky et al. 2016). Figure 4.5 demonstrates the process for calculating the project contingency in FCD©.

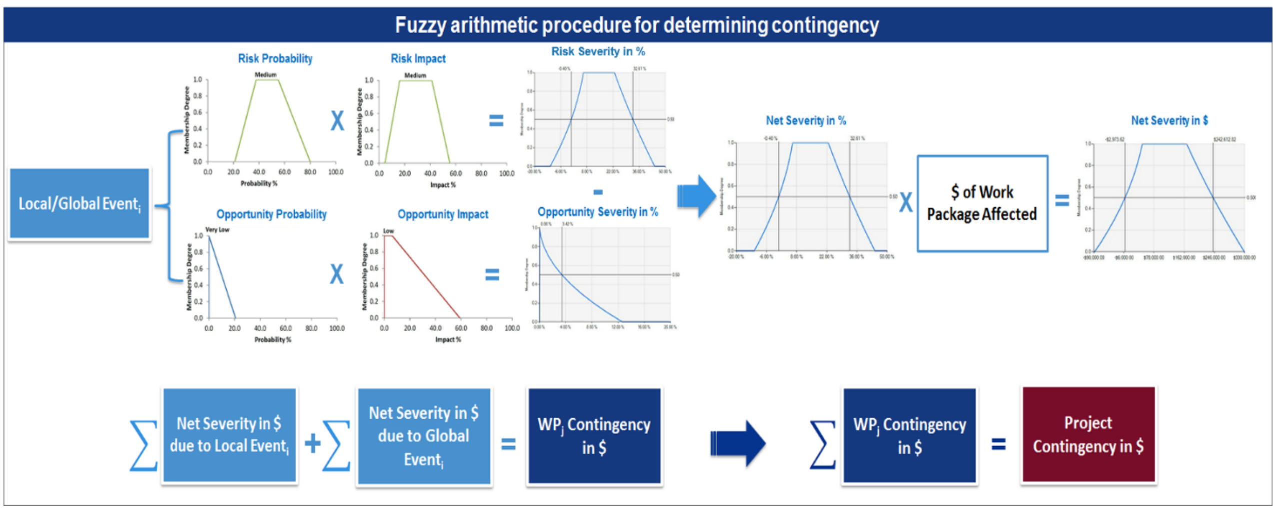

Figure 4.5 Project contingency calculation for construction risk assessment (adapted from Elbarkouky et al. 2016)

The FCD© software represents each construction project as a combination of work packages. Events that may impact individual work packages are considered "local events," as their probability and impact are assessed individually on a work-package basis. However, some risks and opportunities that may result from higher-level project events can be better assessed on an overall-project basis or, if they impact a large group of work packages, their probability and impact may be more efficiently assessed simultaneously for the group of work packages; these events are considered "global events" (Elbarkouky et al. 2016).

Thus, the risk assessment is performed at the lower level in each work package "local events" and at the higher level for the entire construction project (i.e. global events). The events that cause a negative impact on the construction project are considered risk events. The events that cause a positive impact on the construction project (i.e. decreased cost or time of project) are considered opportunity events. Then, the FCD© users are required to determine each event risk and/or opportunity probability and impact of occurrence.

The first step in the case study analysis is to determine the project events from a list of events in the FCD© software. The four experts involved in this case study discussed and agreed on the "balance of plant" phase events potentially leading to risks and/or opportunities during the focus group session. Ultimately, 17 events were identified for all the work packages and agreed upon by the experts. All the events identified in this project were local events only, there were no global events.

The next step is to ask participants to individually input five risk assessment variables in the case study. The five risk assessment variables are: (1) risk probability, (2) risk impact, (3) opportunity probability, (4) impact, and the (5) cost of work package affected in percentage for each event in each work package. The FCD© software previously required participants to follow the consensus reaching process and agree on the data input for each of 5 variables. This research has implemented an aggregation framework that allows each participant to express their individual opinions about each variable as linguistic terms in the software, and then combines all the participants' opinions to provide a unique collective result for construction risk contingency.

In order to assess the probability and impact of risk and opportunity events, the FCD© software uses linguistic terms, that are represented by fuzzy numbers (ElBarkouky et al. 2016). The linguistic scales terms are based on the five-Point scale which consists of the terms Very High, High, Medium, Low and Very Low. It is common to represent fuzzy numbers as trapezoidal or triangular shapes. Trapezoidal fuzzy numbers are defined using fuzzy quadruples that consist of four parameters (a_1, b_1, c_1, d_1). The lower and upper bound are represented by a_1 and d_1 respectively, and b_1, c_1 denote the modal values. Triangular fuzzy numbers are a special case of trapezoidal shapes, where the value of b_1 equals the value of c_1 (Siraj et al. 2016).

The aggregation of heterogeneous experts' opinions is performed at each of the 5 risk assessment variables level since this ensures the trapezoidal fuzzy number standard shape will be maintained. Later on, the group of FCD© users also followed a consensus reaching process in order to agree on 5 data variables in each work package. Thus, the final results would include each individual participant opinion of the work packages events' risk and opportunity values (i.e., through the aggregation process), as well as the group consensus opinion.

As shown in Figure 4.1 in the step "Experts individually assess FCD© software variables", after the experts assessed each of the five variables individually, they were asked to assess the five variables for each event through consensus. In this stage of the data collection, the experts were allowed to communicate and discuss in order to agree on the 5 variables for each event previously identified. Thus, for the case study, both the aggregation framework and the consensus results were obtained.

In the next section (Section 4.4) the results obtained from aggregating the case study experts' opinions is compared to the results obtained from the group consensus. The results obtained with different aggregation operators will be compared against the MCS benchmark results in order to obtain a suitable aggregation operator for a specific case study application in construction risk assessment.

4.4 Verifying the Aggregation Framework Case Study Results

In order to verify the aggregation framework, the project contingency results for the case study, obtained using the framework, are compared against a benchmark. The ideal benchmark is the actual contingency results for case study at project completion. However, collecting final contingency values was not possible, since the case study project was still underway at the time of data collection. Therefore, the MCS results were used as benchmark, since MCS is a commonly used method in the construction risk assessment field to determine project contingency. The MCS project contingency value in this case study is obtained at P50 which represents the confidence level of 0.5 of the project contingency value (analogous to the α-cut confidence level explained in Section 4.3.2). In addition, for comparison purposes, the experts were also asked to reach a consensus on the probabilities and impacts of the same risk and opportunity events previously assessed through the aggregation process. Thus, the results of the proposed framework are compared to the consensus result as well.

