Developing Risk Breakdown Matrix for Onshore Wind Farm Projects Using Fuzzy Case-Based Reasoning

by

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Abstract

Many countries have invested in the development of renewable energy projects, particularly onshore and offshore wind farm projects because of their low adverse environmental impact on the environment. However, onshore and offshore wind farm projects are novel types of projects in most countries and risk identification of them are hindered by the scarcity of historical data, high cost for acquiring expert knowledge, and/or the limited research available on this topic. Previous research on risk identification of onshore and offshore wind farm projects are mainly focused on offshore wind farm projects because of its high-risk marine environment. The few studies conducted on risk identification of onshore wind farm projects focus mainly on project-level risks; work-package–level risks are not investigated in order to develop Risk Breakdown Matrix (RBM). Therefore, there is a gap in the research on the risk identification of onshore wind farm projects to develop RBM.

Existing risk identification techniques mostly rely on expert knowledge, and available research on project type. However, implementing those techniques is not appropriate for onshore wind farm projects because there are the limited research and historical data available on this topic. Acquiring expert knowledge is also challenging because of the high cost of it. In addition, successful expert interviews highly depend on expert abilities, attitudes and thoroughness which is a limitation of this technique. CBR techniques are well-known for their application to solve a new problem based on the similarity between different types of projects. However, there are a few studies on CBR techniques in hazard and risk identification, and those techniques did not consider subjective information in their techniques. Therefore, there is a gap in the research on developing the fuzzy-case based reasoning (FCBR) technique for risk identification of the novel type of project which captures the subjectivity of construction project information.

To address these limitations, the main contributions of this research are twofold: (1) develop a risk breakdown matrix (RBM) for onshore wind farm projects by mapping each risk to those construction work packages affected by the risk. (2) proposes a new risk identification framework suitable for novel types of construction projects that are not comprehensively studied in the literature and have limited historical data.

Preface

This thesis is an original work by Sahand Somi. Parts of chapter 3 have been published as Somi, S., Gerami Seresht, N. and Fayek, A. R. (2020). “Framework for Risk Identification of Renewable Energy Projects Using Fuzzy Case-Based Reasoning”, Sustainability, published June 27, 2020. Moreover, parts of chapters 3 and 4 have been submitted for publication as Somi, S., Gerami Seresht, N. and Fayek, A. R. (2020). “Developing Risk Breakdown Matrix for Onshore Wind Farm Projects Using Fuzzy Case-Based Reasoning”, in review, submitted Journal of Cleaner Production. I was responsible for the major parts of the data collection, analysis, and composition of the manuscript. N. Gerami Seresht was the postdoctoral fellow who assisted with the data analysis and was involved with composition and editing of the manuscript. A. R. Fayek was the supervisory author and was involved with concept formation, composition and editing of the manuscript.

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Dedication

To God;
I appreciate all the wonderful blessings you have given me.

To my beloved parents, Sorour and Samad Somi;
Without your support, I would not have been able to get to this stage.

To my darling wife, Parastoo Eivazi Ziaei;
You helped me through this journey.

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To the memory of my grandmother Zeynab Zanjanabi;
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AI	Artificial intelligence
AHP	Analytic hierarchy process
ANP	Analytic network process
CBR	Case-based reasoning
CWP	Construction work packages
DCP	Deepest common predecessor
FCBR	Fuzzy case-based reasoning
IT	Identicality threshold
NLP	Natural language processing
RBM	Risk breakdown matrix
RBS	Risk breakdown structure
SWOT	Strengths, weaknesses, opportunities, threats
WBS	Work breakdown structure

CHAPTER 1 – INTRODUCTION

1.1. Background

The number of wind farm projects has been significantly increasing worldwide, including Canada because of the ongoing trend toward developing infrastructure for renewable energy sources and the technological advancements achieved in the production of highly efficient wind turbines (REN21 2018). The global wind power capacity increased by 45 GW annually on average from 2013 until 2018, which makes wind farms the fastest-growing type of renewable energy projects, ahead of solar power, hydropower, and geothermal power projects (IRENA 2019). Despite its fast growth in production capacity, wind farm projects only produced 24 percent of world renewable energy in 2018 (IRENA 2019).

Among the world's top ten countries in wind energy capacity, Canada has enormous wind power potential greater than 1000 GW (Sahu et al. 2013). In fact, Canada after Russia has the greatest onshore wind power potential (Lu and McElroy 2017) but it is not feasible to exploit full potential because of geographical constraints. Canada's onshore wind energy capacity is 13413 MW in 2019 which Ontario is the leading provincial region in terms of installed capacity followed by Quebec and Alberta (Canada Wind Energy Association 2019a). In order to meet Canada's onshore wind energy capacity target for 2040, 510 MW onshore wind energy needs to be installed annually on average (Canada Wind Energy Association 2019b). However, challenges associated with developing onshore wind farm projects, such as insufficient risk management practices, may prevent this 2040 target. Therefore, improving the risk management practice of onshore wind farm projects can facilitate forecasted growth by facilitating wind farm development and the successful delivery of projects within budget and on schedule.

According to the Project Management Institute (PMI 2016), the life cycle of construction projects can be divided into five phases: conception, design, construction, commissioning, and closeout. Among these, the construction phase consumes the largest portion of project budget and time; thus, the implementation of risk management practices during the construction phase is essential for the successful delivery of projects within budget and schedule, and failing to do so can negatively impact the project objectives (Fera et al. 2012; Siraj and Fayek 2019). Risk identification is the first step in risk management, and successful risk identification results in the accurate assessment of threats and opportunities in onshore wind farm projects during the construction phase.

Many research studies have been performed and techniques have been proposed for identifying risks associated with construction projects, including literature review (Siraj and Fayek 2019); the strengths, weaknesses, opportunities, threats (SWOT) technique (Gao and Low 2014); checklist analysis (Guo et al. 2019); and Delphi technique (Perrenoud 2018). While risk identification has a significant impact on the successful delivery of wind farm projects, the novelty of these types of construction projects means that application of traditional risk identification techniques is hindered by lack of historical data, high cost of acquiring expert knowledge, and/or lack of comprehensive research on this topic. Case-based reasoning (CBR) is an artificial intelligence technique used to identify the characteristics (e.g., risks) of an unknown or less-known phenomenon (e.g., onshore wind farm projects) based on its similarity to the other well-known phenomena (e.g., other types of construction projects) (Watson 1999). Thus, CBR is capable to solve challenges associated with risk identification in novel types of construction projects. CBR is widely used in different domains to solve different types of problems, including cybersecurity (Abutair et al. 2019), medical sciences (Ehtesham et al. 2019; Marie et al. 2019), and engineering (Tan 2006).

Despite its application in a wide range of engineering problems, CBR lacks the capacity to capture the subjective uncertainty exhibited by different elements of real-world systems. Such limitation becomes more prominent in construction risk identification, where CBR cannot capture the subjectivity associated with assessing partial similarity between two types of construction projects (projects that are neither identical nor fully dissimilar). To address this challenge, fuzzy logic and CBR are integrated to develop fuzzy case-based reasoning (FCBR) to represent the subjective uncertainties of a real-world system. There are few examples of FCBR applications in the engineering domain, but the use of FCBR is gaining more attention in civil engineering research. Zima (2015) developed an FCBR model for cost estimation that defines cases using 15 characteristics, next represents each by linguistic terms that are determined as triangular fuzzy numbers and then retrieves cases based on the defuzzified value of similarity indices. Lu et al. (2016) combined fuzzy rule-based systems (FRBS) with CBR in modelling to forecast precipitation. They also compared the fuzzy CBR with the stand-alone application of CBR and the fuzzy rule-based system, which showed that FCBR is more accurate in predicting the level of precipitation. Thus, the FCBR technique is capable to solve challenges associated with risk identification in novel types of construction projects while capturing the subjective uncertainty in similarity calculation.

1.2. Problem Statement

Despite the extensive research on risk identification techniques and their application in off- and onshore wind farm projects during the construction phase, there are still some gaps in the research, and they are discussed in this section. Previous research on the risk identification of wind farm projects mostly has focused on offshore wind farm projects because of their complex marine environment. There are few studies on construction risk identification of onshore wind farm projects (e.g., Fera et al. 2017) and researchers only identified construction risk factors at the project-level. Therefore, the **first gap** is identified in risk identification of onshore wind farm projects, where the problem is that construction risk factors at the work-package level of onshore wind farm projects have not been well documented or identified in the literature.

There are several techniques for risk identification of construction projects but most of them rely on expert knowledge or historical data. Applying those techniques in novel infrastructure projects (i.e., onshore wind farm projects) is very challenging because there is not enough historical data for a specific project and also acquiring expert knowledge is very challenging. Tan (2006) developed the CBR model for road construction projects and her model can identify risk factors for a road construction project based on the similarity of the objective data to other projects. The similarity functions of the model only consider objective data for similarity calculation (e.g., project time and cost) and subjective data (e.g., project type and involving CWPs) are ignored in the model since the CBR cannot capture the uncertainty inheres within subjective data. The **second gap** is identified in CBR risk identification techniques, where the problem is that CBR techniques do not consider subjective data because their similarity functions cannot capture uncertainty inherent in the similarity between subjective data.

Fuzzy set theory is well-known for its unique solution to capture uncertainty in construction projects (Fayek 2018) but there are few studies on fuzzy case-based reasoning (FCBR) in the construction domain. Those research integrated CBR with fuzzy rule-based or fuzzy decision-making techniques such as AHP to capture subjectivity in similarity calculation. However, those FCBR techniques highly rely on expert knowledge for developing a rule-based structure and decision-making process. Thus, the **third gap** is identified in FCBR techniques, where the problem is that existing FCBR techniques in the literature rely on expert knowledge in order to calculate the similarity between cases.

1.3. Research Objectives

The overall objective of this research is to identifying construction risk factors for onshore wind farm projects at the work-package level by developing a novel FCBR technique for risk identification of infrastructure projects if traditional risk identification techniques are hindered by lack of historical data, high cost of acquiring expert knowledge, and/or lack of comprehensive research on this topic. To achieve this objective, this thesis set the following detailed objectives:

1. To identify construction risk factors at the work-package level of onshore wind farm projects and present results in the form of a risk breakdown matrix (RBM), which is fulfilled in chapter 4.
2. To develop a novel FCBR technique for risk identification at the work-package level which can capture the uncertainty in construction projects, which is fulfilled in chapter 3.
3. To improve FCBR techniques by using triangular fuzzy numbers and fuzzy distance methods in order to calculate similarity without relying on expert knowledge, which is fulfilled in chapter 3.

1.4. Expected Contributions

This thesis is intended to provide contributions that will positively impact risk management of construction projects especially renewable energy projects in Canada. Some of the contributions will benefit future researchers and are classified under academic contributions, while some contributions will primarily benefit the industrial construction sector and are discussed under industrial contributions.

1.4.1. Academic Contributions

The expected academic contributions of this research include:

- Contribute to the body of knowledge related to risk management as a technique for identifying construction risk factors at a work-package level based on similarity to other projects.
- Develop the novel FCBR technique which can identify construction risk factors. The FCBR technique can capture subjectivity uncertainty and calculate the fuzzy similarity between projects in order to identify construction risk factors.
- Improve current practice in FCBR technique which can use subjective data only to calculate the similarity between cases without relying on expert knowledge.

1.4.2. Industrial Contributions

The expected industrial contributions of this research include:

- Provide a comprehensive risk factor list for onshore wind farm projects at the work-package level.
- Provide RBM for onshore wind farm projects by mapping risk factors onto the construction work packages.
- Provide industrial construction companies with a tool that can be used to identified construction risk factors without relying on expert knowledge.
- Provide flexible technique in which experts can revised errors in similarity values by changing linguistics terms based on his/her expertise.
- Facilitate risk identification process for industrial construction companies with a tool that can consider all their previous construction projects in order to provide comprehensive risk factors for a specific project.

1.5. Research Methodology

The objectives of this research (see Section 1.3) are achieved in four stages, as described below.

1.5.1. The First Stage

An extensive literature review is conducted on relevant topics which are as follows: first, previous research on the risk identification of onshore wind farm projects is reviewed. Thereafter, current risk identification techniques and their application in construction projects are reviewed. Next, previous applications of CBR techniques in construction and other engineering domain are reviewed, followed by a literature review of FCBR techniques.

1.5.2. The Second Stage

The FCBR technique for risk identification at the work-package level is developed. FCBR techniques consist of five steps: (1) case representation, (2) retrieve, (3) reuse, (4) revise, and (5) retain. In this stage, two characteristics of construction projects are selected to represent each previous case in the database. Then, fuzzy numbers are used to define the similarity value between the previous cases and the problem case (e.g., onshore wind farm projects). Next, the similarity values determine which risk factors can be retrieved for the problem case through the revise and reuse step.

1.5.3. The Third Stage

The developed FCBR technique is implemented in onshore wind farm projects to identify risk factors at the work-package level. First, previous cases are stored in the database after conducting a literature review on research that identified risk factors at the work-package level. Then, the FCBR technique is developed in MATLAB®. The final result, list of risk factors, revised based on the scope of onshore wind farm projects and then represented as RBM in table format.

1.6. Thesis Organization

Chapter 1 provides background information about this thesis. In addition, Chapter 1 discusses the expected contributions and methodology of the research.

Chapter 2 provides a literature review on the relevant topics, including the risk identification of onshore wind farm projects and applications of CBR techniques in construction and other engineering domain, followed by a literature review of FCBR techniques and their application in construction.

Chapter 3 presents the framework of the FCBR model for construction projects risk identification. The chapter provides a step-by-step method to implement the FCBR for risk identification of construction projects based on previous cases and the problem case.

Chapter 4 illustrates the application of the developed framework for construction risk identification of onshore wind farm projects at the work-package level. Then, the RBM for onshore wind farm projects is developed based on the retrieved risks.

Chapter 5 describes the conclusions, contributions, and limitations of the study, as well as recommendations for future research.

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CHAPTER 2 – LITERATURE REVIEW

2.1. Literature review on the risk identification of onshore wind farm projects

The International Organization for Standardization (ISO 2016) defines risk as "the effect of uncertainty on objectives", which includes opportunities with positive impact as well as threats with negative impact. Construction projects are highly influenced by various risks because of their complex nature and numerous external factors affecting them (Siraj and Fayek 2019). Therefore, researchers work to identify and assess risks that adversely affect construction projects and determine appropriate risk management practices. Risk identification is the first step in risk management and successful risk identification results in the accurate assessment of threats and opportunities in onshore wind farm projects during the construction phase (Fera et al. 2017).

