Decision-Support System for Construction Risk Management in Onshore Wind Projects

by

Emad Hamdan Hamed Mohamed

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Department of Civil and Environmental Engineering
University of Alberta

Abstract

Wind energy is emerging as a primary source of renewable energy in Canada, attracting over $23 billion in investment. Steadily increasing, a total capacity of 31,640 MW of wind energy must be installed by 2040 to meet the requirements of the Paris Agreement on Climate, requiring the construction of new Canadian wind farms and supporting infrastructure. As with other types of construction, the execution phase of wind farm projects is associated with unanticipated risks (e.g., weather-related challenges and unknown stakeholder interactions), which create uncertainty during project execution. Uninformed decisions made in response to such risks can lead projects to deviate from original objectives, resulting in time and cost overruns, safety issues, and quality deficiencies.

Risk management has become a popular approach in the construction industry to reduce project uncertainties and risks for improved decision-making. However, previous research studies do not address the distinctive characteristics, unique risks, and data limitations associated with wind farm construction, restricting the ability of practitioners to adequately assess the risks affecting the construction phase of onshore wind projects—particularly in the Canadian wind energy sector. In particular, the identification of project-specific (i.e., contextual) risk factors still relies heavily on traditional risk identification techniques that are demanding in terms of time and effort. This, together with a lack of historical data and methods to deal with data insufficiency, hinder the use of advanced quantitative techniques, such as simulation, to assess risks. Finally, distinctive characteristics, including location-bias to high wind speeds, impose unique challenges during the execution of these projects that are not addressed by existing methods.

This thesis describes the development of a novel decision-support system designed to

address current limitations by facilitating and enhancing the identification, analysis, and assessment of risk factors affecting the construction phase of onshore wind farm projects. The decision-support system was developed by adopting existing analytical methods and simulation. First, critical generic risk factors affecting onshore wind projects in Canada were identified. Then, a context-driven approach for identifying project-specific risk factors was developed. Once risk factors were identified, a method to enhance the input modelling of these risk factors for quantitative risk assessment was proposed. Next, a domain-specific risk assessment method was proposed for onshore wind projects. Finally, since adverse weather was identified as the most critical risk factor affecting the construction phase of onshore wind projects in Canada, a simulation-based approach was proposed to more effectively model weather risk.

This research contributes to the state-of-the-art by (1) providing a systematic and thorough analysis—focused exclusively on the construction phase—of the risk factors affecting onshore wind projects, (2) identifying the most critical risk factors in onshore wind projects in Canada using a hybrid multi-criteria approach; (3) developing a context-driven approach that considers the specific characteristics of a project to facilitate the identification of project risks; (4) developing an integrated simulation approach for assessing risks in onshore wind projects that considers both the cost and time impact of risks; (5) proposing a method for deriving probability distributions of a risk factor's impact using fuzzy logic and multivariate analysis to enhance input modelling for improved Monte Carlo simulation; and (6) developing a simulation-based approach that allows decision-makers to dynamically and rapidly assess the impact of upcoming weather conditions on project performance during lookahead scheduling.

Preface

This thesis is an original work by Emad Mohamed. The thesis follows a paper-based format. Various chapters, or portions thereof, are in submission, revision, or have been published in peer-reviewed journals.

Chapter 2 of this thesis explores the critical construction risk factors affecting onshore wind projects in Canada using a hybrid fuzzy multi-criteria approach. E. Mohamed was responsible for questionnaire design, data curation, analysis, and manuscript composition. N. Gerami Seresht, assisted with conceptualization, questionnaire design, and edits to the manuscript. P. Jafari assisted with data curation, manuscript review, and editing. Dr. S. AbouRizk was the supervisory authority and was involved with concept formation, funding acquisition, and manuscript review and editing. This chapter is prepared for submission as a journal paper.

Chapter 3 of this thesis explores context-driven ontology-based risk identification for onshore wind farm projects. E. Mohamed was responsible for conceptualization, data curation, analysis, and manuscript composition. N. Gerami Seresht assisted with conceptualization and edits to the manuscript. Dr. S. AbouRizk was the supervisory authority and was involved with conceptualization, funding acquisition, and manuscript review and editing. This chapter is prepared for submission as a journal paper.

Chapter 4 of this thesis has been published as E. Mohamed, P. Jafari, & S. AbouRizk. (2020). Fuzzy-based multivariate analysis for input modeling of risk assessment in wind farm projects. *Algorithms*, *13*(12), 325, https://doi.org/10.3390/a13120325, and has been reprinted with the permission of MDPI. E. Mohamed was responsible for conceptualization, methodology, validation, formal analysis, investigation, writing original draft, and editing. P. Jafari assisted with investigation and manuscript writing, review, and editing. Dr. S. AbouRizk was the supervisory authority and was involved with the conceptualization, methodology, funding acquisition, and manuscript review and editing.

Chapter 5 of this thesis has been published as E. Mohamed, N. Gerami Seresht, S. Hague, A. Chehouri, and S. AbouRizk, (2021). Domain-specific risk assessment using integrated simulation: A case study of an onshore wind project. *Canadian Journal of Civil Engineering*, https://doi.org/10.1139/cjce-2021-0099, and has been reprinted with permission of Canadian

Science Publishing. E. Mohamed was responsible for conceptualization, data curation, formal analysis, methodology, and manuscript writing, review, and editing. N. Gerami Seresht assisted with project administration, manuscript review, and editing. S. Hague assisted with software development and manuscript review and editing. A. Chehouri assisted with data curation, manuscript review, and editing. Dr. S. AbouRizk was the supervisory authority and was involved with conceptualization, funding acquisition, and manuscript review and editing.