The symmetric mean absolute percentage error (SMAPE) error calculation method avoids limitations associated with the traditional error measures including mean absolute error (MAE), root mean square error (RMSE), Pearson correlation coefficient (r), coefficient of determination (r^2), and others (Ji and Gallo 2006). For instance, MAE and RMSE are both dimensional and scale dependent; RMSE is highly affected by extreme values and gives considerable weight to large errors; r and r^2 tend to measure linear covariation rather than measuring actual differences (Ji and Gallo 2006, Willmott and Matsuura 2005). Furthermore, problems such as asymmetry and easily being affected by outliers which are commonly associated with Mean Absolute percentage error (MAPE) are also addressed by the SMAPE (Willmott and Matsuura 2005).

The SMAPE value ranges from 0 to 200%, and a value of 0% implies a perfect agreement between the two models (ElBarkouky et al. 2016). The SMAPE measure is expressed in Equation 4.4:

$$SMAPE = \frac{100}{n} \frac{|P_i - O_i|}{(P_i + O_i)/2} \tag{4.4}$$

where P_i and O_i are the project contingency values predicted by the model under consideration and the benchmark, respectively. Again, in this case the benchmark is the MCS P50 estimate.

Since there are many possible combinations of fuzzy aggregation operators, fuzzy arithmetic methods, and defuzzification methods that can be used in the proposed framework to obtain the project's risk contingency, many combinations were tested. Table 4.3 shows the SMAPE for many configurations of the risk assessment framework and the consensus approach. Since project in this case study is considerably small, with only 8 work packages, the results analysis is performed by comparing the project contingency results.

An analysis of the SMAPE results presented in Table 4.3 shows that using the FOWA operator with the MOM defuzzification formula in the proposed framework provides the smallest error with respect to the MCS risk contingency results, only 0.08, independently of the fuzzy arithmetic method used. In addition, it can be seen from Table 4.3 that both, the aggregation operators and the defuzzification methods, have a great impact on the SMAPE. Also, different defuzzification formulae might be more appropriate for different aggregation operators. In general, the FWA aggregation operator results have the highest SMAPE values (all FWA values higher than 80%). Even FWG operator has a poor performance in terms of SMAPE when compared to FOWA operator (all FWG values higher than 7%). Thus, the FWA and FWG results are not in agreement with the MCS results and are considered unsuitable aggregation operators to combine heterogeneous experts' opinions for this case study. Furthermore, the SMAPE values variations among the different aggregation operators presented in Table 4.3 are a consequence of the different equations (Equations 2.9, 2.12, 2.20) and characteristics (Table 4.1) of each aggregation operator.

Table 4.3 Case study aggregation and consensus results compared to MCS results by the SMAPE error calculation

SMAPE values	**Defuzzification Methods**	α-cut	Minimum t-norm	Product t-norm	Drastic t-norm	Bounded t-norm
CONSENSUS	COA	95.78	95.78	86.00	72.78	74.93
	MOM	72.69	72.69	72.69	72.69	72.69
	SOM	43.22	43.22	43.22	43.22	43.22
	LOM	92.83	92.83	92.83	92.83	92.83
Fuzzy Weighted Average	COA	110.53	110.53	107.60	104.20	104.40
	MOM	104.22	104.22	104.22	104.22	104.22
	SOM	84.98	84.98	84.98	84.98	84.98
	LOM	117.95	117.95	117.95	117.95	117.95
Fuzzy Weighted Geometric	COA	68.46	68.46	46.88	8.00	19.57
	MOM	7.85	7.85	7.85	7.85	7.85
	SOM	45.89	45.89	45.89	45.89	45.89
	LOM	42.32	42.32	42.32	42.32	42.32
Fuzzy Ordered	COA	24.43	24.43	12.81	7.56	1.43

SMAPE values	**Defuzzification Methods**	α-cut	Minimum t-norm	Product t-norm	Drastic t-norm	Bounded t-norm
Weighted Average	**MOM**	**0.08**	**0.08**	**0.08**	**0.08**	**0.08**
	SOM	46.33	46.33	46.33	46.33	46.33
	LOM	0.20	0.20	0.20	0.20	0.20

On the other hand, the fuzzy arithmetic methods do not cause great impact in most cases, except when the COA defuzzification formula is used. In this case, the impact of the fuzzy arithmetic method is considerable and the method that provides the smallest error is either, the extension principle using Drastic t-norm or Bounded t-norm, depending on the aggregation operator used. Last, note that with the right choice of parameters, the proposed framework hugely improves the SMAPE in comparison to the best result obtained by the consensus approach, 0.08 vs 43.22. results

The findings of this case study show that applying the aggregation process to construction risk assessment GDM provides results in higher agreement with the MCS project contingency than the results obtained through consensus. Furthermore, amongst the three aggregation operators tested, the FOWA demonstrated results with the highest MCS agreement for this specific case study and the fuzzy arithmetic methods did not affect the results when defuzzification formulae other than COA were used. The risk assessment framework proposed assists researchers and industry experts in advancing the GDM approaches for construction risk assessment through the aggregation process by using a systematic, transparent, and flexible methodology to combine experts' risks and opportunities assessments.

4.5 Concluding Remarks

The second step of the aggregation process (i.e. applying an aggregation operator to combine the experts' opinions) was addressed by conducting a review of the most common aggregation operators applied in the construction risk assessment field to combine heterogeneous experts' opinions in GDM. A comparative analysis of suitable aggregation operators to apply in a specific case study was further reviewed. The practical application of this study will be for estimating the construction projects risk contingency through aggregating heterogeneous experts' opinions in GDM. A construction company case study tested which is the most suitable aggregation operator to be used in this specific application. An aggregation framework that supports the FAHP model for assigning importance weights to experts and the aggregation operators discussed in this chapter is developed and illustrated through a case study that used FCD© risk contingency software as a tool. Thus, this research facilitated the aggregation of the opinions of experts in a heterogeneous group decision making scenario when conducting risk assessment and contingency determination.

The structured approach for applying the aggregation framework in a case study involved calculating the importance weights of the four experts in the case study (Table 4.2). Furthermore, the four participants were required to provide data input for the list of criteria (Section 4.2) to evaluate experts' expertise level in construction risk assessment. The questionnaire data results obtained were applied to the FAHP model for assigning importance weights to experts to generate the importance weights for each of the 4 experts in the construction company case study. It is important to note that there were 2 data collection sessions during this research, the first group meeting with 8 experts to validate the list of criteria and FAHP model for assigning importance weights to experts and the second group meeting with 4 participants that provided personal data and opinions for illustrating the aggregation framework in the risk assessment case study.