Construction risks are traditionally represented in the form of risk breakdown structure (RBS), which is a hierarchical structure of risks categorized based on their potential sources. Hillson et al. (2006) introduced the RBM as a new format for identifying and representing risks in construction projects. There is a noticeable similarity between WBS and RBS which WBS constitutes the basic framework for the management of a project; likewise, RBS is used as a powerful tool in the risk management process (Hillson 2003; PMI 2016). Thus, the interconnection between the WBS and RBS of a project is a useful technique, which allows the project team to control and monitor the risk at a level of detail appropriate to the specific project context (Rafele et al. 2005). RBM can guide researchers and practitioners to have an in-depth understanding of risks and their effects on CWPs, including (Hillson et al. 2006):

- Identifying which activities have more associated risks.
- Identifying the most important single risk with the highest severity.
- Marking the most significant relationship between risks and associated CWP (i.e., determine the most important risk associated with the CWP with high contribution to project risks).

In an RBM, the hierarchical structure of risks is presented like the RBS, and each risk is mapped to those work package(s) the risk affects. RBM can be presented in the form of matrices or diagrams. Li et al. (2013) developed an RBM for bridge construction projects, presented in the form of a matrix, in which research the work breakdown structure (WBS) of bridge construction is developed first. Next, two-level RBS of bridge construction projects is developed, in which risks are classified into internal and external risks at the first level and classified based on their sources at the second level (e.g., material and equipment risk, personal risk, contract risk, etc.). Finally, the RBM of the project is developed by mapping the second-level risks onto the work packages in the project WBS.

Past literature in construction contains few studies that are specifically focused on construction risk identification of wind farm projects. Fera et al. (2017) ranked 42 identified risks in wind farm projects based on their severity index determined using the analytic network process (ANP), which revealed that the quality of concrete curing has the highest severity on project objectives. However, Fera et al. (2017) study is criticized for lack of representation about the level of identified risk since they did not specify their risk identification methodology. Enevoldsen (2016) did a comprehensive literature review of onshore wind farm projects in forest areas that focused on the construction, operation, and commissioning phases of onshore wind farm projects. The result revealed that construction is the highest risk-prone phase because of risks associated with land use (e.g., land ownership transferring, renting, etc.). Gatzert and Kosub (2016) investigated the risks affecting onshore and offshore wind farm projects throughout their lifecycle and identified 58 risks classified into 7 categories: business, construction, operation, legal, market, counterparty, and policy risks. However, the main focus of this study conducted was offshore wind farm projects, and the majority of risks identified were only related to onshore and offshore wind farm projects. Gatzert and Kosub (2016) did identify two risks that apply to onshore wind farm projects: (1) grid connection and (2) damage to the turbine or theft during transportation or construction. Using a simulation model, Prostean et al. (2016) identified 16 risks affecting onshore and offshore wind farm projects throughout their life cycles in Romania. Delay in completion of turbines by the manufacturer, delay in obtaining construction permits, and lack of qualified labor was found to be the major risks for the construction phase. Finlay-Jones (2007) conducted an extensive literature review to identify the risks affecting wind farm projects focused primarily on risks that affect project cost. He interviewed eight project managers in Australia who were experts in onshore and offshore wind farm projects to validate the list of identified risks. Finlay-Jones (2007) research results showed that delays due to weather conditions, transportation of large machinery and turbine components, and availability of labour and resource are the most severe construction-phase risks. Considering Finlay-Jones (2007) research, it becomes evident that the majority of prior research is focused on offshore wind farm projects. Moreover, among those few research who focused on risk identification of onshore wind farm projects, risk factors at the project-level are mainly investigated and there is a gap in risk identification at the work-package level. This study aims to fill the research gap for comprehensive risk identification of onshore wind farm projects by identifying work package-level risks that affect their construction by developing RBM in order to help the effectiveness of risk management in onshore wind farm projects.

2.2. Literature review on risk identification techniques

According to the Project Management Institute, the first step in the risk management process is risk identification (PMI 2016); and appropriate risk identification ensures risk management effectiveness (Banaitiene and Banaitis 2012). Many tools and techniques have been proposed for identifying risks associated with construction projects, including literature review (Siraj and Fayek 2019); the strengths, weaknesses, opportunities, threats (SWOT) technique (Gao and Low 2014); checklist analysis (Guo et al. 2019); and Delphi technique (Perrenoud 2018). According to Siraj and Fayek (2019), the information-gathering techniques (e.g., literature review, questionnaire survey, expert interview) were more widely used than diagramming techniques (e.g., influence diagrams, cause-and-effect diagrams) because diagramming techniques do not consider the root causes of risk and their interdependencies. Among the information-gathering techniques, the literature review is mostly used because it is straightforward and easily helps to assess historical data from specific previous projects (Siraj and Fayek 2019). Siraj and Fayek (2019) conducted a comprehensive literature review; and based on 130 research, identified the 571 project-level risk factors for construction projects. Alavi and Nadir (2020) conducted a literature review about the oil and gas projects; and they identified 58 risks based on seven research which had investigated the oil and gas industry in terms of risk identification and assessment. Thus, implementing a literature review in novel infrastructure can be challenging due to a lack of research about the project. Park et al. (2019) conducted an interview survey with experts selected from 15 construction management firms in order to identify the organizational-level risk factors affecting construction projects during the construction phase. Kassem et al. (2019) conducted a questionnaire survey on the risk factors influencing the oil and gas industry in Yemen, and they identified the risk factors that affect the time and cost objectives of oil and gas. Although expert knowledge is valuable input for the risk identification process, acquiring expert knowledge is very challenging and has some limitations. Expert knowledge predominately is based on experience and according to Hubbard (2020) some limitations are as follow:

- Experience is a selective memory throughout our life which results in bias decisions.
- Human seems to be very inconsistent in using his/her experience.
- Experience is a nonscientific sample of events.

According to the above limitations in information-gathering techniques, the knowledge-based approach has been gaining more popularity in the construction project. Hammad (2009) mentioned that acquiring knowledge from project information results in wisdom in the decision-making process. In the context of risk management, knowledge plays a critical role because one of the main reasons for the risk management process failure is improper knowledge management (Rodriguez and Edwards 2014). However, there are a few studies on knowledge-based techniques in the risk identification process. One of the notable applications of Knowledge-based techniques in hazard identification is done by Xing et al. (2019). They developed a knowledge-based model for safety risk identification of metro construction based on the ontology of previous metro construction projects.

According to the abovementioned limitations of common risk identification techniques, there is a research gap on existing risk identification techniques, where these techniques highly rely on expert knowledge or the prior knowledge of projects acquired through the literature review or historical data. Consequently, the application of common risk identification techniques in renewable energy projects is a challenging process due to the limited availability of historical data, and a lack of comprehensive research in this context. In order to overcome the aforementioned challenges, Tan (2006) proposed the CBR model for risk identification of road construction projects. However, CBR has some limitations which are discussed in the following section.

2.3. Literature review on the applications of CBR and FCBR in construction

Many artificial intelligence (AI) and knowledge-based techniques have been developed to imitate the learning process of humankind. Kolodner (1992) introduced CBR as a new technique for solving problems based on previous knowledge about similar cases, which imitate the human reasoning process of applying knowledge acquired through previous experiences to new situations. In a comprehensive literature review of 91 papers from 1996–2015, Hu et al. (2016) found CBR applied to 17 construction areas and a high proportion of problems involving cost estimation and bidding. An et al. (2007) combined the analytic hierarchy process (AHP) with CBR to determine the weights of each attribute, creating a hybrid CBR-AHP model for forecasting the construction cost of residential buildings. They defined 9 attributes for residential buildings: gross floor area, number of stories, total unit, unit area, location, roof type, foundation type, usage of the basement, and finishing grades. Next, they used these weights to calculate the similarity index in the CBR technique. Kim (2013) similarly developed a hybrid CBR-AHP model for forecasting construction cost of highway projects. Jin et al. (2016) expanded the application of CBR in estimating the duration of residential projects in the preliminary stage. In their model, similarity indexes are first calculated based on the similarity between each characteristic of problem case and previous cases (e.g., total floor area, foundation type, etc.) then used for calculating revised duration. They concluded that compared to the regression model (i.e., a statistical regression model developed to predict projects' duration based on their characteristics), their CBR model more accurately predicted actual duration.

Despite its numerous strengths for use in construction risk identification, CBR is not yet widely used in the construction risk management context. Goh and Chua (2009) applied CBR for construction hazard identification using a semantic taxonomy for representing each case to systematically retrieve similar information from previous cases and expanded their model using similarity indices to delete, add, and modify similar hazards from retrieved cases (Goh and Chua, 2010). Lu et al. (2013) developed the same CBR technique to implement a safety risk analysis of subway construction. However, their model could not automatically adopt previous studies into problem cases and only retrieved similar cases. Forbes et al. (2010) developed a CBR model for selecting appropriate risk management techniques in the built environment based on six characteristics of projects and the risks associated with them, including project phase, involving risks, risk owner, and the fuzziness, randomness, and incompleteness of the risk. Fan et al. (2015) broadened the application of CBR to the area of construction risk management, generating risk response strategies and their cost of implementation in subway construction projects. Zou et al. (2017) used natural language processing (NLP) techniques in CBR phases to increase the accuracy of the application of CBR in the safety risk management of construction projects. They used an NLP technique (bag of words) for representing cases and calculated similarity based on the frequency of words in each incident case. In light of the above applications in construction, CBR shows great potential in solving construction problems. More importantly, CBR is not considered a black-box model (Richter and Weber 2013), where the expert can find the logic behind each reasoning made by the model. However, CBR techniques do not have the capability to capture the subjectivy of the information and as a consequence cannot consider subjective information in similarity calculations. Therefore, there is a research gap in the application of the FCBR technique in risk identification in order to capture the subjectivity. This study aims to fill the research gap for risk identification technique by developing novel FCBR technique which can capture subjectivity in similarity calculations.

CBR has been combined with fuzzy set theory (Zadeh 1965) in order to capture the subjectivity and imprecision that exists in real-world systems (Richter and Weber 2013). Zuo et al. (2014) used fuzzy set theory in the retrieval phase of a CBR model for reinforced concrete structures, in which the user assigns weights to the key characteristics of the problem case in linguistic terms (Very Important, Important, General, Not Important, and Not to Be Considered). Then, these fuzzy weights are used to calculate the similarity between characteristics. Zima (2015) developed an FCBR model for cost estimation that defines cases using 15 characteristics, next represents each by linguistic terms that are determined as triangular fuzzy numbers and then retrieves cases based on the defuzzified value of similarity indices. Lu et al. (2016) combined fuzzy rule-based systems (FRBS) with CBR in modelling to forecast precipitation. In their model, the most similar rule (i.e., the rule with the highest membership degree) is only activated in the fuzzy rule-based system. They also compared the fuzzy CBR with the stand-alone application of CBR and FRBS, which showed that FCBR is more accurate in predicting the level of precipitation. However, those FCBR techniques highly rely on expert knowledge for developing a rule-based structure and decision-making process.

According to the FCBR application, there is a research gap in FCBR techniques implementations since FCBR techniques highly rely on expert knowledge. This study aims to improve FCBR techniques by using triangular fuzzy numbers and fuzzy distance methods in order to calculate similarity without relying on expert knowledge.

2.4. Summary

This chapter provides a literature review on the risk identification of onshore wind farm projects, risk identification techniques, and the application of CBR and FCBR in construction. There are a few research that investigated the construction phase of onshore wind farm projects to identify risks; and they mostly focused on project-level. Thus, the work-package level of onshore wind farm projects gave not been investigated to develop RBM. Therefore, the **first gap** in risk identification of onshore wind farm projects is the lack of research on developing comprehensive RBM for onshore wind farm projects.

Information-gathering techniques are widely used for risk identification; however, the following limitations are identified in research on risk identification techniques for novel infrastructure: relying on expert knowledge and lack of historical data. Due to the capability of CBR techniques, it is an appropriate technique for risk identification of novel infrastructure, but it cannot capture the subjectivity of information. Thus, the **second gap** is the lack of CBR risk identification techniques which can capture subjectivity that exists in information between projects in similarity calculations.

Current FCBR techniques in construction literature mostly rely on expert knowledge to calculate similarity values between projects. this expert knowledge can be used to build rules for similarity calculation. Therefore, the **third gap** is the lack of FCBR technique which can calculate fuzzy similarity value without relying on expert knowledge.

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CHAPTER 3 – Developing Risk Breakdown Matrix for Onshore Wind Farm Project Using Fuzzy Case-Based Reasoning[1,2]

3.1. Introduction

The number of wind farm projects has been significantly increasing worldwide because of the ongoing trend toward developing infrastructure for renewable energy sources and the technological advancements achieved in the production of highly efficient wind turbines (REN21 2018). The global wind power capacity increased by 45 GW annually on average from 2013 until 2018, which makes wind farms the fastest-growing type of renewable energy projects, ahead of solar power, hydropower, and geothermal power projects (IRENA 2019). Despite its fast growth in production capacity, wind farm projects only produced 24 percent of world renewable energy in 2018 (IRENA 2019). To meet the global target of onshore wind power for 2030, the current capacity needs to be tripled (IRENA 2018). However, challenges associated with developing onshore wind farm projects, such as construction-phase risk management, may prevent this 2030 global target. Therefore, improving the risk management practice of onshore wind farm projects can facilitate forecasted growth by facilitating wind farm development and successful delivery of projects within budget and on schedule.