Chapter 6 of this thesis has been published as E. Mohamed, P. Jafari, A. Chehouri, & S. AbouRizk. (2021). Simulation-based approach for lookahead scheduling of onshore wind projects subject to weather risk. *Sustainability* 2021, *13*(18), 10060; https://doi.org/10.3390/su131810060 and has been reprinted with the permission of MDPI. E. Mohamed was responsible for conceptualization, data curation, formal analysis, methodology, software, and manuscript writing, review, and editing. P. Jafari assisted with data curation, manuscript review, and editing. A. Chehouri assisted with data curation, manuscript review and editing. Dr. S. AbouRizk was the supervisory authority and was involved with conceptualization, funding acquisition, and manuscript review and editing.

Because this thesis follows a paper-based format, the literature review was detached in each chapter instead of providing a comprehensive chapter for literature review.

The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Human Research Ethics Board, Project Name "Identification and Assessment of Critical Risks Affecting a Wind Farm Projects", No. Pro00091184, July 15, 2019.

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Chapter 1 : Introduction

1.1 Background

Canada is a global leader in renewable energy and is currently moving to increase its energy generation from renewable sources such as hydro, wind, solar, biomass, geothermal, and marine sources. According to the Alberta Climate Leadership Plan (*Climate Leadership Plan - Implementation Plan 2018-19* 2018), it is expected that 30% of Alberta's electricity will be generated from renewable resources such as wind, hydro, and solar by 2030. Alberta will add 5,000 MWs (megawatts) of renewable energy capacity through its Renewable Electricity Program (REP) with new investments (estimated at $10.5 billion) flowing into the provincial economy by 2030 (*Climate Leadership Plan - Implementation Plan 2018-19* 2018).

Wind energy projects require building a large number of wind turbines to harvest wind energy and convert it to electricity. The turbines themselves are manufactured, shipped to the site, and assembled. Other project components, such as foundations, the substations that collect electricity from the turbines to feed into the electrical network, and access roads to the construction site, must also be constructed. The construction industry is generally recognized as a risk-prone industry that operates within a very complex and dynamic environment (Siraj and Fayek 2019). Risks and uncertainties are inherent in all construction projects from initiation to completion regardless of the size, nature, complexity, or place of execution (Siraj and Fayek 2019). Managing risks in construction projects is crucial to successfully achieving project objectives in terms of time, cost, quality, safety, and environmental sustainability (Zou and Zhang 2009). Risk management continues to be a concern in the planning and construction phases of renewable energy infrastructure due to the negative effects of risks on project objectives in terms of cost overruns and time extensions (Gatzert and Kosub 2016a). The unique project characteristics, increased number of stakeholders, and increased complexity of wind farm projects adds uncertainty during the construction phase. For the growing volume of planned renewable energy projects, risk management is a critical element in securing project financing and achieving the project objectives (Gatzert and Kosub 2016a). To reduce uncertainty and increase control over deviations, risk-based planning approaches must be properly applied to these types of projects. Thus, the purpose of this research is to develop a decision support system for the risk management of onshore wind farm projects.

1.2 Problem Statement

Risk management in construction has developed significantly in the last four decades where many approaches and models for risk identification and assessment have been introduced (Taroun 2014). Those approaches are different in their underlying principles and philosophy. Also, those models are rarely used because they are poorly understood by practitioners (Laryea 2008). The increasing variety of risk management techniques and methods lead to challenges for risk managers/analysts in onshore wind farm projects to pull together the suitable tools. Taroun (2014) concluded that although researchers in risk analysis have investigated different theories and techniques for improving risk assessment in construction, a gap separates theory and practice of risk modelling and assessment. A major barrier to effective risk management is the lack of a formal risk management system (Choudhry and Iqbal 2013). Developing a unified decision support system for risk management that integrates selected tools is required to develop a comprehensive framework for identifying and analyzing project risks (Zhang 2011). Currently, risk management in wind farm projects lacks a profound decision support system. Therefore, this research proposes a holistic approach for risk management in wind farm projects. The proposed approach fuses available techniques and current knowledge in construction risk management. This approach is expected to work better and achieve good results for risk management in onshore wind projects because it is a special purpose application developed specifically for onshore wind projects.

Risk management process has been developed to deal with risks in different types of projects. This process is defined as a comprehensive and systematic way of identifying, analyzing, and responding to risks to achieve the project objectives (Mills 2001) (Al-Bahar and Crandall 1990) as presented in Figure 1.1. This thesis will focus mainly on the risk identification and risk quantification stages of the risk management process. Risk identification and risk analysis are the most widely-studied stages of risk management in the literature. However, there are still some gaps in risk identification and risk analysis research when applied to onshore wind projects. The current gaps that will be addressed in this research are summarized in this section.

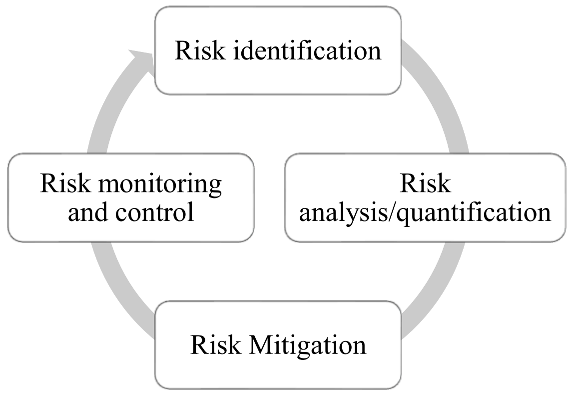


Figure 1.1. Risk management process.