The comparison of the aggregated results using different aggregation operators showed that the FOWA aggregation operator application in the case study, obtained more consistent and reasonable results that aligned with the MCS project contingency results. Nevertheless, the aggregation framework applied in the FCD© software risk contingency case study can be generalized to other fields of application. The approach presented for the aggregation framework application, such as the FAHP model for assigning importance weights to experts and the different aggregation operators in the case study, is a general procedure that can be better directed and adjusted according to the specific field of application. The importance of defining the context and field of application of the aggregation framework is pertinent in analyzing the results obtained as well, since depending on the context the results can vary. In order to generalize the aggregation framework, some of the steps of the aggregation framework need to be adjusted such as: list of criteria, pairwise comparison for relative importance of criteria, eliciting new expert weights, and testing all the aggregation operators. In the next chapter, the state of art advancement provided by the aggregation framework is presented.

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CHAPTER 5 CONCLUSION AND FUTURE RESEARCH

This chapter provides a review of the study conducted in this research, and summarizes its contributions. Limitations of the developed framework and recommendations for future research are also outlined.

5.1 Research Summary

In the construction risk assessment field, groups of experts with different levels of expertise are often involved to make decisions and reach a common solution. However, there is no structured and clear aggregation framework to combine heterogeneous experts' opinions in construction risk assessment GDM. The aggregation framework illustrated in this paper presents a systematic and flexible multi-step methodology to assess heterogeneous experts' expertise level and assign experts' importance weights in the construction risk assessment GDM aggregation process. The methods used in the aggregation framework advance the practical application of evaluating heterogeneous experts in construction, while the combination of experts' risk assessments through aggregation advances construction industry GDM practice.

This thesis introduces a structured approach for developing an aggregation framework in construction risk assessment. The presented framework can be adapted according to the field of study and application of the aggregation process. The research in this thesis was divided into three main stages: (1) Literature Review of group decision making techniques and a comprehensive review of existing aggregation operators; (2) Compilation and validation of a list of criteria to assess experts' expertise level and development of the fuzzy importance model for assigning importance weights to experts; (3) Analysis and selection of a suitable aggregation operator by the illustrating the aggregation framework in a risk assessment case study using a contingency estimating software.

5.1.1 First Stage

In the first stage, two common approaches used in GDM for combining heterogeneous experts' opinions were surveyed: consensus reaching process and aggregation process. The most suitable technique has been concluded to be the aggregation approach, thus an investigation of different aggregation operators' features, properties, mathematical formulation, and the situations in which each can be applied was developed. Furthermore, in order to account for the subjective uncertainties in expert risk assessments, the aggregation methods apply fuzzy logic as a valuable tool to handle subjectivity and imprecision.

5.1.2 Second Stage

In the next stage, in order to improve and facilitate the fuzzy aggregation process involving experts with different level of expertise, a new model for assigning importance weights to experts is developed. The experts' importance weights are assigned based on a clear and validated list of criteria to assess experts' expertise level in construction risk assessment. The FAHP model for assigning importance weights to experts addresses the subjectivity and uncertainty characteristic of the construction risk environment by allowing decision makers to represent pairwise comparison matrices using fuzzy linguistic scales. Also, the FAHP model for assigning importance weights to experts involves considerable simple implementation and requires minimal computational efforts in execution which improves its significance and practicality in the GDM construction risk assessment field.

5.1.3 Third Stage

The assessment of risks and opportunities in construction projects is a very complex topic and frequently involves multiple experts with different expertise levels. In the last stage instead of relying on the time consuming and expensive CRP where all the experts need to reach an agreement on the risk assessments, a new aggregation framework is proposed. The proposed framework provides a systematic multi-step methodology that assesses the experts' expertise level in construction risk assessment and assigns weights to the experts according to their expertise. The experts' opinions for both the qualification criteria assessment and the risk assessment are captured by linguistic terms, which are modelled using fuzzy numbers. In this way, the framework is also able to process the subjectivity and vagueness inherent in human assessments.

The framework was applied in a case study of a real construction project and compared with the results obtained by the MCS P50. The framework was able to obtain similar results to the MCS approach, however in a quicker process and with no necessity of obtaining sufficient historical data for probabilistic distribution estimation. The performance of the framework was also quite superior from the one obtained through consensus process. Some guidelines to select the most appropriate aggregation operator and defuzzification formula were also discussed, which in this case study was the FOWA operator and the MOM formula.

5.2 Research Contributions

This research study has produced several contributions. Some contributions advanced the state of art for researchers and academics and thus are grouped under academic contributions. Other contributions benefited the construction industry advancement and thus are grouped under industry contributions.

5.2.1 Academic Contributions

The academic contributions presented in this research are:

1. The aggregation framework developed avoids the subjectivity or bias that could be introduced by the moderator assessing experts' expertise level by eliminating the moderator judgement from the process of assigning weights to experts in construction risk assessment, and thus avoiding the subjectivity and bias introduced by the moderator.

2. The aggregation framework addresses previous research gap of assigning experts' importance weights arbitrarily and subjectively by developing a method to weight experts' importance in risk assessment based on a clear and consistent list of criteria, metrics and scales of measure to evaluate experts' risk assessment expertise.

3. The aggregation framework applies fuzzy set theory to process the subjectivity and vagueness inherent in human assessments since the experts' opinions for both the qualification criteria assessment and the risk assessment are captured by linguistic terms, which are modelled using fuzzy numbers, in the aggregation framework.

4. The aggregation framework presents a structured guideline for applying aggregation in a construction risk assessment GDM scenario by providing a systematic multi-step methodology that assesses the experts' expertise level in construction risk assessment and assigns weights to the experts according to their expertise.

5.2.2 Industrial Contributions

The industrial contributions outlined in this research are:

1. The aggregation framework provides a model for construction risk assessment experts to express their opinions as linguistic terms in comparing and ranking the list of criteria, which better represent human thinking.

2. The aggregation framework improves performance in construction risk assessment GDM by providing a more efficient process than the consensus reaching process. The aggregation framework also has the potential of increasing the accuracy of the collective group decision making results.

3. The aggregation framework improves the process of heterogeneous group decision making in the construction risk assessment field by proposing a clear and consistent list of criteria to assess experts' expertise levels and assigning experts' importance weights in the aggregation framework.

4. The aggregation framework provides a structured methodology for combining heterogeneous experts' opinions in construction risk assessment. The methodology can

be applied to develop aggregation frameworks for other construction industry applications.