According to the Project Management Institute (PMI 2016), the life cycle of construction projects can be divided into five phases: conception, design, construction, commissioning, and closeout. Among these, the construction phase consumes the largest portion of project budget and time; thus, the implementation of risk management practices during the construction phase is essential for the successful delivery of projects within budget and schedule, and failing to do so can negatively impact project objectives (Fera et al. 2012; Siraj and Fayek 2019). Risk identification is the first

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[2] Parts of this chapter have been submitted for publication: Somi, S., Gerami Seresht, N., and Fayek, A. R. (2020). “Developing Risk Breakdown Matrix for Onshore Wind Farm Projects Using Fuzzy Case-Based Reasoning.” Journal of Cleaner Production (submitted Nov. 12).

step in risk management, and successful risk identification results in the accurate assessment of threats and opportunities in onshore wind farm projects during the construction phase. Many tools and techniques have been proposed for identifying risks associated with construction projects, including literature review (Siraj and Fayek 2019); the strengths, weaknesses, opportunities, threats (SWOT) technique (Gao and Low 2014); checklist analysis (Guo et al. 2019); and Delphi technique (Perrenoud 2018). While risk identification significantly impacts the successful delivery of construction projects, in the case of onshore wind farm projects, the application of traditional risk identification techniques is often hindered by the incomprehensive research literature, lack of historical data, and high cost of acquiring expert knowledge. These challenges can be addressed by the application of case-based reasoning (CBR), which is an artificial intelligence technique used to identify the characteristics (e.g., risks) of an unknown or less-known phenomenon (e.g., onshore wind farm projects) based on its similarity to the other well-known phenomena (e.g., other types of construction projects) (Watson 1999). Therefore, CBR can potentially be used to solve challenges associated with risk identification in novel types of construction projects. CBR is widely used in different domains to solve different types of problems, including cyber security (Abutair et al. 2019), medical sciences (Marie et al. 2019; Ehtesham et al. 2019), and engineering (Tan 2006).

Despite its application in a wide range of engineering problems, CBR lacks the capacity to capture the subjective uncertainty exhibited by different elements of real-world systems. Such limitation becomes more prominent in construction risk identification, where CBR cannot capture the subjectivity associated with assessing partial similarity between two types of construction projects (projects that are neither identical nor fully dissimilar). To address this challenge, fuzzy logic and CBR are integrated in this study to develop fuzzy case-based reasoning (FCBR) to represent the subjective uncertainties of a real-world system. This paper introduces a novel FCBR-based construction risk identification framework to address the challenges associated with risk identification in novel types of construction projects. This framework uses fuzzy numbers to capture the partial similarity between different types of construction projects and was applied in this study to identify the risks associated with the construction of onshore wind farm projects at the work-package level and develop the risk breakdown matrix (RBM) of these projects by mapping each risk to those construction work packages (CWPs) affected by the risk. The contributions of this paper are twofold: (1) proposing a new risk identification technique based on case-based reasoning and fuzzy logic that suits novel types of construction projects with limited or no pre-existing knowledge; and (2) developing a generic RBM for onshore wind farm projects to improve the risk management process.

3.2. Research Methodology

This section discusses the methodology for using FCBR to develop a new construction risk identification framework. CBR was introduced by Aamodt and Plaza (1994) and consists of five steps: (1) case representation, (2) retrieve, (3) reuse, (4) revise, and (5) retain. FCBR uses fuzzy logic in the retrieve step (Richter and Weber 2013). Figure 3.1 illustrates these five steps, which are further discussed in the following sub-sections.

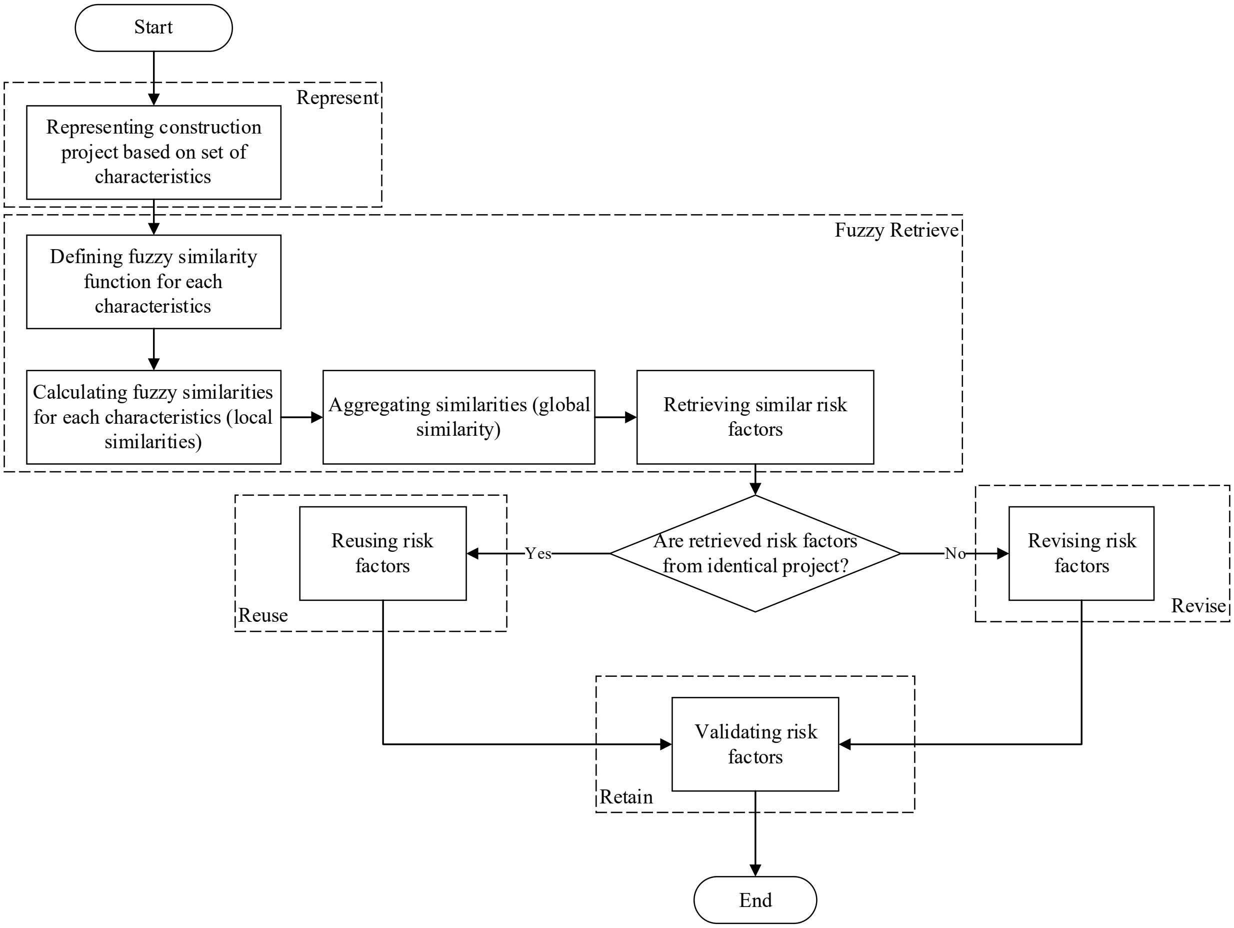

Figure 3.1. Research methodology for implementing FCBR for risk identification

3.2.1 Case representation

In case representation, different cases (e.g., projects, text documents, natural language speech) are represented by a set of characteristics or attributes, which are selected based on the scope of the problem. For representation of complex cases, which cannot be directly represented by a few characteristics or attributes, the local-global principle is used, which is based on the presumption that complex cases are built up in a hierarchical manner starting from basic elements at the bottom of the hierarchy and comprehensive elements at the top (Richter and Weber 2013). To implement the local-global principle in case representation, each case is first decomposed into its basic elements. Then, similarity between the basic elements of different cases, called local similarity, is calculated. Next, local similarities are aggregated to calculate the overall similarity between the two cases, called global similarity. One aggregation method is the product method, which simply multiplies the local similarities to determine the global similarity (Goh and Chua 2009). The product method is a non-compensatory technique; and using this method improves the model's performance because cases with high similarity values in one characteristic cannot overbalance shortfalls on others.

In the case study discussed in this paper, the local-global principle was applied for case representation using two characteristics: project type, and CWPs of onshore wind farm projects. The project type characteristic is represented using hierarchical representation, in which cases are represented in the form of a taxonomy, and the similarity between cases is determined based on their location in the taxonomy (Richter and Weber 2013). The taxonomy of construction projects is developed using the Central Product Classification (United Nations 2015) and presented in Figure 3.2.

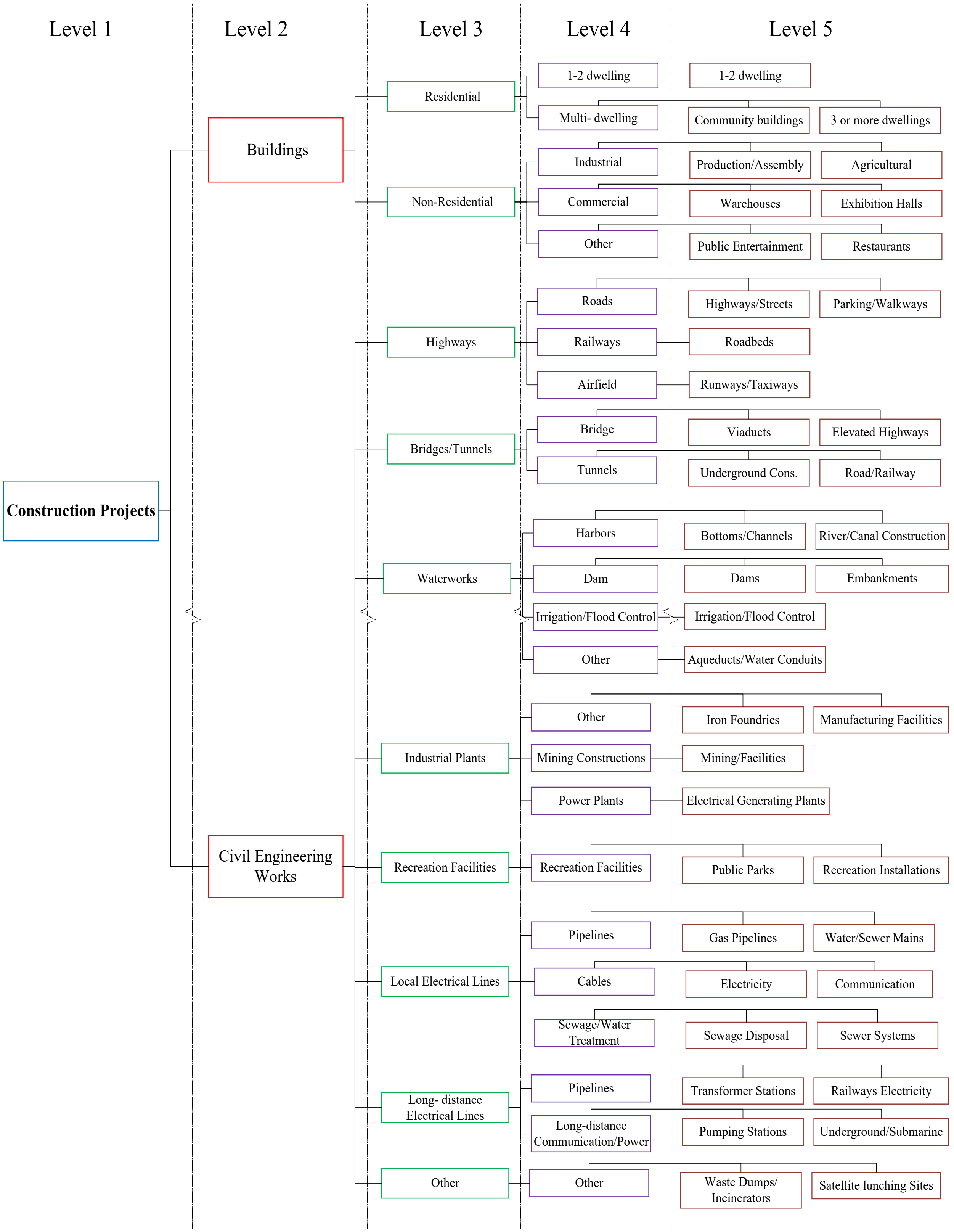

Figure 3.2. Taxonomy of construction project types

This taxonomy starts with level 1 as all construction, level 2 is general concepts of construction sectors (e.g., buildings and civil engineering works) and is broken down into three more levels of categorization, with the lowest level being specific types of construction projects, such as electrical generating plants, restaurants, and embankments.

The proposed framework identifies construction risks at the work-package level, so CWPs are used as the second characteristic of construction projects. In this framework, each CWP is represented as the set of different construction activities that are included in its execution (Richter and Weber 2013). While this framework is designed to develop a comprehensive list of risks associated with a specific type of construction project, the context-specific characteristics of projects, such as project location and work package cost and time, are not selected for case representation.

3.2.2 Fuzzy retrieve

In the case retrieval step, the project under study is compared to other construction project types based on two local characteristics and similarity between types. Similarity functions are selected based on the type of information represented by each characteristic (e.g., numeric value, text, image), and the similarity index may be 0 for distinct cases, 1 for identical cases, or a value in the range of (0,1) for non-identical cases. Since determining the similarity between two types of construction projects is a subjective assessment, crisp similarity indices are not an appropriate representation where the compared projects have partial similarity, and fuzzy numbers are used instead.

In this study, 5 triangular fuzzy numbers are used to represent the similarity between project types in linguistic terms. These fuzzy numbers are based on previous studies conducted by Etemadinia and Tavakolan (2018) and Khatwani et al. (2015) represented in Figure 3.3.3 and Table 3.1. Triangular fuzzy numbers and. Using linguistic terms to represent similarity improves the performance of FCBR in this study by (1) helping experts more easily interpret the framework reasoning process (i.e., transparency) and (2) FCBR allows experts to provide the similarity between two cases using linguistic terms, which results in greater flexibility of the model as needed.