Risk factors affecting construction projects may differ from one project type to another according to the characteristics of each project. Projects of similar type are affected by common risk factors that are routinely encountered across similar projects. For example, researchers identified risk factors affecting different types of projects such as: road construction (Creedy et al. 2010; El-Sayegh and Mansour 2015; Mahamid 2011); bridge construction (Choudhry et al. 2014b; Mortazavi et al. 2020; Naderpour et al. 2019a); subways and tunnels projects (Choi et al. 2004; Hwang et al. 2016; Zhang et al. 2016; Zou and Li 2010); oil and gas project (A. Kassem et al. 2019; A Kassem et al. 2020; Kraidi et al. 2019); modular construction projects (Abdul Nabi and El-adaway 2021; Wuni et al. 2019; Xian et al. 2013). Although previous research studies have examined risk factors across most phases of the lifecycle of onshore wind projects, the construction phase of onshore wind projects was overlooked in previous research studies. Moreover, risk factors differ from one country to another, and none of the previous research addressed the risk factors in the Canadian wind energy sector. Thus, the ***first gap*** that will be addressed in this thesis is the lack of understanding of the critical risk factors affecting the construction phase of onshore wind projects in Canadian wind energy sector.

Risk identification is the first step of the risk management process, and it is a knowledge intensive process where knowledge is acquired either by collecting expert knowledge or by reviewing various aspects of the project, including financial, environmental, social, regulatory, political, or a combination thereof (De Zoysa and Russell 2003). Risk identification in construction projects has received considerable attention from researchers; thus, many tools and techniques have been developed in the literature. These techniques can be classified as traditional risk identification techniques and advanced risk identification techniques. Traditional methods implement the risk identification process manually without any support of information and communications technology (ICT) techniques (Zhang and Zhong 2014), while advanced techniques tend to automate the risk identification process using some form of (ICT) techniques (Ding et al. 2012).

Traditionally, experts identify risk factors in onshore wind projects through traditional risk identification tools (e.g. risk registers, documentation review, brainstorming, etc.) that store knowledge acquired from previous projects (Somi et al. 2020). This knowledge is obtained from different and detached sources (e.g., specialist experience, previous project information, construction plans, and other projects' documentation). Thus, current risk identification techniques used in onshore wind projects rely heavily on expert knowledge (Somi et al. 2020), which increases the burden on experts and the amount time needed to perform risk identification for onshore wind projects (Somi et al. 2020). Furthermore, current risk identification methods lack the capacity to map project contexts to the identified risk factors, increasing the burden on risk analysts to contextualize previous projects and determine their similarity to the current project. Thus, the ***second gap*** that will be addressed in this thesis is the lack of automated context-based approaches for risk identification of onshore wind projects.

Following the identification of risk factors, risk assessment can begin. Input modelling is the first step in conducting a risk assessment using a simulation approach, where the impact and probability of risk factors must be determined. Monte Carlo simulation (MCS) is an extremely powerful tool used for understanding and quantifying the potential effects of uncertainty on a project (Kwak and Ingall 2007) that has been widely applied to simulate cost and time in construction (Kwak and Ingall 2009). As with many quantitative methods, however, the application of MCS is constrained by the need for variables to be input as probability density functions, limiting its use in the planning and early construction phases of a project. As a relatively novel type of infrastructure, wind farm construction is characterized by a lack of relevant literature and a scarcity of historical data. The development of risk management for these types of projects, therefore, are highly dependent on the collection of expert knowledge (Somi et al. 2020). While the boom in the wind energy industry has encouraged new contractors to engage in the construction of these projects, a lack of data represents a challenge for new contractors when conducting risk management. In addition to that, previous studies considered the cost and schedule impacts of a risk factor as independent variables, which can cause under or over estimation of project contingencies. Inadequate risk assessments can have a detrimental impact on these large-scale projects, resulting in negative effects on cost, time, quality, and safety, while simultaneously discouraging contractors from engaging in wind farm construction.

Thus, the ***third gap*** that will be addressed in this thesis is the lack of appropriate tools for input modelling capable of considering the detailed subjective knowledge of domain experts.

The area of project risk management (PRM) has witnessed expansion and growing concern in the development of risk methodologies due to the increase in project complexity, size, and importance. While the number of project risk analysis models has increased dramatically in recent years (Taroun 2014), these models are rarely used because they are poorly understood by practitioners (Laryea 2008). The construction industry has a reputation for underperforming in risk analysis when compared with other industries, such as finance or insurance (Kululanga and Kuotcha 2010) (Laryea 2008). After a comprehensive literature review of risk modelling and assessment approaches used in construction since 1980, (Taroun 2014) concluded that a gap separates theory and practice of risk modelling and assessment. Also, (Choudhry and Iqbal 2013) investigated barriers limiting the application of risk management systems to the construction industry and concluded that the major barrier to effective risk management is the lack of a formal risk management system. The increasing variety of risk assessment techniques causes challenges for risk managers/analysts in wind farm projects because of the inability to select the most suitable risk assessment method specific to wind farm projects. Thus, the ***fourth gap*** that will be addressed in this thesis is the lack of a domain-specific model for assessing risk factors and determining contingencies for project cost and time.