5.3 Research Limitations and Future Research Recommendations

Despite the contributions outlined in the previous section, this research contains certain limitations. These limitations can be summarized as per below:

1) This research was not expanded to other construction applications that require expert assessments. The proposed aggregation framework can be applied in other areas of construction, besides risk assessment.

2) In the FAHP criteria and sub-criteria assessment, the criteria and sub-criteria were considered independent. The relative importance of criteria and sub-criteria did not take into consideration any correlation between criteria and/or sub-criteria.

3) The model for assigning importance weights to experts developed considers the weights of the experts fixed throughout the aggregation process and it does not change according to the criteria or alternatives being analyzed (such as the work packages in a construction project).

4) A comparison of the aggregation framework results and the actual case study contingency results was not performed since the project is still undergoing and contingency data will have to be collected in the future. Also, the aggregation framework results were illustrated through one case study only.

In the future, in order to address the current research limitations the following steps are recommended:

1) Expand the proposed framework to other construction applications that requires experts' assessments and adapt the framework for different contexts. This can be achieved by adjusting the steps in the framework such as: list of criteria, pairwise comparison for relative importance of criteria, eliciting new expert weights, and testing all the aggregation operators.

2) Improve the FAHP analysis by assessing the correlation between criteria and/or sub-criteria, in order to obtain the relative importance between criteria and sub-criteria.

3) Propose a more dynamic model for assigning importance weights to experts to assess experts' expertise level that would consider the experts' knowledge and expertise on the specific criteria and/or alternative being assessed such as the work packages in a construction project. For example in the work package "underground collection" experts that have a geotechnical background have higher expertise level and thus the weights should be adjusted accordingly

4) Improve the verification of the aggregation framework results by comparing it with the actual project contingency results at project completion.

5) Implement the framework using more case studies results in order to validate the aggregation framework.

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APPENDIX A: LIST OF CRITERIA FOR ASSESSING EXPERTS' EXPERTISE LEVEL IN CONSTRUCTION RISK ASSESSMENT

The list of criteria below was initially compiled by reviewing literature: Brown 1968, McKee et al. 1991, Medsker et al. 1995, Yang 1995, Kanazawa 1998, Muralidharan et al. 2002, Shanteau et al. 2002, Cornelissen et al. 2003, Cooke and Goosens 2004, Herrera-Viedma et al. 2005, Baker et al. 2006, Farrigton-Darby and Wilson 2006, Hoffmann et al. 2007, Sun et al. 2008; Marsh and Fayek 2010, Wang and Yuan 2011, Awad and Fayek 2012a, Yildiz et al. 2014, Omar and Fayek 2016.

Table A.1 Initial preliminary list of criteria for assessing experts' expertise level in construction risk assessment

Criteria	*Sub-Criteria*	*Criterion*	*Description*
1. Experience	1.1	Total Years of Experience	Number of years expert has been working in his/hers discipline
	1.2	Diversity of Experience	Number of different companies expert worked for
	1.3	Relevant Experience	Number of years working in risk management
	1.4	Applied Experience	Number of projects in which expert performed risk management tasks
	1.5	Supervisory Experience	Number of employees supervised by expert
2.Knowledge	2.1	Academic Knowledge	Years of study in expert's discipline
	2.2	Education Level	Highest degree achieved to date
	2.3	Awards	Number of awards received by expert on field he/she currently works in
	3.1	Current occupation in the company	Occupation in company currently working for
	3.2	Years in current occupation	Number of years in current occupation at company
	3.3	Years since PEng certification	Years since obtained Professional Engineer (PEng) certification
	3.4	Previous Key Employee	Maximum number of years in

Criteria	*Sub-Criteria*	*Criterion*	*Description*
3.Professional Performance		Commitment	which expert worked for the same company
	3.5	Current Key Employee Commitment	Number of years expert has been working in current company
	3.6	Expertise Self-Evaluation	Level of risk management expertise that participant expert acknowledges about himself/herself
	3.7	Level of Construction Training	Total number of Construction Engineering trainings or workshops expert has participated in
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
	4.2	Level of Risk Management training	Number of hours attended in risk management training or workshops
	4.3	Risk Management conferences experience	Number of risk management conferences expert has attended
	4.4	Risk identification and planning	Experience level with proper risk identification and 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
	4.6	Crisis management	Experience level with understanding possible crises, understanding the time phase of crises (to be reactive or proactive), having systems to prevent crises, understanding stakeholders
5. Project Specifics	5.1	Project Size Limit	Monetary value of the largest risk management project expert worked on in current company

Criteria	*Sub-Criteria*	*Criterion*	*Description*
	5.2	Commitment to time deadlines	Percentage of projects finished on time by all projects done by expert
	5.3	Commitment to cost budget	Percentage of projects finished on budget by all projects done by expert
	5.4	Safety adherence	Number of major incidents in all projects supervised by expert
	5.5	Geographic Diversity Experience	Number of different project locations that expert has worked on
6.Reputation	6.1	Social Acclamation	Number of participants that indicate one specific participant expert to be the most relevant expert in risk management
	6.2	Willingness to participate in survey	Quality of responses of experts who participated in the research
	6.3	Professional Reputation	Level of credibility of expert based on consistency and reasonableness (use of engineering judgement) of previous decisions
	6.4	Enthusiasm and Willingness	Level of Enthusiasm and Willingness in performing risk management tasks in current company
	6.5	Level of risk conservativeness	Level of conservativeness of experts' risk assessment
7.Personal Attributes and Skills	7.1	Level of communication skills	Expert's level of maintaining interpersonal skills with team and clearly expressing their point of view
	7.2	Level of teamwork skills	Expert's level of participating as an active and contributing member to achieve the team's goals
	7.3	Level of leadership skills	Expert's level of finding resources, training and offering tools to support team members
	7.4	Level of Analytical skills	Expert's level of anticipating and identifying problems in daily tasks while accounting for any missing data
	7.5	Level of Ethics	Expert's level of conforming to

Criteria	***Sub-Criteria***	***Criterion***	***Description***
			any legal or regulatory framework enforced by company

Table A.2 Validated list of criteria containing quantitative and qualitative metrics and scales of measure to assess expert's expertise level in construction risk assessment