Table 3.1. Triangular fuzzy numbers

Linguistic Term	**Similarity**
Very Low	[0.0, 0.0, 0.25]
Low	[0.0, 0.25, 0.5]
Medium	[0.25, 0.5, 0.75]
High	[0.5, 0.75, 1.0]
Very High	[0.75, 0.75, 1.0]

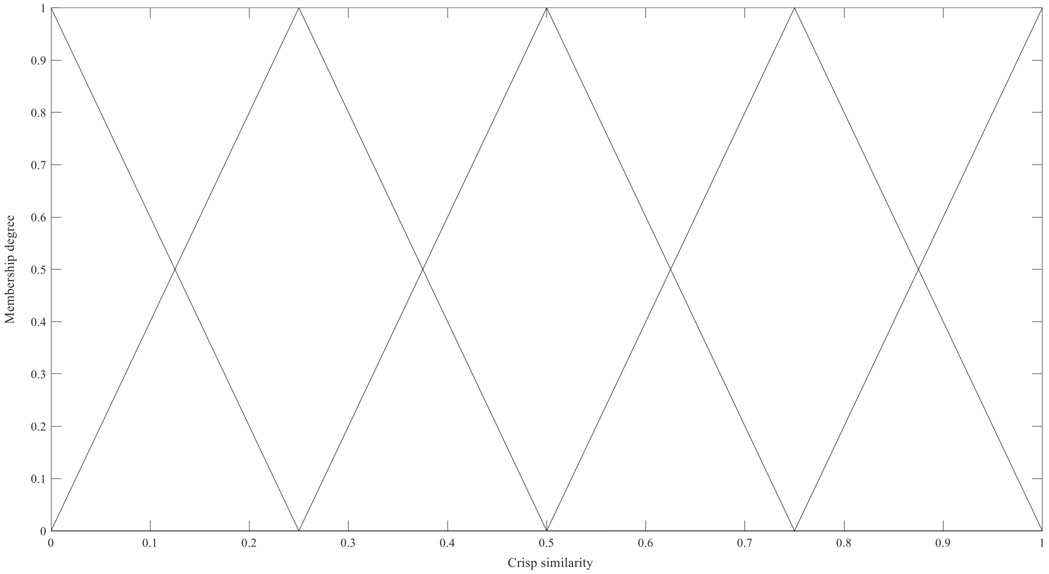

Figure 3.3. Triangular fuzzy numbers for similarity

The structure-oriented similarity function is used for the project type characteristic and the counting similarity function is used for the CWP characteristic. The structure-oriented similarity function is also called "path-oriented similarity" since the path between two project types in the hierarchy determines their similarity. In the counting similarity function, the number of common elements between the two sets determines the similarity of the two CWPs.

3.2.2.1. Project type similarity

In addition to the position of projects in the taxonomy of construction projects (see Figure 3.2), similarity between two project types is determined based on the deepest common predecessor (DCP) between them. DCP has five possible similarity values represented by fuzzy numbers, as shown in Figure 3.3.3: 1= “Very Poor,” 2 = “Poor,” 3 = “Medium,” 4 = “High,” and 5 = “Very High.” The structure-oriented similarity function used for determining the similarity between two types of construction projects is represented in Equation (3.1).

$$\mathrm{P_{sim}}(\mathrm{p_p}, \mathrm{s_p}) = \begin{cases} \text{Very Poor} & \mathrm{DCP}(\mathrm{p_p}, \mathrm{s_p}) = 1 \\ \text{Poor} & \mathrm{DCP}(\mathrm{p_p}, \mathrm{s_p}) = 2 \\ \text{Medium} & \mathrm{DCP}(\mathrm{p_p}, \mathrm{s_p}) = 3 \\ \text{High} & \mathrm{DCP}(\mathrm{p_p}, \mathrm{s_p}) = 4 \\ \text{Very High} & \mathrm{DCP}(\mathrm{p_p}, \mathrm{s_p}) = 5 \end{cases} \tag{3.1}$$

3.2.2.2. CWP similarity

In order to determine similarity, each CWP of a wind farm project is decomposed into its constituent activities. Next, the similarity function measures the number of construction activities in common between two CWPs and the number of construction activities specific to each. In this paper, the well-known Tversky similarity method is used to calculate the similarity between two CWPs, or sets P, and S, as presented in Equation (3.2).

$$\mathrm{T_{Sim}}(\mathrm{S}, \mathrm{P}) = \frac{(\mathrm{s} \cap \mathrm{p})}{(\mathrm{s} \cap \mathrm{p}) + \alpha(\mathrm{s} - (\mathrm{s} \cap \mathrm{p})) + \beta(\mathrm{p} - (\mathrm{s} \cap \mathrm{p}))} \tag{3.2}$$

where S and P are the two CWPs for which similarity is being assessed; $s \cap p$ is the number of common activities between the two CWPs; and the parameters α, β are weights for defining the importance of exclusive activities of S and exclusive activities of P. The value of the parameters α, β are assumed to be $\alpha = \beta = 0.5$ (Richter and Weber 2013). Next, in order to determine the appropriate fuzzy number to represent the similarity between two CWPs, the distance between T_{Sim}

(see Equation [3.2]) and the five triangular fuzzy numbers are calculated using the fuzzy distance measure introduced by (Xie et al. 2019). The distance between two trapezoidal fuzzy numbers $\widetilde{\mathrm{A}} = (\mathrm{a}_1, \mathrm{a}_2, \mathrm{a}_3, \mathrm{a}_4; \mathrm{w}_{\widetilde{\mathrm{A}}}), \widetilde{\mathrm{B}} = (\mathrm{b}_1, \mathrm{b}_2, \mathrm{b}_3, \mathrm{b}_4; \mathrm{w}_{\widetilde{\mathrm{B}}})$ is calculated using Equation (3.3), where $\mathrm{w}_{\widetilde{\mathrm{A}}}, \mathrm{w}_{\widetilde{\mathrm{B}}} \in [0,1]$ stands for the height of the fuzzy numbers $\widetilde{\mathrm{A}}$ and $\widetilde{\mathrm{B}}$, respectively.

$$\mathrm{S}(\widetilde{\mathrm{A}}, \widetilde{\mathrm{B}}) = \mathrm{se} * \mathrm{sw} \tag{3.3}$$

where

$$\mathrm{se} = \begin{cases} \mathrm{e}^{-|\mathrm{a}_1 - \mathrm{b}_1|}, & \mathrm{a}_4 = \mathrm{a}_1 \text{ and } \mathrm{b}_4 = \mathrm{b}_1 \\ \mathrm{e}^{-(\mathrm{k}+\mathrm{z}+\mathrm{h}+\mathrm{lr})/\mathrm{w}}, & \text{Otherwise} \end{cases} \tag{3.4}$$

and *k* is the support difference, *z* is the maximum distance between the two left or right endpoints of $\widetilde{\mathrm{A}}$ and $\widetilde{\mathrm{B}}$, *h* is the core difference between $\widetilde{\mathrm{A}}$ and $\widetilde{\mathrm{B}}$, w is the maximum span of $\widetilde{\mathrm{A}}$ and $\widetilde{\mathrm{B}}$, and *lr* is the maximum distance between the boundaries of the cores of $\widetilde{\mathrm{A}}$ and $\widetilde{\mathrm{B}}$, as shown below:

$$\mathrm{k} = |(\mathrm{a}_4 - \mathrm{a}_1) - (\mathrm{b}_4 - \mathrm{b}_1)|$$

$$\mathrm{z} = \max(|\mathrm{a}_1 - \mathrm{b}_1|, |\mathrm{a}_4 - \mathrm{b}_4|)$$

$$\mathrm{w} = \max(\mathrm{a}_4 - \mathrm{a}_1, \mathrm{b}_4 - \mathrm{b}_1)$$

$$\mathrm{h} = |(\mathrm{a}_3 - \mathrm{a}_2) - (\mathrm{b}_3 - \mathrm{b}_2)|$$

$$\mathrm{l}_\mathrm{r} = \max(|\mathrm{a}_2 - \mathrm{b}_2|, |\mathrm{a}_3 - \mathrm{b}_3|)$$

and

$$\mathrm{sw} = \frac{\min(\mathrm{w}_{\widetilde{\mathrm{A}}}, \mathrm{w}_\mathrm{B})}{\max(\mathrm{w}_{\widetilde{\mathrm{A}}}, \mathrm{w}_\mathrm{B})}.$$

After the distance between the similarity index, T_{Sim}, and the triangular fuzzy numbers is calculated, the fuzzy number with the smallest distance is selected to represent the fuzzy similarity, C_{Sim}, between the two CWPs. The fuzzy distance measure can then be applied to crisp numbers – $\mathrm{a}_1 = \mathrm{a}_2 = \mathrm{a}_3 = \mathrm{a}_4$, or T_{Sim} in this case – as well as triangular fuzzy numbers – $\mathrm{a}_1 < \mathrm{a}_2 = \mathrm{a}_3 < \mathrm{a}_4$, the five fuzzy numbers that represent the fuzzy similarity indices.

3.2.2.3. Global similarity

The global similarity is determined by aggregating the two local similarity indices, C_{Sim}, and P_{Sim}, using the product aggregation method. Total similarity S is defined by Equation (3.5) (Richter and Weber 2013):

$$\mathrm{S} = \mathrm{C}_{\mathrm{Sim}} \otimes \mathrm{P}_{\mathrm{Sim}} \tag{3.5}$$

Fuzzy multiplication (represented as ⊗ in Equation [3.5]) uses one of two approaches. The α-cut approach is widely used in many different applications because of its computational simplicity, but it causes overestimation of uncertainties in the resulting fuzzy number (Gerami Seresht and Fayek 2019). In recent applications, the extension principle approach is therefore preferred, since it can eliminate the problem of overestimating uncertainty. Gerami Seresht and Fayek (2019) developed a computational method for implementing fuzzy arithmetic operations on a triangular fuzzy number using two t-norms: product t-norm and Lukasiewicz t-norm. Both result in a fuzzy number with a lower level of uncertainty compared to the α-cut approach, and the Lukasiewicz t-norm is more sensitive than the product t-norm to changes in the input fuzzy numbers. Therefore, this study uses the product t-norm. Also, the computational method proposed by Gerami Seresht and Fayek (2019) for implementing fuzzy multiplication on triangular fuzzy numbers is used to determine the global similarity index.

Once the global similarity index for each identified risk is calculated, risks are retrieved that have an index higher than a prespecified threshold, known as the retrieval threshold. In this study, the retrieval threshold (RT) was set to "Medium" similarity, meaning that any risk with a global similarity of "Medium" or higher is retrieved as a potential risk in onshore wind farm construction. Equation (3.6) calculates the fuzzy distance between the global similarity index of each risk $\mathrm{S_j}$ and the retrieval threshold RT.

$$\mathrm{d}(S_j, T) = \frac{\sum_{i=1}^{n} |\mu_S(x_i) - \mu_T(x_i)|}{n} \tag{3.6}$$

where the universe of discourse of both fuzzy numbers $X = \{x_1, x_2, \dots, x_n\}$ is discretized to n discrete points. A distance between the global similarity and the five triangular fuzzy numbers is calculated. The fuzzy number with the smallest distance is then selected to represent the global similarity in the linguistic term. Finally, risks are retrieved that have an index higher than the RT threshold.

3.2.3 Reuse

In the reuse step, retrieved cases are reused in one of two ways: (1) risks retrieved from identical cases (i.e., with full similarity to the project being studied) are selected and transferred to the retain step with no revisions; and (2) risks retrieved from partially similar cases are reviewed and revised by the user/expert before being transferred to the retain step. In CBR, determining cases with full similarity (i.e., identical cases) is straightforward, being indicated by the full global similarity $S = 1$. However, determining fully similar cases in FCBR is challenging. In FCBR, if the local similarity between two cases is assessed to be the maximum value, “Very High” for both the project type and CWPs’ characteristics, the global similarity between the two cases is not “Very High”. In the proposed framework, this challenge is addressed by defining a threshold for full similarity between two cases, named identicality threshold (IT).

In the case study of the risk identification of onshore wind farm projects (see Chapter 4), *IT* was set to “High” similarity, meaning that any risk with a global similarity of “High” or “Very High” is directly transferred to the retain step. The value of the *RT* was selected through a trial-and-error process based on the following considerations: if the majority of the risks retrieved are irrelevant to onshore wind farm projects, the value of the retrieval threshold needs to be increased; and if a small number of risks retrieved and/or the list of risks is not comprehensive, the value of the retrieval threshold needs to be decreased. In this study, the retrieval threshold was set to “Medium” to retrieve any risk factor with the value of local similarities equal to “High” or higher to onshore wind farm projects. Retrieved risks with a global similarity less than “High” were revised before being considered as a risk that effects onshore wind farm projects.

3.2.4 Revise

In the proposed framework, at the revise step, risks identified from partially similar cases are investigated in more detail to reduce the inaccuracy of the model. The user/expert may conduct revisions directly while considering the risk sources and/or project characteristics. For example, in offshore wind farm projects, delay due to unstable sea conditions is a risk that affects the installation of wind turbines, and the risk source is the project environment, or more specifically, the sea conditions. According to the high similarity between the two project types of off- and onshore wind farm projects and the high similarity of the CWP "installation of wind turbines" in the two projects, this risk may be retrieved by the proposed framework as a potential risk to onshore wind farm projects. However, this risk cannot be applied to onshore wind farm projects, since these projects are not developed in open bodies of water. Therefore, the user may remove this risk in the revise step, and such adding/modifying increases the reliability of the results (i.e., the list of identified risks). In the case study presented in chapter 4, the authors made revisions to the risks identified for the different CWPs of onshore wind farm projects.

3.2.5 Retain

Finally, the list of identified risks is validated using expert knowledge. The retain step provides dynamic learning capacity to the proposed risk identification framework, and the validated list of risks can be used for risk identification in other types of construction projects in the future. The retain step provides two advantages. First, the risk identification framework utilizes expert knowledge and does not rely solely on computational algorithms to identify construction risks; therefore, any errors recognized during the validation process can easily be corrected by the experts. Second, expanding the framework's database of construction risks makes it more robust for identifying risks in new types of construction projects. For verification purposes, the proposed risk identification framework was applied to a case study of onshore wind farm projects.

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CHAPTER 4 – Case Study: Onshore Wind Farm Projects[1]

4.1. Developing a database for the proposed risk identification framework

Through an extensive literature review, a database was developed in Microsoft Excel® to store the risks associated with the target construction projects, which have one or more CWP(s) in common with the onshore wind farm projects. First, two common scientific databases, Scopus® and Google Scholar®, were searched. The name of each CWP was searched in Scopus® to find any journal articles, conference papers, or technical/engineering reports that in its keywords, abstract, or title that include both the CWP name and at least one of the four following terms *risk identification, risk management, risk assessment, or construction risk*. The same search methodology was used with Google Scholar®, but it lacks advanced search options in Google Scholar® for searching within specific sections of the documents, so the aforementioned terms were searched for within whole documents. Searches in Scopus® and Google Scholar® were not limited to a specific time frame, meaning the upper limit for the publication date is 2020 (i.e., the time of conducting this research), and the earliest paper found was published in 1990. A total of 37 articles were found that identify risks associated with the CWPs of onshore wind farm projects, yielding a database inclusive of 347 risks collected (see Table A1) from 15 different types of construction projects that have common CWPs. For identified articles in literature, 28 CWPs are selected (see Table A2) and 49 activities (see Table A3) are defined for those CWPs based on article information. In the articles where the involving activities are not mentioned for CWPs, activities are defined based on the Central Product Classification (United Nations 2015). Table 4.1 presents the list of 37, the types of construction projects studied, and risks identified by each article. It should be noted, this model can use different project data (e.g., subway, road, building, and hydropower projects) from stakeholders risk database which stores the previous project risk information (e.g., identified risks, the severity of risks, etc.). However, in this study, literature review is used to collect different project data as input to the model.