Wind farm projects have unique characteristics that make them different from other types of construction projects. For example, the wind farm turbines are constructed in high wind-speed areas to maximize electricity generation; however, this high wind speed represents a significant challenge during construction because the turbines require large cranes to reach an average height of 100 meters to lift and assemble turbine sections. Safety regulations require that lifting activities by cranes must be stopped once a threshold of 14 meter/second for wind speed is reached. In addition, other construction activities of onshore wind projects are executed outdoors and are directly affected by weather risk. Indeed, adverse weather was identified as the third most critical risk factor affecting onshore wind construction in Canada (Chapter 2). Current models that have been developed to understand weather uncertainty on the project schedule can only analyze the weather impact during the bidding stage of the project. A model that can support the understanding and quantification of weather uncertainty during the construction phases of onshore wind projects has yet to be developed in literature. Thus, the ***fifth gap*** that will be addressed in this thesis is the lack of models that consider short-term weather impact on the construction activities on an onshore wind project.

Currently, risk management in wind farm projects lacks a profound and established decision support system. Therefore, this research is proposing a decision support system for risk management in wind farm projects. The proposed decision support system (DSS) fuses available techniques, approaches, and current knowledge in construction risk management. As such, the developed decision support system is expected to provide a generic risk-management framework for wind farm projects. The proposed decision support system is expected to aid practitioners in wind farm construction as they make use of the advancements in risk research to improve their practice.

1.3 Objectives

The overall goal of this research is to create an approach for risk management in onshore wind projects that can easily be emulated and implemented by industry practitioners in any onshore wind project. Thus, a novel decision support system to enhance risk management practices with focus on risk identification and risk quantification is proposed. Once the decision support system is accomplished, a better understanding and analysis of the risk factors will be achieved. This research intends to achieve the following objectives:

Objective 1: improve the *risk identification* process for onshore wind projects. The following sub-objectives were conducted to achieve objective 1:

- Understand and analyze the generic critical risk factors affecting the construction phase of onshore wind projects
- Develop a method that supports the identification of context specific risk factors of an onshore wind project

Objective 2: improve the *risk assessment* process for onshore wind projects. The following sub-objectives were conducted to achieve objective 2:

- Develop a method for enhancing the input modelling of Monte Carlo simulation risk assessment in situations characterized by limited historical data
- Propose a domain-specific risk assessment method that is more suitable for risk analysis of onshore wind projects.
- Develop a simulation model that considers short-term weather forecast data to enhance the lookahead planning of onshore wind projects subject to weather risk.

1.4 Research Methodology

The research was conducted in five modules to achieve the stated objectives, as shown in Figure 1.2. In the first module, a literature review was conducted to identify risk factors affecting onshore wind projects during the construction phase. Based on the final set of factors, a questionnaire was designed and developed to evaluate the impact and likelihood of each factor. The purpose of the questionnaire was to identify critical risk factors based on subject matter experts from the Canadian wind energy industry. Experts were asked to provide their opinions on the identified list to prioritize them and determine the most critical factors. A hybrid multi-criteria approach (i.e., fuzzy analytical hierarchy process (FAHP) and fuzzy technique for order of preference by similarity to ideal solution (FTOPSIS)) was used to analyze the collected survey responses. Lack of management experience, shortage of resources, adverse weather were determined to be the most critical risk factors according to the sampled population of Canadian contractors.

In the second module, a method was developed to enhance and support the identification of context-driven risk factors using ontology-based approach. Ontology is usually used to represents domain knowledge as a set of concepts along with the connections (i.e., relationships) between them (El-Diraby et al. 2005; El-Diraby 2013). Data for 7 onshore wind projects and the risks associated with them were collected, and a risk ontology model was developed to model the associations between project and risk information. Protégé which is a free, open-source ontology editor and framework for building intelligent systems developed by Stanford university (Rubin et al. 2007) was used in building the risk ontology. The risk ontology was designed to support experts in identifying risk factors based on the context of the project. Ontology was selected for its ability to map the relationships between related knowledge and for its ability to automatically reason and discover knowledge.

In the third module of this research, input modelling, which allows defining a statistical distribution, for the risk impact of the identified risk factors was explored. A fuzzy-based multivariate modelling approach was proposed to overcome data limitations and to consider correlations between cost and schedule impacts of a risk factor. This approach allows experts to develop statistical distributions based on their detailed subjective knowledge. In addition to that, the multi-variate analysis allows to consider the correlation between cost impact and schedule impact of risk factors that have both impacts.

In the fourth module, a domain specific risk assessment was proposed to quantitatively assess risk factors of onshore wind projects to assist project managers with cost and time contingency estimating. Monte Carlo Simulation-Critical Path Method (MCS-CPM) was selected as a suitable approach due its ability to consider cost and schedule impacts simultaneously while considering the uncertainty inherent in construction. In this research, Simphony Projects (Mohamed et al. 2020a) was used as a simulation tool to assess the schedule and cost impacts of risk factors. Recommendations and guidelines for industry practitioners were drawn when using the MCS-CPM approach.