Criteria	*Sub-Criteria*	*Criterion*	*Description*	*Scale of Measure*	*Range/ Reference variables*	*Predetermined ratings (1-5) Descriptions*
1. Experience	1.1	Total Years of Experience	Number of years expert has been working in his/hers discipline	Integer	0-40	-
	1.2	Diversity of Experience	Number of different companies expert worked for	Integer	1-5	-
	1.3	Relevant Experience	Number of years working in risk management	Integer	0-35	-
	1.4	Applied Experience	Number of projects in which expert performed risk management tasks	Integer	0-100	-
	1.5	Varied Experience	Number of different functional areas or project types worked with in the entire expert's career	Integer	0-20	-
2.Knowledge	2.1	Academic Knowledge	Number years of study in expert's discipline	Integer	0-15	-
	2.2	Education Level	Highest degree achieved to date	Categorical	High School, College, Technical Degree, Bachelor, Master	-
	2.3	On the job training	Number of courses taken in current discipline	Integer	0-30	-
3.Professional Performance	3.1	Current occupation in the company	Occupation in company currently working for	Categorical	Project Engineer, Senior	-

Criteria	*Sub-Criteria*	*Criterion*	*Description*	*Scale of Measure*	*Range/ Reference variables*	*Predetermined ratings (1-5) Descriptions*
					Engineer, Project Manager, Manager, Senior Manager	
	3.2	Years in current occupation	Number of years in current occupation at company	Integer	0-30	-
	3.3	Expertise Self-Evaluation	Level of risk management expertise that participant expert acknowledges about himself/herself	1-5 Predetermined Rating	Self-explanatory ratings	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	0-48	-
	4.2	Level of Risk Management	Number of certifications obtained from risk	Integer	0-15	-

Criteria	*Sub-Criteria*	*Criterion*	*Description*	*Scale of Measure*	*Range/ Reference variables*	*Predetermined ratings (1-5) Descriptions*
		training	management training sessions or workshops			
	4.3	Risk Management conferences experience	Number of risk management conferences expert has attended	Integer	0-35	-
	4.4	Risk identification and planning	Adequately identifying possible risks in a construction project, and effectively developing an overall risk management plan with risk response planning	1 - 5 Predetermined rating	Proper risk identification, Development of an overall risk management plan with risk response planning	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*	*Criterion*	*Description*	*Scale of Measure*	*Range/ Reference variables*	*Predetermined ratings (1-5) Descriptions*
						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
5. Project Specifics	5.1	Project Size Limit	Monetary value of the largest risk management project expert worked on in any company	Real Number(dollar value)	$1,000,000-$1,000,000,000	-
	5.2	Commitment to time deadlines	Percentage of projects finished on time by all projects expert has been involved in	Real Number (%)	0-100	-
	5.3	Commitment to cost budget	Percentage of projects finished on budget by all projects expert has been involved in	Real Number (%)	0-100	-

Criteria	***Sub-Criteria***	***Criterion***	***Description***	***Scale of Measure***	***Range/ Reference variables***	***Predetermined ratings (1-5) Descriptions***
	5.4	Safety adherence	Number of projects expert worked in with zero incident rates	Integer	0-30	-
	5.5	Geographic Diversity Experience	Number of different project locations that expert has worked on	Integer	0-25	-
6.Reputation	6.1	Social Acclamation	Level of the experts' social acclamation by others	1-5 Predetermined Rating	Self-explanatory ratings	1.VERY LOW social acclamation, 2. LOW social acclamation, 3. AVERAGE social acclamation, 4. HIGH social acclamation, 5. VERY HIGH social acclamation
	6.5	Level of risk conservativeness	Level of conservativeness of experts' risk assessment	1-5 Predetermined Rating	Self-explanatory ratings	1. VERY AGGRESSIVE risk-taking, 2.AGGRESSIVE risk-taking, 3. MODERATE, 4. CONSERVATIVE, 5. VERY CONSERVATIVE

Criteria	*Sub-Criteria*	*Criterion*	*Description*	*Scale of Measure*	*Range/ Reference variables*	*Predetermined ratings (1-5) Descriptions*
7.Personal Attributes and Skills	7.1	Level of communication skills	Expert's level of maintaining interpersonal skills (i.e. getting along with others and getting the job done) with team members, eloquently and clearly expressing their point of view, and ability to communicate with others who are at different levels (technical/language/knowledge)	1-5 Predetermined Rating	Interpersonal Skill, Eloquence, and Vertical Communication	1. VERY POOR interpersonal skills, NO eloquence, and VERY POOR vertical communication, 2. POOR interpersonal skills, NO eloquence and POOR vertical communication , 3.AVERAGE interpersonal skills, SOME eloquence, and AVERAGE vertical communication , 4.GOOD interpersonal skills, CLEAR eloquence, and GOOD vertical communication , 5. VERY GOOD interpersonal skills, CLEAR eloquence, and

Criteria	*Sub-Criteria*	*Criterion*	*Description*	*Scale of Measure*	*Range/ Reference variables*	*Predetermined ratings (1-5) Descriptions*
						VERY GOOD vertical communication
	7.2	Level of Teamwork skills	Expert's level of participating as an active team member in risk management (i.e. listening and suggesting ideas and feedback), and contributing team member (i.e. giving valuable input to discussions) to achieve the team's goals	1-5 Predetermined Rating	Active team member and contribution to team	1. VERY INACTIVE team member and NO contribution to team's goals, 2. INACTIVE team member and NO contribution to team's goals, 3. AVERAGE ACTIVE team member and SOME contribution to

Criteria	***Sub-Criteria***	***Criterion***	***Description***	***Scale of Measure***	***Range/ Reference variables***	***Predetermined ratings (1-5) Descriptions***
						team's goals, 4.ACTIVE team member and FAIR contribution to team's goals, 5. VERY ACTIVE team member and FAIR contribution to team's goals

APPENDIX B. Sample questionnaires to collect list of criteria, metrics and, scales of measure

B.1. Qualification criteria for experts' risk management expertise assessment

This section of the survey identifies the relevant qualification criteria for evaluating experts' risk management expertise level. An "Agreement Scale" is given to determine the extent to which you agree/disagree with the presence of a given criteria to assess the expert's risk management expertise. The agreement scale should demonstrate your ***agreement level with the presence of this criterion to EVALUATE THE EXPERT'S EXPERTISE LEVEL*** in risk management. Blank rows are left intentionally to add additional criteria that you feel are critical in the assessment of the experts' risk management expertise.