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[1] Parts of this have been submitted for publication: Somi, S., Gerami Seresht, N., and Fayek, A. R. (2020). “Developing Risk Breakdown Matrix for Onshore Wind Farm Projects Using Fuzzy Case-Based Reasoning.” Journal of Cleaner Production (Submitted Nov. 12).

Table 4.1. List of retrieved cases for each CWP

CWP	**Type of Project** (References)
Pre-construction activities	**Onshore wind farm project** (Manwell et al. 2006); **hydropower project** (Baroudi and McAnulty 2013); **highway project** (Diab et al. 2017; Vishwakarma et al. 2016); **water importation and pipeline project** (Kershaw et al. 2009); **electricity transmission project** (Sidawi 2012)
Surveying	**Pipe jacking construction project** (Cheng and Lu 2015); **highway project** (Diab et al. 2017); **electricity transmission project** (Sidawi 2012)
Turbine foundation	**Subway projects** (Fan et al. 2015; Zhou and Zhang 2011; Zhou et al. 2017); **onshore wind farm project** (Hassanzadeh 2012); **road construction project** (Amey Consulting PLC 2016); **bridge construction project** (Issa and Ahmed 2014); **infrastructure projects-general** (Hosny et al. 2018, Hussein and Goble 2000); **hydropower project** (Stantec 2017)
Turbine assembly	**Onshore wind farm project** (Chou and Tu 2011, Mustafa and Al-Mahadin 2018); **windmill construction project** (Sanders and Shapira 2011); **on- and offshore wind farm projects** (Canada Wind Energy Association 2018); **infrastructure projects-general** (Marquez et al. 2014)
Electrical collector lines	**Transmission and distribution line construction** (Albert and Hallowell 2013); **highway project** (Zayed et al. 2008)
Electrical distribution substation	**Onshore wind farm project** (Hassanzadeh 2012, Canada Wind Energy Association 2018); **hydropower project** (Stantec 2017); **transmission and distribution line construction** (Albert and Hallowell 2013); **UHV power transmission construction** (Zhao and Guo 2014)
Access road	**Highway project** (Creedy et al. 2010; Tawalare 2019; Vishwakarma et al. 2016; Zayed et al. 2008)
Stormwater management	**Infrastructure projects-general** (United States Environmental Protection Agency 1991, Government of Western Australia 2012,

CWP	**Type of Project** (References)
	Infrastructure Health & Safety Association 2019); **public utility projects** (Jannadi 2008)
Meteorological tower	**Telecommunication tower project** (Davies 2011, Rosu et al. 2018); **modular construction** (Li et al. 2013); **Infrastructure projects-general** (Marquez et al. 2014)
Dewatering	**Infrastructure projects-general** (Government of Western Australia 2012)
O & M building	**Modular construction project** (Li et al. 2013); **building projects** (Canadian Home Builders' Association 1988, Enshassi et al. 2008, Valipour et al. 2017)

4.2. Implementing the FCBR model for risk identification

Following the methodology discussed in chapter 3, the local characteristic of project type was represented using the taxonomy of construction project types (see Figure 3.2). To represent the second local characteristic of CWPs, the WBS of onshore wind farm projects were extracted from Hao et al. (2019), who identified the following 11 CWPs: pre-construction activities, surveying, turbine foundation, turbine assembly, electrical collector line, electrical distribution substation, access road and parking lot, stormwater management system, meteorological tower, dewatering, and operation and maintenance (O & M) buildings.

Case retrieval was accomplished through the methodology discussed in chapter 3 using MATLAB® programming language to automate the process. As noted in chapter 3, RT was set to "Medium" and IT was set to "High". Table shows a total of 169 risks identified by the proposed framework for the 11 CWPs of onshore wind farm projects. The results of this study reveal that among the 11 CWPs of onshore wind farm projects, the largest number of risks are associated with "turbine foundation" with 61 risks. Moreover, the risks that are common among several CWPs are: "harsh weather conditions," which affects 8 CWPs; and "lack of skilled workers," which affects 6 CWPs.

Table 4.2. List of risk factors associated with CWP in onshore wind farm projects

CWP (No. of risks)	Risks (* indicates risks retrieved from identical rather than partially similar cases)
Pre-construction activities (15)	(1) *Delay due to public (environmental) protest against wind farm development; (2) *Delay in obtaining permits / long regulatory permitting process; (3) *Land ownership issues (transferring, renting claims); (4) *Lack of skilled workers; (5) *Delay in delivery times for materials and equipment; (6) *Difficulty procuring materials and equipment; (7) *Significant communication problem; (8) Error in right-of-way; (9) Inadequate reviews of plans by designers and contractors/design errors; (10) Increased utility relocation costs; (11) Utility damages by contractors/subcontractors faults in construction; (12) Presence of cultural/archaeological resources; (13) Difficulty transferring construction waste and disposal; (14) Unavailability of owner engineers on the remote project's site due to their workload; (15) Delay in the approval of contractor submissions by the owner
Surveying (4)	(1) Inaccurate surveying and layout; (2) Late/erroneous surveys; (3) Inaccuracy of existing utility locations/survey data; (4) Delay in conducting of field survey by contractor
Turbine Foundation (61)	(1) *Poor material; (2) *Poor execution of work; (3) *Faulty detailing; (4) Longitudinal instability due to rainfall, poor soil, etc.; (5) Foundation deformation; (6) Gushing water and sand; (7) Creation of preferential pathways through a low-permeability layer, to allow potential contamination of underlying aquifer; (8) Creation of preferential pathways, through a low-permeability surface layer, to allow upward migration of land gas, soil gas, or contaminant vapors to the surface; (9) Direct contact of site workers and others with contaminated soil

CWP (No. of risks)	Risks (* indicates risks retrieved from identical rather than partially similar cases)
	arisings brought to the surface; (10) Direct contact of piles or engineered structures with contaminated soil or leachate causing degradation of pile materials; (11) Driving of solid contaminants down into an aquifer during pile driving; (12) Contamination of groundwater and surface waters by concrete, cement paste, or grout; (13) Overexposure of soil / rainfall immersion; (14) Leakiness of sealed drill holes; (15) Shallow inserted depth of diaphragm wall; (16) Waterproof precaution failure; (17) Poor subsoil; (18) Negative effects of soil reinforcement; (19) Unsuitable operation; (20) Overloads; (21) Running on uneven ground; (22) Gyrating too quickly; (23) Using inappropriate tools; (24) No use for separation materials between piles during casting; (25) Incorrect preparation / poor choice of casting/curing area; (26) Poor curing of precast piles; (27) Weak connection between pile reinforcement and pile edge; (28) Pile arrangement / number of piles in casting/curing area; (29) Using inappropriate surveying devices to steer piling machine; (30) Difficulties implementing marks to locate pile over the water; (31) Poor system of fixing piling machine, e.g., using buoy or temporary timber piles; (32) Lack of specialized laborers running machine; (33) Extreme weather conditions; (34) Characteristics of waterway section, e.g., channel width, water velocity; (35) Handling pile in an unsafe manner or from non-specific lifting places; (36) Distance of transferring pile from casting/curing area to specified pile location; (37) Inability of pile to bear stresses resulting from handling process; (38) Differences between soil boring report and soil nature; (39) Machine or pile not vertical; (40) Non-suitability of hammer distance and driving rate for pile; (41) Collapsing of pile head due to not using a cushion to absorb the driving energy; (42) Stopping during

CWP (No. of risks)	Risks (* indicates risks retrieved from identical rather than partially similar cases)
	driving a certain pile; (43) Environmental problems due to driving, e.g. noise or steam; (44) Problems due to site conditions, e.g., railway adjacent to site; (45) Lack of follow-up / slow decision-making during driving process; (46) Major events, e.g., earthquakes, wars, revolution; (47) Improper/inadequate soil assessment; (48) Delay in designer's response; (49) Poor communication with project stakeholders; (50) Insufficient organizational structure; (51) Poor qualification of staff; (52) Delay in inspection/testing; (53) Delay in approval of contractor's submittals; (54) Ineffective decision-making; (55) Labor mistakes, rework, and idle times; (56) Labor shortage; (57) Labor conflicts/disputes; (58) Safety issues; (59) Labor cost fluctuations; (60) Lack of managerial skills; (61) Low credibility
Turbine assembly (11)	(1) *Missing information/inconsistencies in installation document; (2) *Bolt had insufficient strength due to bolt quality; (3) *Insufficient torsion applied to bolt due to human error; (4) *Lack of qualified labor; (5) *Inconstancies between parties' documents (e.g., torsion magnitude in owner's and contractor's inspection documents); (6) *Transportation of wind turbine parts via public and access roads; (7) *Slipping risk; (8) *Tripping risk; (9) *Falling risk; (10) Reduction in crane capacity due to wind; (11) Improper ground connection
Electrical collector lines (5)	(1) Electrocution; (2) Sub-contractor delays; (3) Weather / natural causes of delay; (4) Rock encountered; (5) Extra cost due to remote location
Electrical distribution substation (12)	(1) Poor material; (2) Poor execution of work; (3) Faulty detailing; (4) *Errors/omissions in construction documents; (5) *Issues with circuit switcher after long-term storage in substation; (6) *Moisture content in transformer oil after long-term storage in substation;

CWP (No. of risks)	Risks (* indicates risks retrieved from identical rather than partially similar cases)
	(7) *Electrical outage/failure construction; (8) *Delays due to unforeseeable site conditions; (9) *Delays due to equipment transportation; (10) Improper ground connection; (11) Environmental risk of SF6 circuit breakers; (12) Electrocution risk
Access road (21)	(1) Lack of design quality; (2) Lack of expert human resources; (3) Schedule delay due to rejection of unqualified materials; (4) Schedule delay due to late delivery of materials; (5) Inadequate labor/skill availability; (6) Changed orders due to political pressure; (7) Delay due to lawsuits by landowner’s for higher compensation; (8) Labor absenteeism; (9) Delay due to rain/weather causes; (10) Uncertain construction market conditions; (11) Contractor productivity issues; (12) Uncertainty in horizontal alignment; (13) Improper basic parameters; (14) Construction in hilly regions; (15) Uncertainty in landscaping activities; (16) Uncertain land acquisition cost; (17) Uncertain land acquisition schedule; (18) Fuel availability/price; (19) Local disturbances; (20) Quality of construction/product; (21) Access road closure due to weather condition (spring and winter)
Stormwater management (5)	(1) Collapsing trench wall due to rainy weather; (2) Failure/collapse of soil in trench due to material/equipment too near edge; (3) Damage to existing utilities during excavation; (4) Unskilled or untrained equipment operators, workers, and foremen; (5) Insufficient, improper, and/or non-existent shoring system
Meteorological tower (19)	(1) Missing information and inconsistencies in the installation document; (2) Bolt had insufficient strength due to bolt quality; (3) Insufficient torsion applied to bolt due to human error; (4) Lack of qualified labor; (5) Inconstancies between parties’ documents (e.g.,

CWP (No. of risks)	Risks (* indicates risks retrieved from identical rather than partially similar cases)
	torsion magnitude in the owner's and contractor's inspection documents); (6) Slipping risk; (7) Tripping risk; (8) Falling risk; (9) Insufficient rigging plan; (10) Inadequate reinforcement for construction loads; (11) Guy wire slippage; (12) Tower failure due to ice/wind with ice; (13) Installation flaw; (14) Hurricanes, tornadoes, straight-line winds; (15) Anchor failure; (16) Corrosion of anchor; (17) Tower failure; (18) Delays due to wind; (19) Reduction in crane capacity due to wind
Dewatering (9)	(1) Loss of existing environmental value linked to receiving waters; (2) Poses significant threat to aquatic fauna/flora, especially in sensitive environments; (3) Soil erosion or local flooding; (4) Harm to native vegetation (via flooding or toxicity); (5) Erosion of structures or services; (6) Sediment build-up in drains, waterways, or wetlands; (7) Significant change of PH in soil, surface water, or groundwater; (8) Leaching of contaminant in concentrations likely to harm downstream water values; (9) Settlement due to incorrect or inappropriate dewatering
O & M building (7)	(1) Rushed design; (2) Gaps between implementation and specifications due to misinterpretation of drawings; (3) Lower work quality due to time constraints; (4) Delayed dispute resolutions; (5) Unmanaged cash flow; (6) Environmental factors; (7) New governmental acts or legislations

Figure 4.1 and Figure illustrate global fuzzy numbers for two different thresholds in the turbine foundation work-package. Considering "high" linguistic term for IT results in 2 cases and choose "Medium" linguistic term for RT increase number to 9 cases which 7 cases need to revise according to the scope of the project. It should be noted all retrieved cases for turbine foundation is related to foundation work-packages in different projects, namely, subway, bridge, road, industrial buildings, and onshore wind farm projects.