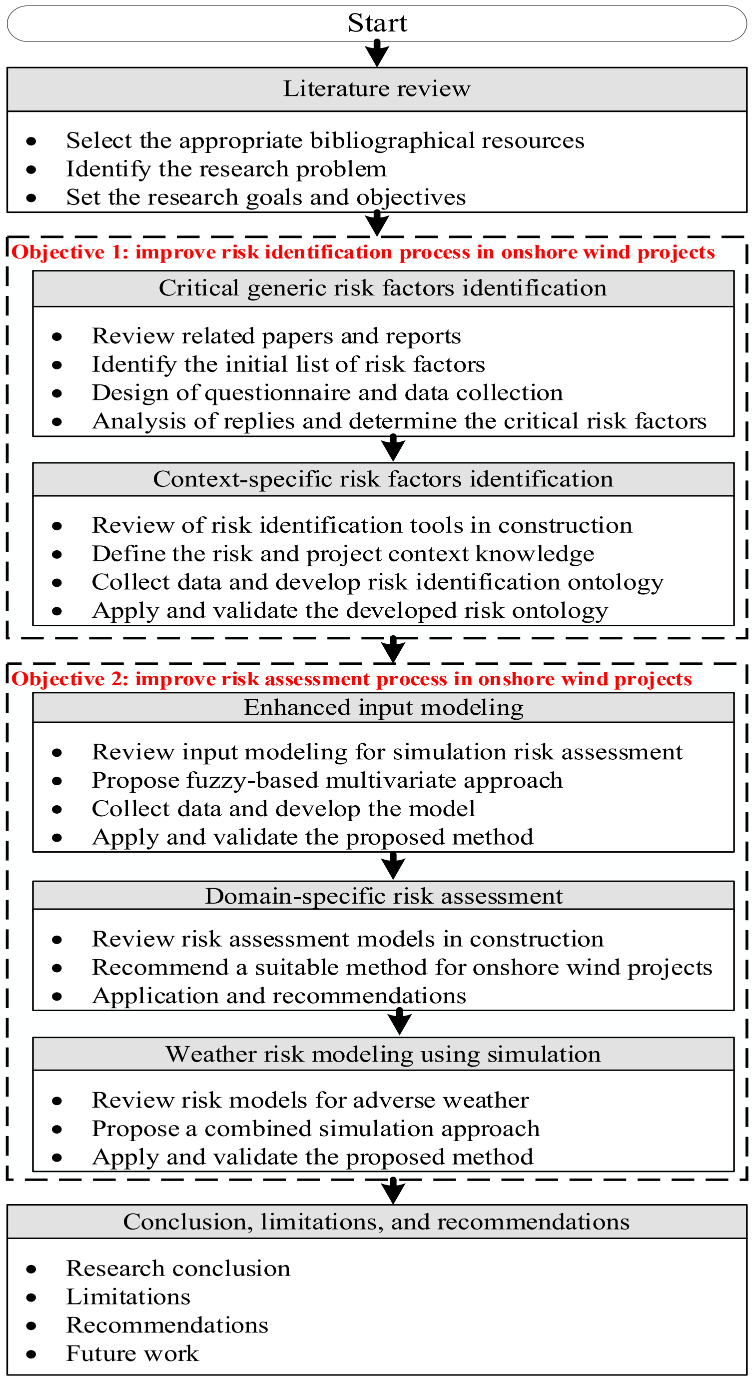


Figure 1.2. Research Methodology.

In the fifth module, a combined discrete event and continuous simulation model, capable of considering short-term weather forecasts, was developed to assist managers with the decision-making processes associated with the planning and scheduling of construction activities. Simulation was selected as a suitable approach due its ability to capture dynamic and complex interactions of construction processes while considering the uncertainty inherent in construction and external factors (AbouRizk 2010). In this research, Simphony.NET (AbouRizk et al. 2016) was used as a simulation tool since it is programmable, can be customized for further developments, and has been successfully used in previous studies.

1.5 Expected Contributions

The main expected contribution of this thesis is providing a decision support system for risk management of wind farm projects during construction phase that pull together various methods for risk identification and assessment. The DSS will show how these methods works for wind farm projects and provide guidelines for decision makers who are involved in risk management of wind projects. In addition to that, the following detailed contributions are expected by each module of the decision support system:

1- The first module is expected to provide a systematic and thorough analysis of risk factors affecting construction of onshore wind projects in Canada. In addition to that, ranking of the risk factors and determining the most critical risk factors is expected too.

2- The second module is expected to provide a context-driven approach which considers the specific characteristics of a project for accurate identification of a specific risks that belong to that project due to its context.

3- The third module is expected to provide a method that enhance the input modeling for

Monte Carlo simulation which allows experts to establish the probability distributions of risk factors' impact using their detailed subjective knowledge.

4- The fourth module is expected to provide a domain-specific risk assessment model in onshore wind projects that considers the cost and time impacts of risks simultaneously.

5- The fifth module is expected to provide a simulation-based approach which allows decision makers to assess the weather impact dynamically and accurately on the project schedule by considering the real-time weather effect.

1.6 Thesis Organization

This thesis is organized following a paper-based format that is consistent with the research framework shown in Figure 1.2. Detailed contents of each chapter are listed as follows.

Chapter 2 focuses on identifying, from the perspective of project experts who are involved in the wind energy industry in Canada, critical risk factors affecting the construction phase of onshore wind projects. A questionnaire-based methodology was used to collect responses, and hybrid multi-criteria was applied to analyze the results. A set of the top 10 risk factors was established.