Table A.3 Focus Group Questionnaire for agreement of Criteria Categories presence to evaluate experts' expertise in risk assessment

Main Category	***Agreement with Criteria presence to evaluate expert's risk management expertise level***				
	Strongly Disagree	***Disagree***	***Neither Agree nor Disagree***	***Agree***	***Strongly Agree***
1. Experience	**1**	**2**	**3**	**4**	**5**
2.Knowledge	**1**	**2**	**3**	**4**	**5**
3.Professional Performance	**1**	**2**	**3**	**4**	**5**
4.Risk Management Practice	**1**	**2**	**3**	**4**	**5**
5. Project Specifics	**1**	**2**	**3**	**4**	**5**
6.Reputation	**1**	**2**	**3**	**4**	**5**
7.Personal Attributes and Skills	**1**	**2**	**3**	**4**	**5**

B.2. Qualification sub- criteria for experts' risk management expertise assessment

This section of the survey identifies the relevant qualification criteria for evaluating experts' risk management expertise level. An "Agreement Scale" is given to determine the extent to which you agree/disagree with the presence of a given sub-criteria in this criteria category to assess the expert's risk management expertise. The agreement scale should demonstrate your ***agreement level with the presence of this sub-criterion IN RELATION TO THE CRITERIA CATEGORY*** it is clustered in, to evaluate expert's risk management expertise. Blank rows are left intentionally to add additional sub-criteria that you feel are critical in the assessment of the experts' risk management expertise in each criteria category.

Table A.4 Focus Group Questionnaire for agreement of Experience Sub-Criteria presence to evaluate experts' expertise in risk assessment

Main Criteria Category	***Criterion ID***	***Criterion***	***Description***	***Agreement with Sub-Criteria in Criteria Category***				
				Strongly Disagree	***Disagree***	***Neither Agree nor Disagree***	***Agree***	***Strongly Agree***
1. Experience	***1.1***	***Total Years of Experience***	***Number of years expert has been working in his/hers discipline***	***1***	***2***	***3***	***4***	***5***
	1.2	***Diversity of Experience***	***Number of different companies expert worked for***	***1***	***2***	***3***	***4***	***5***
	1.3	***Relevant Experience***	***Number of years working in risk***	***1***	***2***	***3***	***4***	***5***

			management					
	1.4	***Applied Experience***	***Number of projects in which expert performed risk management tasks***	***1***	***2***	***3***	***4***	***5***
	1.5	***Supervisory Experience***	***Number of employees supervised by expert***	***1***	***2***	***3***	***4***	***5***

Table A.5 Focus Group Questionnaire for agreement of Knowledge Sub-Criteria presence to evaluate experts' expertise in risk assessment

Main Criteria Category	*Criterion ID*	*Criterion*	*Description*	*Agreement with Sub-Criteria in Criteria Category*				
				Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
2.Knowledge	*2.1*	*Academic Knowledge*	*Years of study in expert's discipline*	*1*	*2*	*3*	*4*	*5*
	2.2	*Education Level*	*Highest degree achieved to date*	*1*	*2*	*3*	*4*	*5*
	2.3	*Awards*	*Number of awards received by expert on field he/she currently works in*	*1*	*2*	*3*	*4*	*5*

Table A.6 Focus Group Questionnaire for agreement of Professional Performance Sub-Criteria presence to evaluate experts' expertise in risk assessment

Main Criteria Category	*Criterion ID*	*Criterion*	*Description*	*Agreement with Sub-Criteria in Criteria Category*				
				Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
3.Professional Performance	*3.1*	*Current occupation in the company*	*Occupation in company currently working for*	*1*	*2*	*3*	*4*	*5*
	3.2	*Years in current occupation*	*Number of years in current occupation at company*	*1*	*2*	*3*	*4*	*5*
	3.3	*Years since PEng certification*	*Years since obtained Professional Engineer (PEng) certification*	*1*	*2*	*3*	*4*	*5*
	3.4	*Previous Key Employee Commitment*	*Maximum number of years in which expert worked for the same company*	*1*	*2*	*3*	*4*	*5*
	3.5	*Current Key Employee Commitment*	*Number of years expert has been working in current company*	*1*	*2*	*3*	*4*	*5*
	3.6	*Expertise Self-Evaluation*	*Level of risk management expertise that participant expert acknowledges about*	*1*	*2*	*3*	*4*	*5*

			himself/herself					
	3.7	***Level of Construction Training***	***Total number of Construction Engineering trainings or workshops expert has participated in***	***1***	***2***	***3***	***4***	***5***

Table A.7 Focus Group Questionnaire for agreement of Risk Management Practice Sub-Criteria presence to evaluate experts' expertise in risk assessment

Main Criteria Category	*Criterion ID*	*Criterion*	*Description*	*Agreement with Sub-Criteria in Criteria Category*				
				Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
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**	**1**	**2**	**3**	**4**	**5**
	4.2	**Level of Risk Management training**	**Number of hours attended in risk management training or workshops**	**1**	**2**	**3**	**4**	**5**
	4.3	**Risk Management conferences experience**	**Number of risk management conferences expert has attended**	**1**	**2**	**3**	**4**	**5**
	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**	**2**	**3**	**4**	**5**
	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**	**2**	**3**	**4**	**5**
	4.6	**Crisis management**	**Experience level with understanding possible crises, understanding the time phase of crises having systems to prevent crises, understanding stakeholders**	**1**	**2**	**3**	**4**	**5**

Table A.8 Focus Group Questionnaire for agreement of Project Specifics Sub-Criteria presence to evaluate experts' expertise in risk assessment

Main Criteria Category	***Criterion ID***	***Criterion***	***Description***	***Agreement with Sub-Criteria in Criteria Category***				
				Strongly Disagree	***Disagree***	***Neither Agree nor Disagree***	***Agree***	***Strongly Agree***
5. Project Specifics	**5.1**	**Project Size Limit**	**Monetary value of the largest risk management project expert worked on in current company**	**1**	**2**	**3**	**4**	**5**
	5.2	**Commitment to time deadlines**	**Percentage of projects finished on time by all projects done by expert**	**1**	**2**	**3**	**4**	**5**
	5.3	**Commitment to cost budget**	**Percentage of projects finished on budget by all projects done by expert**	**1**	**2**	**3**	**4**	**5**
	5.4	**Safety adherence**	**Number of major incidents in all projects supervised by expert**	**1**	**2**	**3**	**4**	**5**
	5.5	**Geographic Diversity Experience**	**Number of different project locations that expert has worked on**	**1**	**2**	**3**	**4**	**5**

Table A.9 Focus Group Questionnaire for agreement of Reputation Sub-Criteria presence to evaluate experts' expertise in risk assessment