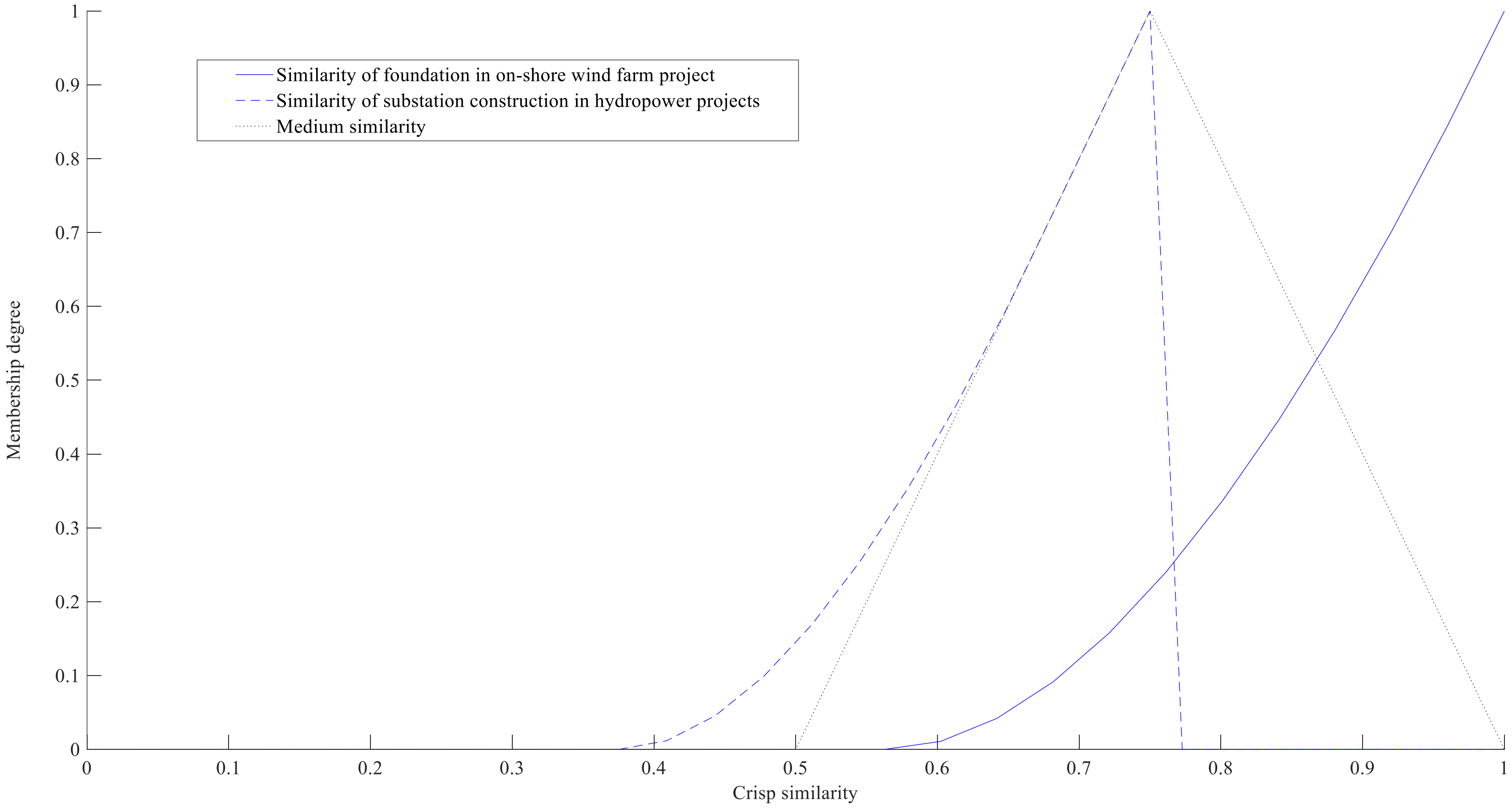

Figure 4.1. Retrieved cases with "High" threshold

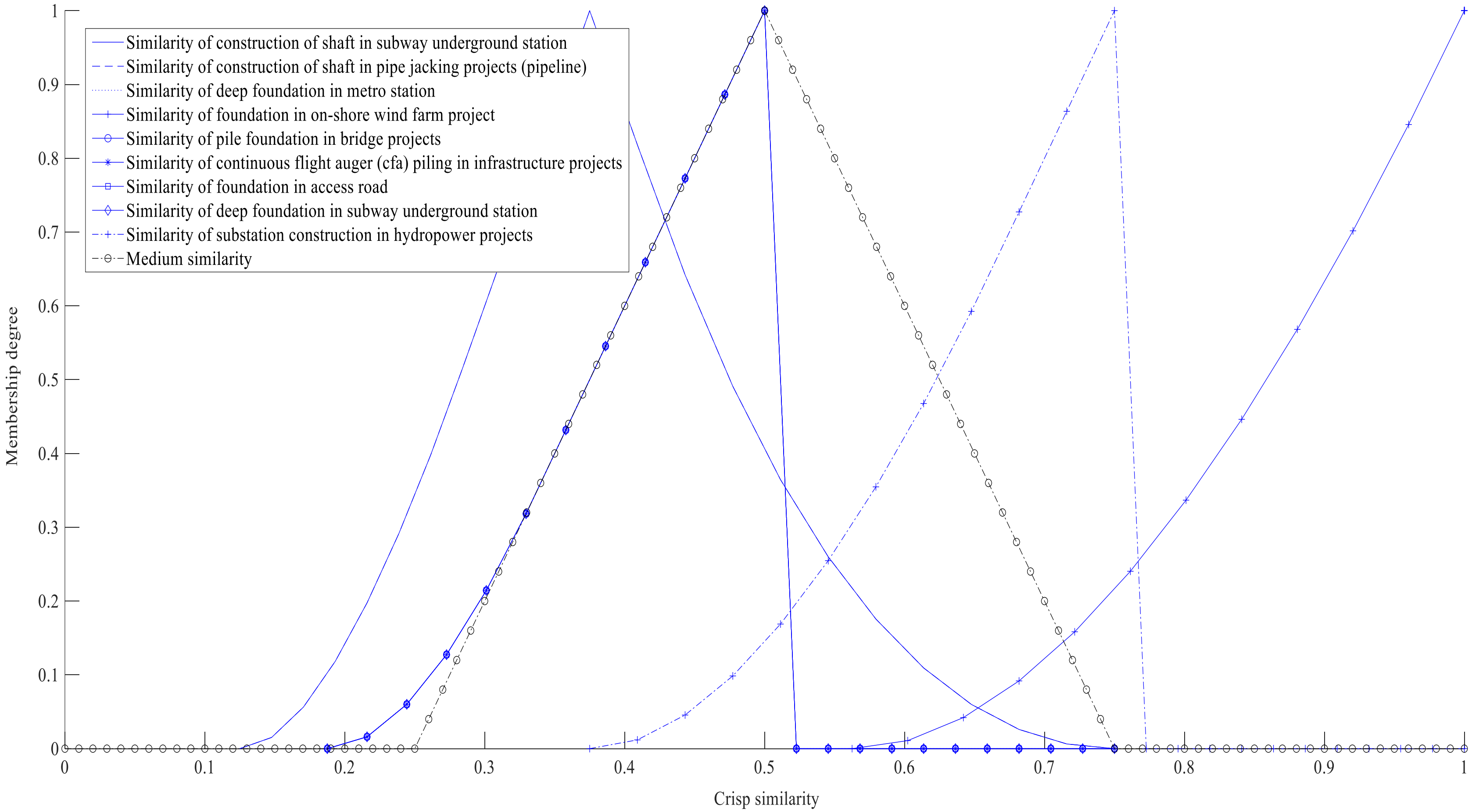

Figure 4.2. Retrieved cases with "Medium" threshold

Piney (2003) introduced four general steps for risk identification. In the fourth step, one technique for validation of risk factors is checking risk factors against the scope of each CWP. In other words, the validation method considers the applicability of risk factors in a specific CWP according to its scope. In this study, the proposed method was used to validate the results and two CWPs were selected: electrical distribution substation and meteorological tower.

The first CWP, is the electrical distribution substation, which is common between different types of power plant projects since (in addition to generating power and transforming it into electricity) it is required to distribute power within the power network. Five cases were retrieved for the identification of risks affecting this CWP from different projects: onshore wind farm, hydropower, transmission and distribution line construction, and UHV power transmission construction projects. The onshore wind farm cases considered safety risks as well as risks associated with the foundation of an electrical distribution substation. The hydropower case only considered risks related to electrical equipment. The rest of the cases consider generic risks such as poor material, faulty detailing, and poor execution. Some risks were common between all cases, namely, electrocution risk and improper ground connection.

The second CWP investigated in this paper is the meteorological towers, which commonly have a very high ratio of tower height to tower width (i.e., width measured at the very bottom of the cross-section of towers). Therefore, these types of structures are prone to structural risks caused by horizontal forces (i.e., wind force, earthquakes), and one of the few options available for addressing these risks is to support the structures with structural cables connected to the ground with anchors. The main function of this type of tower is the carriage of measurement instruments. Four cases were retrieved for the identification of risks affecting this CWP from different projects: telecommunication towers, modular construction, and UHV power transmission construction project. A telecommunication tower project has the same functionality and construction method as a meteorological tower. So, the risks retrieved from a telecommunication tower are related to structural failure of the meteorological tower of onshore wind farm projects. The rest of the cases for the CWP consider installation failure due to wind and unqualified labor.

4.3. Discussion

The use of FCBR for developing the proposed risk identification framework enables the user/expert to customize the linguistic terms and fuzzy numbers for different project types. It also enables the user/expert to understand the reasoning behind the risk identification process and to justify the selection of each risk. Table 2.3 presents a comparison of the proposed risk identification framework, which is based on FCBR, with some other common risk identification methods (noted in chapter 2).

Table 2.3. Comparison of proposed FCBR risk identification framework to other methods

Method **Criterion**	Literature review	Expert interview	Delphi method	SWOT method	CBR	Proposed framework based on FCBR
Capturing subjective uncertainty	–	–	–	–	–	✓
Low reliance on historical data of the project	–	✓	✓	✓	✓	✓
Quantitative analysis	–	–	–	–	✓	✓
Low reliance on expert knowledge	–	–	–	–	✓	✓
Less time-consuming process	✓			✓	✓	✓
Flexibility to customize method for different project types and stages	✓	✓	✓	–	–	✓
Considering all identified risks of other project types.	–	✓	✓	–	✓	✓

The proposed framework is less time-consuming than the literature review method. Moreover, for the risk identification of novel construction projects, the proposed framework is superior to the literature review method since it deals with challenges associated with historical data scarcity by using historical data collected from all different types of construction projects. Acquiring expert knowledge is time-consuming and expensive, so the proposed framework's low reliance on expert knowledge makes it faster and cheaper to implement compared to methods that rely solely on expert knowledge, namely expert interview, Delphi, and SWOT. The proposed framework also captures subjective uncertainty by defining similarities between two cases using linguistic terms. As a result, FCBR can define the partial similarity between projects, which means that it considers a wider range of projects and generates more comprehensive results compared to CBR.

Compared to the FCBR risk identification framework introduced by Somi et al. (2020), the proposed framework in this study first uses the extension principle to eliminate the problem of overestimation of uncertainty in global similarity. Further, using fuzzy distance measures and fuzzy thresholds of similarity and identicality rather than crisp ones enhances the model performance, since it avoids information loss due to the defuzzification of fuzzy numbers (Pedrycz 2017). Figure and Figure illustrates that using fuzzy thresholds instead of crisp value results in retrieving cases that are more similar to the target case, such as the construction of shaft cases. The cases graphically have defuzzified values less than 0.5, but using fuzzy distances results in retrieval of those cases. Moreover, fuzzy thresholds increase the flexibility of the model by allowing the user/expert to use linguistic terms to modify the model.

4.4. Future data collection

The best approach to validate data is by conducting a questionnaire survey to collect expert knowledge. However, the current situation prevented the data collection process. This section represents the steps for future data collection to validate the risks.

4.4.1. Survey design

The first section of each survey is designed to collect background information on the respondents, such as demographic information, the highest level of education obtained, and the current position of employment. The second section is designed to validate risk factors associated with the construction of onshore wind farm projects; by asking the experts "how relevant is each risk factor to the specified construction work package (CWP)?". Experts can assess how relevant is each risk factor to the CWP using one of the following five linguistic terms: “Very Low”, “Low”, “Medium”, “High”, and “Very High”. Table represents the sample question as follow

Table 4.4. Sample Survey

`	Risk Factors	Relevancy				
		Very Low	Low	Medium	High	Very High
Pre-construction activities	Delay due to public (environmental) protest against wind farm development	1	2	3	4	5
	Difficulty procuring materials and equipment	1	2	3	4	5
	Delay in obtaining permits / long regulatory permitting process	1	2	3	4	5
Surveying	Inaccurate surveying and layout	1	2	3	4	5
	Late/erroneous surveys	1	2	3	4	5
	Inaccuracy of existing utility locations / survey data	1	2	3	4	5
Turbine Foundation	Poor material	1	2	3	4	5
	Longitudinal instability due to rainfall	1	2	3	4	5
	Direct contact of site workers and others with contaminated soil arisings brought to the surface	1	2	3	4	5
	Foundation deformation	1	2	3	4	5

4.4.2. Sample Size

As Table represents the sample question, the full survey has 169 questions for the second section which experts score the relevancy of the risk factor to the associated CWP. In order to determine the number of respondents for validation the Equation (4.1) is used (Fellows and Liu 2015):

$$\mathrm{ss} = \frac{\mathrm{Z}^2 \times \mathrm{p}(1-\mathrm{p})}{\mathrm{c}^2} \tag{4.1}$$

Where,

ss = sample size

Z = Z value in normal distribution: (e.g. 1.96 for 95% confidence level).

p = percentage picking a choice, expressed as decimal

c = confidence interval, expressed as decimal.

It should be noted that in the case when the p is unknown, the literature recommends considering $p = 0.5$, since the formula then determines the most conservative sample size (i.e., largest sample size). Moreover, the confidence interval that is considered for this research is determined to accurately distinguish the fuzzy numbers that represent the five linguistic terms (shown in Figure 3.3.3). Accordingly, $c = 0.25$ is equal to the distance between the core of any two consecutive fuzzy numbers as shown in Figure 4.3.