Chapter 3 focuses on developing a context-driven risk identification tool using ontologies. Traditional and advanced risk identification techniques are described. Difficulties in current risk identification tools in practice, such as the lack of data integration between risk factors and project context data, are discussed. A case study manifests the application of the risk ontology for context-driven risk identification. Also, the advantages of risk ontology compared to other techniques was discussed.

Chapter 4 discusses the limitations of current input modelling approaches for developing statistical distributions and proposes a fuzzy-based approach, capable of overcoming existing limitations, to develop statistical distributions based on detailed subjective expert knowledge. Notably, this approach allows experts to express their knowledge about risk impacts in detail, thereby reducing bias when eliciting distribution parameters. A case study is presented to demonstrate the effectiveness and advantages of using the proposed approach in practice.

Chapter 5 focuses on proposing and developing a domain-specific simulation-based approach for quantitatively assessing of risk factors in onshore wind projects. A case study is presented to demonstrate how this simulation approach can be used to evaluate risk factors' impact on project time and cost. Guidelines and recommendations were provided for industry practitioners.

Chapter 6 focuses on developing a combined simulation approach capable of integrating short-term weather forecast data. A case study is presented to demonstrate how this combined simulation approach can be used to understand and evaluate the effect of short-term adverse weather on project scheduling.

Chapter 7 summarizes the conclusions of this thesis and the academic and industrial contributions resulting from this work. Recommendations for future studies are also described.

Chapter 2 : Critical Construction Risk Factors Affecting Onshore Wind Projects in Canada: A Hybrid Fuzzy Multi-Criteria Approach

2.1 Introduction

Developed countries are increasing their capacity for energy production from renewable sources, such as wind and solar power, to decrease the harmful effects of fossil fuel combustion on the environment and to reserve the limited stock of fossil fuels for future generations (Saidur et al. 2010). Wind energy is a clean and renewable energy source with a potential production capacity large enough to become an alternative to fossil fuels around the world (Saidur et al. 2010). The Canadian federal government and provincial governments continuously fund the growth of Canada's wind power assets through different programs and incentives. The government of Canada is planning to reduce greenhouse gas emissions by 30% relative to the 2005 emission level by the end of 2030 through its Federal Sustainable Development Strategy (FSDS) ("Federal Sustainable Development Strategy" n.d.). One component of the FSDS is the development of clean energy systems, including onshore wind farm projects. Canada possesses two critical resources for onshore wind farm projects, which are wind and land. These resources have allowed Canada to become the ninth-largest producer of wind energy in the world. With an installed capacity of more than 13 gigawatts (GW), current Canadian wind farm infrastructure produces enough power to meet about 6 % of the country's total electricity demand ("Installed Capacity" 2020). However, the high levels of risks related to changing policies and politics together with the high complexity of clean energy projects systems such as solar and wind have hindered decision-makers from confidently assessing energy systems' growth trajectory (Prpich et al. 2014a). A better understanding of the risks underlying the construction of clean energy systems, therefore, has the potential to improve decision-making, planning, and overall project success (Prpich et al. 2014a).

The construction phase of a wind farm project's life cycle is associated with a significant amount of uncertainty and complexity due to inherent risks (Alkhalidi et al. 2020). The high levels of intrinsic risks within onshore wind farm projects impose a real obstacle in investment decisions and, consequently, in these projects' construction phase (Montes and Martin 2007). Therefore, exploring and understanding the risk factors will help developers and contractors to understand the system, elucidate the ambiguity, and allow for robust decision-making regarding the risks that affect the project during the construction phase (Prpich et al. 2014a) (Montes and Martin 2007). Risk factors can negatively impact project objectives in terms of cost, time, safety, and quality. Risk management is a critical element in securing project financing and achieving project objectives (Gatzert and Kosub 2016b). Although negative impacts of risk factors are common to construction projects globally, different projects, such as onshore wind projects, are affected differently in various locations: certain risk factors are more critical in some countries but less critical in others.

Negative impacts of risk factors affect construction and operation phases of onshore wind projects. Although numerous studies, including (Nielsen and Sørensen 2014) (Chou and Tu 2011) (Ambühl and Dalsgaard Sørensen 2017) (Tazi et al. 2017) have been conducted to address the risks in onshore wind farm projects, the focus of these studies mainly was related to the operation and maintenance phases of wind farm projects. In contrast, only few studies (Enevoldsen 2016) (Montes and Martin 2007) (Rolik 2017a) (Gatzert and Kosub 2016b) have focused on the risk associated with the construction phase of the onshore wind farm projects. A comprehensive analysis of all the critical risk factors affecting the onshore wind farm projects during the construction phase is, therefore, lacking. Furthermore, none of the previous studies have investigated the construction risks of onshore wind farm projects from the Canadian perspective. Without these investigations, context-dependent risks affecting Canadian projects, including environmental and political factors, have likely been overlooked (Zhi 1995).

In an attempt to address these research gaps, the authors aim to explore the following two questions in an onshore wind farm project:

Q1. What are the main risk factors encountered during the construction phase of wind farm projects?

Q2. Which of these risk factors are of most concerning and critical to Canada's construction wind industry sector?

A multi-criteria decision-making (MCDM) approach of fuzzy AHP and fuzzy TOPSIS was proposed in this study to answer the research questions. Understanding the risk factors associated with the construction phase of onshore wind farm projects is essential to support and increase investments and developments in the Canadian wind farm sector. This research effort is expected to benefit contractors, developers, project managers, and investors of onshore wind farm projects in the Canadian energy sector by comprehensively exploring and identifying the risk factors of these projects and determining the most critical risk factors. The specific contributions of this research are twofold: (1) identify, explore, and develop a comprehensive list of risk factors collected from universal literature; and (2) rank and define the construction risk factors considered most critical to contractors in the Canadian wind energy industry.