Main Criteria Category	*Criterion ID*	*Criterion*	*Description*	*Agreement with Sub-Criteria in Criteria Category*				
				Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
6.Reputation	**6.1**	**Social Acclamation**	**Number of participants that agree on one specific participant expert to be the most relevant expert in risk management**	**1**	**2**	**3**	**4**	**5**
	6.2	**Willingness to participate in survey**	**Quality of responses of experts who participated in the research**	**1**	**2**	**3**	**4**	**5**
	6.3	**Professional Reputation**	**Level of credibility of expert based on consistency and reasonableness (use of engineering judgement) of previous decisions**	**1**	**2**	**3**	**4**	**5**
	6.4	**Enthusiasm and Willingness**	**Level of Enthusiasm and Willingness in performing risk management tasks in current company**	**1**	**2**	**3**	**4**	**5**
	6.5	**Level of risk conservativeness**	**Level of conservativeness of experts' risk assessment**	**1**	**2**	**3**	**4**	**5**

Table A. 10 Focus Group Questionnaire for agreement of Personal Attributes and Skills Sub-Criteria s presence to evaluate experts' expertise in risk assessment

Main Criteria Category	*Criterion ID*	*Criterion*	*Description*	*Agreement with Sub-Criteria in Criteria Category*				
				Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
7.Personal Attributes and Skills	**7.1**	**Level of communication skills**	**Expert's level of maintaining interpersonal skills with team and clearly expressing their point of view**	**1**	**2**	**3**	**4**	**5**
	7.2	**Level of teamwork skills**	**Expert's level of participating as an active and contributing member to achieve the team's goals**	**1**	**2**	**3**	**4**	**5**
	7.3	**Level of leadership skills**	**Expert's level of finding resources, training and offering tools to support team members**	**1**	**2**	**3**	**4**	**5**
	7.4	**Level of Analytical skills**	**Expert's level of anticipating and identifying problems in daily tasks while accounting for any missing data**	**1**	**2**	**3**	**4**	**5**
	7.5	**Level of Ethics**	**Expert's level of conforming to any legal or regulatory framework enforced by company**	**1**	**2**	**3**	**4**	**5**

B.3. Qualification criteria for experts' risk management expertise assessment

This section of the survey identifies "who" should be the data source for obtaining each qualification criteria data input for evaluating experts' risk management expertise level. Please indicate with an X in the data source column who should be interviewed about each expert's qualification criteria in the list below.

Table A. 11 Sample of Data Collection Questions for List of Criteria Data Source in the Experience main criteria category

Main Criteria Category	*Sub-Criteria*	*Criterion*	*Description*	*Data Source*			
				Expert (self)	*Expert's Supervisor*	*Expert's Peers*	*Expert's Subordinates*
1. Experience	1.1	Total Years of Experience	Number of years expert has been working in his/hers discipline				
	1.2	Diversity of Experience	Number of different companies expert worked for				
	1.3	Relevant Experience	Number of years working in risk management				
	1.4	Applied Experience	Number of projects in which expert performed risk management tasks				
	1.5	Supervisory Experience	Number of employees supervised by expert				

B.4. Scales of measure for quantitative qualification criteria for experts' risk management expertise assessment

Please enter if you agree or disagree with the scale of measures used for the quantitative list of qualification attributes (i.e. sub-criteria) below. If you disagree with the scale of measure represented in the description below, please suggest another sub-criterion description.

Table A. 12 Sample of Data Collection Questions for agreement with quantitative criteria scale of measure

Criteria	***Sub- Criterion***	***Description***	***Agreement with Criteria's description to evaluate expert's risk management expertise level***		***If DISAGREE***
			Agree	***Disagree***	***Suggestive Description:***
1. Experience	1.1 Total Years of Experience	Number of years expert has been working in his/hers discipline			
	1.2 Diversity of Experience	Number of different companies expert worked for			
	1.3 Relevant Experience	Number of years working in risk management			
	1.4 Applied Experience	Number of projects in which expert performed risk management tasks			

Criteria	***Sub- Criterion***	***Description***	***Agreement with Criteria's description to evaluate expert's risk management expertise level***		***If DISAGREE***
			Agree	***Disagree***	***Suggestive Description:***
	1.5 Supervisory Experience	Number of employees supervised by expert			

B.5. Scales of measure for qualitative qualification criteria for experts' risk management expertise assessment

In order to objectively evaluate each qualitative qualification criteria a scale of measure is created using predetermined rating scales. In order to determine adequate predetermined ratings a set of reference variables is used. For each qualitative criterion listed below please indicate if you agree or disagree with the reference variables listed and add any extra reference variables that could be used to measure this qualitative criterion in the blank rows.

1. **Risk identification and planning**

"Risk identification and planning" indicates the experts' experience level with risk identification and planning. Please indicate if you agree or disagree with each reference variable used to quantify the qualitative sub-criterion. If you disagree please suggest another reference variable instead of the one listed below. Please add any extra relevant reference variables that are not listed below in the blank rows for each sub-criterion.

Table A. 13 Sample Data Collection Questions for agreement with Risk Identification and Planning Qualitative criteria scale of measure

Criteria	***Sub-Criterion***	***Reference Variable***	***Agree***	***Disagree***	***If DISAGREE Suggestive Description:***
Risk Management Practice	Risk identification and planning	Adequately identifying possible risks in a construction project			

		Effectively developing an overall risk management plan with risk response planning			

APPENDIX C. FAHP model fuzzy pairwise comparison data collection forms

C.1. Sample of criteria pairwise comparison questionnaire

Table A. 14 Sample of Criteria Category Experience Pairwise Comparison of Sub-Criteria

Importance of sub-criteria with respect to the ***EXPERIENCE higher level category*** **Importance of Sub-Criterion 1 over Sub-Criterion 2**											
Question	Sub-Criterion 1	Absolutely more important	Strongly more important	More important	Weakly more important	Approximately the same importance	Weakly less important	Less important	Strongly less important	Absolutely less important	Sub-Criterion 2
Q1	Total Years of Experience										Diversity of Experience
Q2	Total Years of Experience										Relevant Experience
Q3	Total Years of Experience										Applied Experience
Q4	Total Years of										Supervisory Experience

	Experience										
Q5	Diversity of Experience										Relevant Experience
Q6	Diversity of Experience										Applied Experience
Q7	Diversity of Experience										Supervisory Experience
Q8	Relevant Experience										Applied Experience
Q9	Relevant Experience										Supervisory Experience
Q10	Applied Experience										Supervisory Experience

C.2. Sample of criteria pairwise comparison questionnaire

The 21 questions below will assess each criterion's importance when compared to another criterion **with respect to the risk management expertise level**. This will create a ranking of the importance for the **higher level criteria for evaluating experts' risk management expertise level**. The comparison takes the form: "How important is Criterion 1 when compared to Criterion 2 in evaluating expert's risk management expertise?"