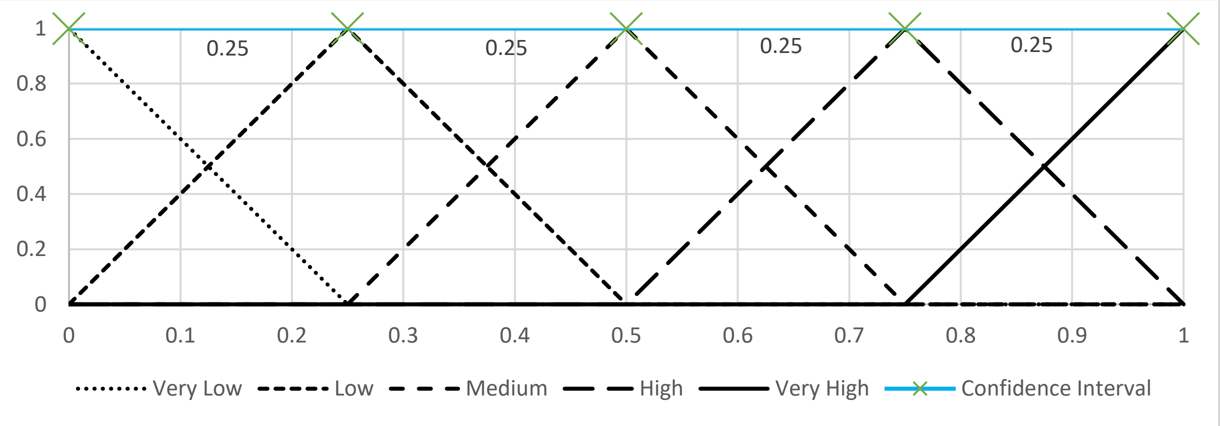

Figure 4.3. Fuzzy Numbers

Table also represents the number of respondents for different confidence level:

Table 4.5. Sample size for different confidence levels

Confidence level	Sample size
95	16
90	11

4.5. References

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CHAPTER 5 – Conclusions and Recommendations

5.1. Introduction

This chapter provides the summary of this research study. The academic and industrial contributions of the research. Also, final sections discuss the limitations of the research and based on those limitations, provides recommendations for future research and development

5.2. Research Summary

This research aimed to fill the gaps in construction research on risk breakdown matrix for onshore wind farm projects. An extensive review of past research in risk identification of onshore wind farm projects and current risk identification techniques revealed several gaps: **Firstly**, the construction literature on risk identification of onshore wind farm projects mostly focuses on project-level and work-package-level risks have not been investigated. Hence, the RBM for onshore wind farm projects has not been developed to improve risk management in onshore wind farm projects because work-package-level risks need to map to their associated CWPs in order to develop RBM. **Secondly**, current risk identification techniques mostly rely on expert knowledge or existing literature; and implementation of those risk identification techniques are very challenging in novel project types because there is not enough historical data or literature for a specific project and also acquiring expert knowledge is very challenging. In construction literature, CBR has been gaining more attention because CBR techniques consider available knowledge in all project types to identify risks for a specific project type. However, CBR cannot consider subjectivity exists in similarity calculation between construction projects. Therefore, there was a lack of risk identification technique which can capture subjectivity exists in similarity calculation between construction projects. **Thirdly**, FCBR techniques are well-known in construction literature for capturing subjectivity to solve construction problems such as dispute resolution, project cost estimation as well as generating a risk response plan. Although those FCBR techniques are very powerful techniques for construction problems, they mainly rely on expert knowledge to calculate the similarity between projects. Thus, there was a lack of FCBR technique which can only rely on existing knowledge without relying on expert knowledge for similarity calculation. The objectives of this research were achieved in three stages, as discussed in this section.

5.2.1. The First Stage

An extensive literature review is conducted on relevant topics which are as follows: first, previous research on the risk identification of onshore wind farm projects is reviewed. Thereafter, current risk identification techniques and their application in construction projects are reviewed. Next, previous applications of CBR techniques in construction and other engineering domain are reviewed, followed by a literature review of FCBR techniques.

5.2.2. The Second Stage

The FCBR technique for risk identification at the work-package level is developed. FCBR techniques consist of five steps: (1) case representation, (2) retrieve, (3) reuse, (4) revise, and (5) retain. In the case representation step, project type and CWP of construction projects are selected as characteristics to represent each previous project in the database. Next, five triangular fuzzy numbers are used to represent similarity values in linguistics terms, namely, very low, low, medium, high, and very high. After defining fuzzy numbers, similarity functions are defined for each characteristic. For project type characteristics, the project type taxonomy is used and based on the deepest common predecessor of two projects in the taxonomy, the similarity value for project type characteristics is calculated. For CWP characteristics, each CWP is decomposed into its constituent activities. The similarity between CWPs is calculated by the Tversky similarity method based on the number of common activities between the two CWPs. Then, the distance similarity measure is used to assign a fuzzy number to the crisp value of the Tversky similarity method. At the end of the retrieve step, both similarity values of project type and CWP characteristics are multiplied in order to calculate the global similarity of the project. In reuse step, identical risks are reused based on IT threshold. In the revise step, risks are revised based on RT threshold in order to be applicable in a specific construction project. Finally, the risks which are retrieved in the reuse and revise step are store in the database as RBM for the specific construction project.

5.2.3. The Third Stage

The developed FCBR technique is implemented in an onshore wind farm project to identify risk factors at the work-package level. First, previous cases are stored in the database after conducting a literature review on research that identified risk factors at the work-package level. Then, the FCBR technique is developed in MATLAB®. The final result, list of risk factors, revised based on the scope of onshore wind farm projects and then represented as RBM in table format.

5.3. Research Contributions

5.3.1 Academic Contributions

The main academic contributions of this research as follows:

- Contribute to the body of knowledge related to risk management as a technique for identifying construction risk factors at a work-package level based on similarity to other projects. The technique uses data from the previous project type and calculates the similarity between the current project between all other project types. The technique considers all risks in order to come up with specific risks for the current project.
- Develop the novel FCBR technique which can identify construction risk factors. The FCBR technique can capture subjectivity uncertainty and calculate the fuzzy similarity between projects in order to identify construction risk factors. The FCBR technique has improved the reasoning part which captures subjectivity in similarity calculation. Thus, the FCBR not only can consider objective data such as cost and time but also it can consider subjective data such as project type, involving CWPs, simultaneously.
- Improve current practice in FCBR technique which can use subjective data only to calculate the similarity between cases without relying on expert knowledge. Previous FCBR techniques are not fully automated in terms of similarity calculation. The proposed technique uses fuzzy distance in order to avoid expert knowledge in similarity calculation.

5.3.2 Industrial Contributions

The main industrial contributions of this research are as follows:

- Provide a comprehensive risk factor list for onshore wind farm projects at the work-package level. Work-package level risks help practitioners to have in-depth knowledge about involving risk at onshore wind farm projects.

- Provide RBM for onshore wind farm projects by mapping risk factors onto the construction work packages. RBM enables the risk assessment step to be more accurate since it shows the risky CWPs as well as the most severe risk in each CWP.
- Provide industrial construction companies with a tool that can be used to identified construction risk factors without relying on expert knowledge. Resource managing is very critical in construction and human as a high-value resource need to manage in an efficient way. This tool helps companies to automate some functions of the risk management team in terms of initial risk identification.
- Provide flexible technique in which experts can revised errors in similarity values by changing linguistics terms based on his/her expertise. Previous techniques in risk identification mostly implicitly mentioned their reasoning but this proposed technique illustrates the reasoning section in linguistic terms and enables experts to revise the reasoning section by only changing linguistic terms.
- Facilitate risk identification process for industrial construction companies with a tool that can consider all their previous construction projects in order to provide comprehensive risk factors for a specific project. construction companies mostly store their project data but there is not any technique to use the stored data for risk identification. The proposed technique helps construction companies to manage those data and use them in an efficient way.

5.4. Research Limitations and Recommendations for Future Research

The following limitations were encountered in the research study and recommendations are suggested for future work:

1. *Analytical validation and comparison with other techniques.* This study represented validation by only checking the scope of each CWP with identified risks. It is possible to conduct a survey to validate each risk using expert knowledge, as shown in Chapter 4, to determine the accuracy of the technique based on the survey results. Moreover, in order to compare the accuracy and effectiveness of the proposed method, it is recommended to compare information-gathering

techniques with the proposed technique in terms of accuracy.

2. *Sensitivity analysis of fuzzy membership function*. In this study, the number of fuzzy numbers for similarity values and their fuzzy membership functions were selected according to previous literature in risk management. However, a sensitivity analysis can be conducted to study the effect of changes in the membership function on the results.

3. *Identifying effecting characteristics for risk identification*. In this study, only two characteristics are used due to limited access to real project data. However, it is also possible to collect companies' project data and conduct a comprehensive study to determine effective characteristics for risk identification. For example, project delivery type and location of the project may have a significant impact on risks. Also, it is also possible to define a hierarchy structure for characteristics. Moreover, conducting an extensive literature review to identify potential characteristics is recommended.

4. *Defining hierarchy similarity fuzzy values*. In this study, the fuzzy numbers are fixed for all projects level. In other words. Some data can be extracted from specific CWP without knowing the specific value for other characteristics. In this case, it is possible to use fuzzy numbers with large support representing a high level of uncertainty.

5. *Using different weights for each characteristic.* This study implemented the global similarity function without considering the weight for each characteristic. However, for weighted aggregation, it is possible to use other methods in the proposed framework to increase the flexibility of the model by considering the relative importance of each local characteristic while assessing the global similarities between different cases.

6. *Using fuzzy similarity value in risk assessment.* This study used data from construction published literature and there is no recorded severity for each risk. In future research, it is possible to use real project risks and their severities in order to calculate new severity for retrieved risk in the current project based on fuzzy similarity values.

7. *Fuzzy distance methods.* This study does not represent sensitivity analysis for different distance

methods. It is recommended to improve this method; an extensive literature review will be conducted in fuzzy distance methods and implement popular ones to compare their performance and choose the best one for future works.

8. *Combining graph neural network (GNN) and Fuzzy case-based reasoning (FCBR):* This study used path- and structure-oriented similarity functions. However, it is possible to ask experts to label each characteristic in linguistic terms for similarity values. Then each project can be represented in the graph as a node and each similarity value is represented as a weight for each edge. By training multi-layer GNN, a new project can add to the graph and it will automatically calculate the similarity between other projects.

9. *Considering different stakeholders' perspectives to define characteristics:* This study introduced a new framework for risk identification of novel projects prior to the construction stage. In the case study, the risk factors were retrieved from the literature that considered the contractor's perspective for risk identification. Hence, the RBM is developed based on the contractor's perspective. It is possible to modify the framework by changing the characteristics to capture other stakeholders' perspectives (e.g., owners) and other risks (e.g., cold climate risks such as heaving) in FCBR and implementing it at different stages of the onshore wind farm project lifecycle or project development. Also, collecting cases that identify risks according to other stakeholders' perspectives in order to improve the database is recommended for future research.

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APPENDIX A

Table A1. Risk factors of database

Risk ID	Risk Factor
R1	Shortage of skilled workers
R2	Availability of special equipment
R3	Delays in material supply
R4	Bad quality of material
R5	Bad quality of workmanship
R6	sub-contractor delays
R7	Weather and natural causes of delay
R8	Physical damage
R9	Collapsing trench wall due to rainy weather
R10	failure and collapse the soil in the trench due to Material or equipment too near the edge
R11	falling down of material and causing accidents
R12	damaging existing utilities during excavation
R13	Unskilled or untrained equipment operators, workers and foremen
R14	Insufficient, improper or nonexistent shoring system.
R15	the risk of the land and house expropriation compensation
R16	the risk of the human resource,
R17	the risk of the groundwater pollution,
R18	the risk of the funding,

Risk ID	Risk Factor
R19	the risk of the surrounding traffic jam,
R20	the risk of the climate,
R21	the risk of the safety,
R22	the risk of the ground subsidence,
R23	the risk of program.
R24	Inaccurate surveying and layout
R25	Missing marks for special section in the survey
R26	Incorrect or inappropriate dewatering
R27	Incorrect excavation for pit
R28	Cast-in-drilled-hole piles construction issues, such as hole collapse, hole shrinkage, hole deviation, pipe sticking, clog, mud contamination of pipe, formation damage, etc.
R29	Diaphragm wall construction issues, such as trench collapse, necking, failure to pull out the steel tubes temporarily positioned at each end of the wall segment
R30	Caisson sinking issues, such as slope, deviation, unusual sinking speed, quicksand, difficulty of bottom sealing
R31	Shaft structure issues, such as concrete cracking, base slab uplift, etc.
R32	Foundation heaving and excessive ground deformation due to failure of foundation reinforcement
R33	Issues during lowering the pipes into shaft, such as the pipe deformation, and damage to the anti-corrosion layer of pipe segment
R34	Unstable jacking tracks and deviation of hydraulic jacking away from the axis center
R35	Issues for soil around launch and reception shafts, such as insufficient soil strength due to poor soil stabilization treatment or excessive soil strength

Risk ID	Risk Factor
R36	Surrounding soil failure or excessive slurry lost when boring machine is pushed out from the ground toward the reception shaft
R37	Jacking too fast or too slow when boring machine is pushed out from the ground toward the reception shaft
R38	Direction deviation when boring machine is thrust into ground from launch shaft
R39	Ineffective water sealing between the pipes and entry or exit eyes on the shaft structure
R40	Insufficient bearing capacity for reaction wall
R41	Ground settlement or heaving issues, caused by unstable soil layer above pipes, loose soil, underground water damage, over-excavation, etc.
R42	Inaccurate axis control
R43	Poor air ventilation inside the pipe
R44	Issues during pipelines cross underground obstacles, such as maglev express line, metro lines, rivers, building foundations, municipal pipelines, etc.
R45	Insufficient jacking force
R46	Jacking cylinders deviate from target route
R47	Distortion and twist of steel pipes
R48	Sediment and clog inside slurry discharge pipe
R49	Electricity leakage in the moisture environment
R50	Poor quality for weld joints
R51	Incorrect or ignorance of anti-corrosion treatment for weld joints
R52	Fire or electric shock accident during welding
R53	Inappropriate layout of intermediate jacking system (IJS)

Risk ID	Risk Factor
R54	Failure of IJS sealing rings due to excessive abrasion
R55	Design scope change due to drainage, environmental issues, design error and pavement materials/depth
R56	Cultural heritage issues
R57	rock encountered
R58	additional stabilizing
R59	removal and replacement of unsuitable material
R60	Material cost increase (asphalt, bitumen price, earthworks, pavement materials and owner supplied components/materials)
R61	Material/process quality issue
R62	Extra cost due to Remote location
R63	Wet weather effects/rework
R64	Error in right-of-way
R65	Land acquisition delay
R66	Inadequate reviews of plan by designers and contractors/design errors
R67	Increased utility relocation costs
R68	Utility damages by contractors/subcontractors' faults in construction
R69	Delay of permits
R70	Late and erroneous surveys
R71	Inaccuracy of existing utility locations and survey data
R72	longitudinal instability due to rainfall, poor soil, etc.