In the remaining sections of this paper, previous research efforts on risk factors are reviewed, and remaining research gaps are discussed. Then, an MCDM model based on fuzzy analytical hierarchy process (fuzzy AHP) and fuzzy technique for order of preference by similarity to ideal solution (fuzzy TOPSIS) is developed to prioritize the risk factors based on the severity of their impact on project cost, time, quality, and safety. Next, a questionnaire survey is used to collect evaluations from experts who are employed in the Canadian wind energy sector. To assess the severity of each risk factor, experts must subjectively evaluate the impact of each risk on the project's cost, time, safety, and quality objectives, as well as the probability of the risk factor. After that, the collected responses are analyzed using the proposed fuzzy AHP and fuzzy TOPSIS approach. Finally, results are presented, discussion and conclusion are drawn.

2.2 Literature Review

2.2.1 Risk Identification of Onshore Wind Farm Projects

The first step of the risk management process is identifying and understanding the risk factors that have the potential to affect project objectives during the construction phase. Risk identification is considered as the crucial step in the risk management process (Chapman 1998): because unidentified risks cannot be controlled or mitigated (Siraj and Fayek 2019), unidentified risks represent unassessed threats to the project objectives (Chapman 2001). Identifying risk factors is the foundation for developing a successful risk management plan for wind farm projects such as qualitative, quantitative analysis, and response planning (Rolik 2017a).

Many studies have focused on improving construction risk identification of wind farm projects. Prpich (Prpich et al. 2014a) reviewed the risk factors that affect the investment decisions and development of wind projects in the United Kingdom. Prpich et al. then used expert opinions from the industry to evaluate risk severity. Michelez et al. (Michelez et al. 2011) investigated the risk factors affecting renewable energy projects, as well as the risk management approaches and response strategies for dealing with the identified risks. Gatzert and Kosub (Gatzert and Kosub 2016b) reviewed the risk factors affecting onshore and offshore wind projects during design, planning, construction, and operation phases, focusing on European countries. They concluded that the construction phase is characterized by a greater number of risks and uncertainty than any of the other phases of the wind farm project's lifecycle (Gatzert and Kosub 2016b). Kucukali (2016) proposed a risk assessment tool for qualitatively evaluating risks at different phases of onshore wind farm projects; however, only a few risks were analyzed in this study. Enevoldsen (2016) reviewed the risks that affect onshore wind farm projects during the construction and operation phases in the Northern European forest area. Rolik (2017a) proposed the Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis technique to help identify the risks associated with wind farm projects. Turner et al. (2013) reviewed the risk of developing wind and solar projects in Australia, China, France, Germany, the UK, and the USA during the construction and operation phases of these projects. Angelopoulos et al. (2016) investigated the investment risk factors for onshore wind farm projects in European countries.

Waissbein et al. (2013) reviewed the risks and proposed strategies to minimize the risk impact on the development of onshore wind farm projects in four countries, including South Africa, Panama, Mongolia, and Panama. Fera et al. (2017) analyzed the risk factors affecting wind farm projects using an analytical hierarchy process in Italy.

It is concluded from the literature review that previous studies were commonly focused on identifying risks in specific geographic areas around the world. However, a study investigating the risk factors of onshore wind farm projects in the Canadian wind energy sector has not yet been conducted. Although projects share similar characteristics, risk characteristics may differ across geographical regions (Zhi 1995). Accordingly, the risk factors that affect the construction of onshore wind farm projects remain concealed for investors and constructors in the Canadian energy sector. This research has been conducted to address this gap and inform the Canadian wind energy sector parties about the risks during a project's construction phase. Previous studies were reviewed to develop a comprehensive list of the risks that affect wind farm projects. Then, a survey was distributed to experts who work in the Canadian wind energy sector to evaluate the severities of identified risks and prioritize them.

2.3 Research Methodology

In construction projects, the overall assessment of risk factors is a multi-criteria decision-making (MCDM) problem (Taylan et al. 2014). Deciding on the most severe risk factors in onshore wind farm projects is best treated as a MCDM problem composed of several criteria including cost severity, time severity, safety severity, and quality severity, as shown in Figure 2.1.From this perspective, the TOPSIS method, a well-known MCDM technique, appears to be an appropriate technique to prioritize critical risk factors affecting onshore wind farm projects.