Table A. 15 Criteria Categories Pairwise Comparison

Importance of criteria with respect to ***EXPERTISE LEVEL in construction risk management*** **Importance of Criterion 1 over Criterion 2**											
Question	Criterion 1	Absolutely more important	Strongly more important	More important	Weakly more important	Approximately the same importance	Weakly less important	Less important	Strongly less important	Absolutely less important	Criterion 2
Q1	Experience										Knowledge
Q2	Experience										Professional Performance
Q3	Experience										Risk Manage

											ment Practice
Q4	Experience										Project Specifics
Q5	Experience										Reputati on
Q6	Experience										Personal Attribute s and Skills
Q7	Knowledge										Professio nal Performa nce
Q8	Knowledge										Risk Manage ment Practice
Q9	Knowledge										Project Specifics
Q10	Knowledge										Reputati on

Q11	Knowledge										Personal Attributes and Skills
Q12	Professional Performance										Risk Management Practice
Q13	Professional Performance										Project Specifics
Q14	Professional Performance										Reputation
Q15	Professional Performance										Personal Attributes and Skills
Q16	Risk Management Practice										Project Specifics
Q17	Risk Management Practice										Reputation

Q18	Risk Managemen t Practice										Personal Attribute s and Skills
Q19	Project Specifics										Reputati on
Q20	Project Specifics										Personal Attribute s and Skills
Q21	Reputation										Personal Attribute s and Skills

APPENDIX D. CASE STUDY EXPERTS' IMPORTANCE WEIGHTS DATA COLLECTION FORMS

D.1. Section 1: quantitative qualification criteria for experts' risk management expertise assessment

<u>Expert's Questionnaire</u>

Please enter each numerical data value for the quantitative list of qualification attributes below according to each of your own personal attributes (self-evaluation).

Table A. 16 Sample of Expert's Data Collection Form to obtain List of Criteria Quantitative qualification attributes data input

Criteria	*Criterion*	*Description*	*Data Value*
1. Experience	1.1 Total Years of Experience	Number of years you have been working in this discipline	
	1.2 Diversity of Experience	Number of different companies you have worked for	
	1.3 Relevant Experience	Number of years you have been working in risk management	
	1.4 Applied Experience	Number of projects in which you performed risk management tasks	

Criteria	***Criterion***	***Description***	***Data Value***
	1.5 Varied Experience	Number of different functional areas or project types worked with in your entire career	
2. Knowledge	2.1 Academic Knowledge	Number years of study in your discipline	
	2.3 On the Job Training	Number of courses taken in current discipline	

D.2. Section 2: qualitative qualification criteria for experts' risk management expertise assessment

Each qualitative qualification criteria is measured using predetermined rating scales described below. Based on your own personal attributes (self-evaluation), please assign a data value for each of the qualitative qualification attributes listed.

1. **Education Level**

"Education Level" indicates the highest academic degree achieved to date by the participant.

Using 1-5 rating scales evaluate the expert's risk management expertise as:

1. High School Degree
2. College Degree
3. Technical Degree
4. Bachelor Degree
5. Master Degree

Table A. 17 Sample of Expert's Data Collection Form to obtain List of Criteria Qualitative Education Level data input

Criterion	***Description***	***Data Value***
Education Level	Highest degree achieved to date	

2. **Current Occupation in Company**

"Current Occupation in Company" indicates your occupation in the company you are currently working for.

Using 1-5 rating scales evaluate your risk management expertise as:

1. Project Engineer
2. Senior Engineer
3. Project Manager
4. Manager
5. Senior Manager

Table A. 18 Sample of Expert's Data Collection Form to obtain List of Criteria Qualitative Professional Performance data input

Criterion	***Description***	***Data Value***
Current occupation in the company	Your Occupation in company currently working for	

3. **Expertise Self-Evaluation**

"Expertise Self- Evaluation" indicates the level of risk management expertise that the participant expert acknowledges about himself/herself.

Using 1-5 rating scales your risk management expertise as:

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

Table A. 19 Sample of Expert's Data Collection Form to obtain List of Criteria Qualitative Professional Performance data input

Criterion	***Description***	***Data Value***
Expertise Self-Evaluation	Level of risk management expertise that participant expert acknowledges about himself/herself	

4. **Risk identification and planning**

"Risk identification and planning" indicates the experts' experience level with risk identification and planning. There are several points related to this issue, such as;

1. Proper risk identification.
2. Development of an overall risk management plan with risk response planning.

Using 1-5 rating scales evaluate your risk management expertise as:

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

Table A. 20 Sample of Expert's Data Collection Form to obtain List of Criteria Qualitative Risk Management Practice data input

Criteria	***Criterion***	***Description***	***Data Value***
Risk Management Practice	Risk identification and planning	Experience level with proper risk identification and development of an overall risk management plan with risk response planning	

D.3. Supervisor validation of qualitative qualification criteria for experts' risk management expertise assessment

Supervisor Questionnaire

Your participation will be limited to completing the survey, which will take approximately *thirty to forty-five minutes* to complete.

This survey consists of an assessment of your team member qualification attributes. **The team member** _______ participated in this research and we would like to assess some qualitative (i.e. linguistic) qualification attributes he/she possesses in order to determine the participant's expertise level in the risk management field in your company.

Each qualitative qualification criteria is measured using predetermined rating scales described below. Based on your own judgement about the participant _______ expertise level, please assign a data value for each of the qualitative qualification attributes listed.

5. **Risk identification and planning**

"Risk identification and planning" indicates the experts' experience level with risk identification and planning. There are several points related to this issue, such as;

1. Proper risk identification.
2. Development of an overall risk management plan with risk response planning.

Using 1-5 rating scales evaluate the expert's risk management expertise as:

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

Table A. 21 Sample of Supervisor's Data Collection Form to obtain List of Criteria Qualitative Risk Management Practice data input

Criteria	***Criterion***	***Description***	***Data Value***
Risk Management Practice	Risk identification and planning	Experience level with proper risk identification and development of an overall risk management plan with risk response planning	

6. **Risk monitoring and control**

"Risk monitoring and control" indicates the expert's level of risk monitoring and control expertise. There are several points related to this issue, such as;

1. Keeping track of identified risks,
2. Monitoring residual risks and identifying new risks
3. Ensuring the execution of risk plans
4. Evaluating their effectiveness in reducing risk

Using 1-5 rating scales evaluate your risk management expertise as:

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 DETAIL 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 DETAIL 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

Table A. 22 Sample of Supervisor's Data Collection Form to obtain List of Criteria Qualitative Risk Management Practice data input

Criteria	***Criterion***	***Description***	***Data Value***
Risk Management Practice	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	