Risk ID	Risk Factor
R73	Foundation deformation
R74	Gushing water and sand
R75	error in the survey process
R76	insufficient breadth and depth of survey
R77	wrong testing method
R78	calculation and parameter error
R79	rock and soil and hydrological condition variation
R80	groundwater control
R81	excavation monitoring construction impact on environment
R82	excessively rapid excavation and overcut
R83	not standardized construction
R84	Cold weather affects productivity
R85	Wind speed affects the productivity of onsite erection
R86	Construction equipment condition
R87	Site condition (Ground condition and neighborhood environment)
R88	delay due to public protest against wind farm development because of environmental concerns
R89	Delay in obtaining permits/long regulatory permitting process.
R90	Land ownership issues (Transferring, Renting and claims)
R91	Access road closure due to weather condition (Spring and Winter)
R92	Existence of cultural resource/ archaeological issues

Risk ID	Risk Factor
R93	Existence of cultural resource/ archaeological issues
R94	Delay in completing design plans
R95	Delay in obtaining permits/long regulatory permitting process.
R96	Poor communication (radio and cellular phone)
R97	Delay in obtaining permits/long regulatory permitting process.
R98	The selection of unskilled workers by the contractor to work on site
R99	Difficulty in transferring construction waste and disposal
R100	Delay in the approval of contractor submissions by the Owner
R101	Unavailability of owner engineers on the remote project's site due to their workload
R102	Delay in conducting of the field survey by the contractor
R103	Problem related to land acquisition due to change in policies
R104	Uncertain land acquisition cost
R105	Uncertain land acquisition time
R106	Lack of skilled worker
R107	Delay in delivery times for materials and equipment
R108	The difficulty in procuring materials and equipment causes
R109	Communication is a significant problem
R110	existence of obstacles in the ground
R111	Use of inappropriate hammer
R112	Insufficient cushion

Risk ID	Risk Factor
R113	Tight pile cap
R114	Misalignment between pile and driving system
R115	difficult driving conditions
R116	Uneven contact between hammer and pile head
R117	Lack of lateral pile support
R118	High soil resistance during installing piles
R119	existence of obstacles in the ground
R120	High soil resistance during installing piles
R121	damage to equipment
R122	The lack of expertise of construction company
R123	lack of knowledge of the construction company about the local circumstance
R124	uncertainties in soil properties
R125	Ground settlement due to the vibrations in the ground
R126	Damage to structure or apparatuses due to vibration
R127	Poor material
R128	Poor execution of work
R129	Faulty detailing
R130	Using inappropriate tools (such as the type of casting mold)
R131	Poor materials quality, for example the gravel gradation
R132	Inappropriate casting method

Risk ID	Risk Factor
R133	No use for separation materials between piles during casting
R134	Incorrect preparation and poor choice for casting and curing area
R135	Poor curing for the precast piles
R136	Weak connection between the pile reinforcement with the pile edge
R137	Piles arrangement and number of piles in the casting and curing area
R138	Using inappropriate surveying devices to steer the pilling machine
R139	Difficulties of implementing marks to locate the pile over the water
R140	Poor system of fixing pilling machine such as using buoy or temporary timber piles
R141	Lack of specialized laborers running machine
R142	Extreme weather conditions
R143	Characteristics of the waterway section such as channel width and water velocity
R144	Handling the pile in an unsafe manner or from non-specific lifting places
R145	Distance of transferring the pile from casting and curing area to the specified pile location
R146	Lack of specialized equipment's
R147	Inability of the pile to bear the stresses resulting from the handling process
R148	Extreme weather conditions
R149	Characteristics of the waterway section such as channel width and water velocity
R150	Lack in using new techniques in driving or in case of obstacles that constrain the driving process
R151	Lack of specialized laborers running machine

Risk ID	Risk Factor
R152	Differences between soil boring report and the soil nature
R153	The machine or the pile is not vertically
R154	Non-suitability of the hammer distance and driving rate for the pile
R155	Collapsing of the pile head due to non-using a cushion to absorb the driving energy
R156	Poor arrangement for piles precedence execution
R157	Stopping during driving a certain pile
R158	Environmental problems due to driving such as noise or steam
R159	Problems due to site conditions such as railways adjacent the site
R160	Lack of follow-up and slow decision during the process of driving
R161	Major forces: such as earthquakes, flood, storms, wars, and revolution.
R162	Weather conditions: such as temperature increase/ decrease, humidity or rain.
R163	Improper or inadequate soil assessment.
R164	Incomplete design or information.
R165	Delay in designer’s response.
R166	Poor communication between project stakeholders.
R167	Improper organizational structure.
R168	Poor qualification of staff.
R169	Delay in inspection and testing.
R170	Delay in approval of contractor’s submittals.
R171	Ineffective decision making.

Risk ID	Risk Factor
R172	Lack of quality management (planning, assurance and control)
R173	Labor mistakes, rework and idle times.
R174	Labor shortage.
R175	Labor conflicts and disputes.
R176	Safety issues.
R177	Labor cost fluctuations
R178	Surveying and site handling mistakes.
R179	Lack of managerial skills.
R180	Delay in delivering project requirements.
R181	Low credibility.
R182	Insufficient design strength.
R183	Inadequate dimensions.
R184	Lack of reinforcement.
R185	Poor placement and finishing techniques.
R186	Improper curing.
R187	Inadequate cold weather precaution
R188	Overwatering.
R189	Inadequate hot weather precautions
R190	Shrinkage cracks.
R191	Deterioration from salt attack.

Risk ID	Risk Factor
R192	Settlement from inadequate bearing.
R193	Improper backfilling procedures
R194	Inadequate site drainage.
R195	Improperly install led weeping tile.
R196	Inadequate damp proofing and waterproofing.
R197	Creation of preferential pathways, through a low permeability layer (an aquitard), to allow potential contamination of an underlying aquifer
R198	Creation of preferential pathways, through a low permeability surface layer, to allow upward migration of land gas, soil gas or contaminant vapors to the surface
R199	Direct contact of site workers and others with contaminated soil arisings which have been brought to the surface;
R200	Direct contact of the piles or engineered structures with contaminated soil or leachate causing degradation of pile materials
R201	The driving of solid contaminants down into an aquifer during pile driving;
R202	Contamination of groundwater and, subsequently, surface waters by concrete, cement paste or grout.
R203	the fall or dislodgement of earth or rock
R204	falls from one level to another
R205	falling objects
R206	inappropriate placement of excavated materials, plant or other loads
R207	the instability of any adjoining structure caused by the excavation
R208	the instability of the excavation due to persons or plant working adjacent to the excavation
R209	the presence of or possible inrush of water or other liquid

Risk ID	Risk Factor
R210	hazardous manual tasks
R211	hazardous chemicals
R212	hazardous atmosphere in an excavation
R213	vibration and hazardous noise
R214	Crane failure due to operational faults
R215	Crane failure due to harsh weather condition
R216	Missing information and inconsistencies in the installation document
R217	Bolt had insufficient strength due to bolt quality
R218	Insufficient torsion applied to bolt due to human errors
R219	Lack of qualified labor
R220	Inconstancies between parties' documents (for example torsion magnitude in the owner's and contractor's inspection documents)
R221	Transportation of wind turbine parts via public and access road
R222	Slipping Risk
R223	Tripping Risk
R224	Falling Risk
R225	Reduction in crane capacity due to wind
R226	Change in scope of work
R227	Lack of equipment efficiency
R228	Bad quality of workmanship
R229	Improper construction method

Risk ID	Risk Factor
R230	Land acquisition delay
R231	Lack of coordination between construction parties
R232	Delay in project permits and approval
R233	Culture of corruptions and bribes
R234	Poor preliminary soil information and investigations
R235	Unclear and inadequate details in drawings
R236	Lack of design quality
R237	Lack of expert human resources
R238	Schedule delay caused by rejection of unqualified materials
R239	Schedule delay due to late delivery of materials
R240	Inadequate labour/ skill availability
R241	Changed orders by political pressure
R242	Delay due to lawsuits by land owner's for higher compensation
R243	Labour absenteeism
R244	Machineries
R245	Delay due to rain or other causes
R246	Uncertain construction market conditions
R247	Contractor productivity issues
R248	Uncertainty in horizontal alignment
R249	Design errors and omissions

Risk ID	Risk Factor
R250	Consideration of improper basic parameters
R251	Construction in hilly region
R252	Uncertainty in landscaping activities
R253	Issues related to obtaining Railway Permits
R254	Issues related to obtaining Govt. Permits
R255	Other Political or external issues
R256	Change in policies
R257	Uncertain land acquisition cost
R258	Uncertain land acquisition schedule
R259	Skilled Labour
R260	Knowledge level of lead group
R261	Unanticipated damage during construction
R262	Fuel: availability, price
R263	Mineral mining issues
R264	Local disturbances
R265	Unforeseen climatic conditions
R266	Quality: construction, product
R267	Funds/Money
R268	Insufficient Rigging Plan
R269	Inadequate Reinforcement for Construction Loads

Risk ID	Risk Factor
R270	Guy Wire Slippage
R271	Tower failure due to ice and wind with ice
R272	Installation Flaw
R273	Hurricanes, Tornadoes and Straight-Line Winds
R274	Anchor Failure
R275	Corrosion of Anchor
R276	Falling
R277	Tower Failure
R278	Delays due to wind
R279	Power cutoff and dewatering and draining stopped
R280	Tap water pipe burst
R281	Waterlogging caused by rain
R282	Overexposure of soil
R283	Rainfall immersion
R284	Leakiness of sealed drill holes
R285	Shallow inserted depth of diaphragm wall
R286	Waterproof precaution failure
R287	Poor subsoil
R288	Bad effects of soil reinforcement
R289	Overbreak

Risk ID	Risk Factor
R290	Unsuitable operation
R291	Overloads
R292	Running on uneven ground
R293	Gyrating too quickly
R294	loss of any existing environmental value linked to receiving waters
R295	pose a significant threat to aquatic fauna or flora, especially in sensitive environments,
R296	soil erosion or local flooding
R297	harm to native vegetation (via flooding or toxicity)
R298	erosion of structures or services
R299	sediment build-up in drains, waterways or wetlands
R300	significant change of pH in soil, surface waters or groundwater
R301	leaching of contaminant concentrations likely to harm downstream water values
R302	nuisance to the local community such as foul odors; harm to plants or property
R303	hazard to human health or safety
R304	loss or discernible reduction of flow in public or private water sources.
R305	Settlement due to Incorrect or inappropriate dewatering
R306	Electrocution
R307	Errors/Omissions in Construction Documents
R308	Issues with Circuit Switcher after long-term storage in substation
R309	Moisture content in Transformer oil after long term storage in the substation

Risk ID	Risk Factor
R310	Electrical outage/failure Construction
R311	Unforeseeable site conditions Delays
R312	Delays due to equipment transportation
R313	Improper ground connection
R314	Environmental risk of SF6 circuit breakers
R315	materials and equipment falling into the trench
R316	slips and falls as workers climb on and off equipment
R317	being struck by moving equipment
R318	falls as workers climb in or out of an excavation
R319	falling over equipment or excavated material
R320	exposure to toxic, irritating, or flammable gases.
R321	Risk of soil erosion and sediment
R322	Financial failure of the contractor
R323	Defective design (incorrect)
R324	Delayed payments on contract
R325	Poor communication between involved parties
R326	Unmanaged cash flow
R327	Awarding the design to unqualified designers
R328	Inflation
R329	Supplies of defective materials

Risk ID	Risk Factor
R330	Undocumented change orders
R331	Exchange rate fluctuation
R332	Legal disputes during the construction phase among the parties of the contract
R333	Delayed disputes resolutions
R334	Lower work quality in presence of time constraints
R335	Unavailable labor, materials and equipment
R336	Gaps between the Implementation and the specifications due to misinterpretation of drawings
R337	Occurrence of accidents because of poor safety procedures
R338	Difficulty to access the site
R339	Inaccurate quantities
R340	Rushed design
R341	Varied labor and equipment productivity
R342	Design changes
R343	Adverse weather conditions
R344	Difficulty to get permits
R345	Actual quantities differ from the contract quantities
R346	Environmental factors
R347	New governmental acts or legislations

Table A2. CWPs of database

CWP ID	CWP name
CWP1	Access road
CWP2	Connection of steel pipe segments
CWP3	Construction of shaft
CWP4	Construction surveying
CWP5	Continuous flight auger (CFA) piling construction
CWP6	Deep foundation
CWP7	Dewatering of construction site
CWP8	Dewatering of foundation
CWP9	Electrical line installation
CWP10	Equipment installation and pipe crane
CWP11	Excavation
CWP12	Foundation
CWP13	Highway road
CWP14	Installation of intermediate jacking station
CWP15	Installation of modules
CWP16	Jacking operation
CWP17	Lifting works by Crane
CWP18	Pile foundation
CWP19	Pre-construction activities
CWP20	Push the boring machine into the entry or exit eyes in shafts
CWP21	Residential building
CWP22	Stormwater management
CWP23	Substation construction
CWP24	Telecommunication tower installation
CWP25	Trenching
CWP26	Turbine tower
CWP27	Wind power facility electrical

CWP ID	CWP name
CWP28	Windmill erection

Table A3. Activities of database

Activity ID	Activity Name
A1	Clearing
A2	Earthmoving
A3	Dewatering
A4	Embankment
A5	Base course
A6	Paving
A7	Signage
A8	Trenching
A9	Stabilizing walls
A10	Install the pipe
A11	Backfilling
A12	Compacting grouting
A13	Open-cut Excavation
A14	Installation of struts
A15	Removal of struts
A16	Installing the backstop
A17	Setting up the jacking frame and hydraulic jacks
A18	Installing laser guidance system
A19	Mating the thrust ring to the boring machine
A20	Topographical surveying
A21	Stadia surveying
A22	Ground stability
A23	Advancing the boring machine
A24	Retract the jacks and push plate
A25	Mate the push plate to the pipe and pipe to the boring machine
A26	Welding
A27	Installing intermediate jacking stations next to boring machine

Activity ID	Activity Name
A28	Site preparation
A29	Getting permits
A30	placing rebars
A31	Concrete purring
A32	Concrete curing
A33	Installing support system
A34	Lifting by crane
A35	Connecting with bolts
A36	Installing pile
A37	Connecting pile to foundation
A38	Connecting to tower by bolt
A39	Turbine unloading
A40	Cable installation
A41	Anchor installation
A42	Form working
A43	Sand bedding
A44	Stripping and removal of topsoil
A45	Nacelle assembly
A46	Rotor assembly
A47	Boom assembly
A48	Base plate assembly
A49	Dewatering by pump