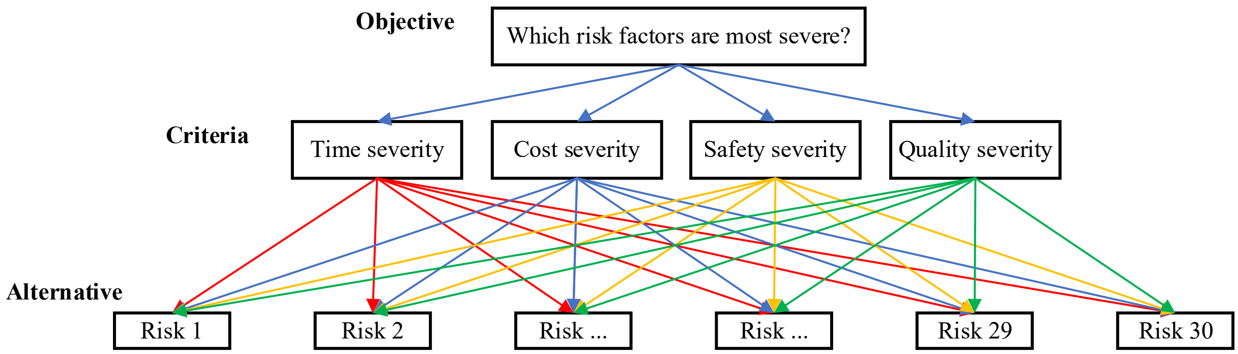


Figure 2.1. Hierarchical structure of the risk problem

Multi-Criteria Decision Making (MCDM) techniques allow sorting a group of decision alternatives based on multiple decision criteria to support decision-making (Şengül et al. 2015). Many MCDM techniques have been developed to solve decision-making problems, such as AHP and TOPSIS. As most MCDM techniques alone cannot fully address a decision-making problem, hybrid approaches have become prevalent in literature (Jato-Espino et al. 2014). These hybrid methods emerged as a solution to some of the shortcomings presented by the unique MCDM techniques (Jato-Espino et al. 2014). For example, two of the most popular methods used in the MCDM in construction problems are AHP and TOPSIS (Jato-Espino et al. 2014). AHP is well-suited for conducting pairwise comparisons between a few decision alternatives, which makes it an appropriate technique to be combined with other MCDM techniques (e.g., TOPSIS) for assigning weights to the decision criteria. Then, an outranking method like TOPSIS can be used to rank a large number of alternatives (Jato-Espino et al. 2014).

The basis of TOPSIS is to rank the alternatives by simultaneously measuring the distances of each alternative to both positive and negative ideal solutions (Salih et al. 2019). Evaluation criteria usually have different dimensions in the MCDM problems (Yoon and Hwang 1995); therefore, TOPSIS normalizes the evaluations for each criterion. Moreover, TOPSIS is a compensatory MCDM method that allows trade-offs between the criteria (Heravi and Seresht 2018). The trade-off means a low evaluation in one criterion can be compensated by a high evaluation in another criterion (Heravi and Seresht 2018). Furthermore, TOPSIS compares all the alternatives in only one step without the need for a lengthy process of pairwise comparisons characteristic of methods such as AHP (Heravi and Seresht 2018). This advantage makes TOPSIS a more efficient method than the pairwise comparison methods (e.g., AHP) for solving MCDM problems with many alternatives and criteria (Heravi and Seresht 2018). Moreover, compared to other MCDM techniques, TOPSIS has the following advantages (Fouladgar et al. 2012): (1) the logic of TOPSIS is transparent and understandable; (2) the computation process is easy; (3) it determines the best and the worst assessments of the alternatives for each criterion; and (4) the weights of the criteria are incorporated into the comparison procedure.

Conversely, AHP and FAHP have been widely and extensively applied to assess risk factors in construction projects (Taroun 2014), such as (Mustafa and Al-Bahar 1991), (Zhang and Zou 2007), (Nieto-Morote and Ruz-Vila 2011), (Zhi 1995), (Hastak and Shaked 2000), (Dikmen and Birgonul 2006), (Zeng et al. 2007), (Zayed et al. 2008). However, AHP and FAHP have some limitations in their application for construction risk assessment, including (Taroun et al. 2011): (1) these techniques require the experts to make a large number of comparisons between different risk factors, which becomes more challenging in construction projects with numerous risks, (2) the consistency of comparisons for these techniques must be within an acceptable range, which may not always be achievable, and (3) there is a lack of options for ignoring inapplicable evaluations.

In this paper, fuzzy AHP is used to assign weights to the evaluation criteria used by the fuzzy TOPSIS component. Another limitation of conventional MCDM, such as AHP and TOPSIS, is that crisp values are used to compare different decision alternatives. However, human experts commonly express their evaluations as a subjective values such as low, medium, and high rather than crisp numbers. To address this limitation and capture the subjective uncertainty in the natural language used by experts, fuzzy sets were integrated with MCDM techniques (Jato-Espino et al. 2014). In construction risk management, experts often face challenges to provide a precise numerical evaluation of each risk factor; therefore, fuzzy linguistic variables were usually employed for risk assessment applications (Taylan et al. 2014).

Several researchers widely apply fuzzy AHP and fuzzy TOPSIS for risk assessment in the construction industry. For example, Taylan et al. (Taylan et al. 2014) used fuzzy AHP and fuzzy TOPSIS to assess the severity of risk in construction projects and rank projects based on their severities on time, cost, quality, safety, and environmental sustainability. Fouladgar et al. (Fouladgar et al. 2012) used fuzzy TOPSIS to assess the construction risks of tunnelling projects and rank them based on four criteria: consequence, detectability, vulnerability, and reaction. Haghshenas et al. (Haghshenas et al. 2016) assessed the construction risks of dam projects and ranked them using the fuzzy TOPSIS method based on three criteria: repeat chance, occurrence possibility, and efficacy. Wang and Elhag (Wang and Elhag 2006) proposed a fuzzy TOPSIS model to assess the risks related to the maintenance of bridges and to rank bridges according to risk severity.

It was concluded that the integration of fuzzy set theory, AHP, and TOPSIS through a hybrid approach of fuzzy AHP and fuzzy TOPSIS would provide a powerful technique for assessing the risk factors of onshore wind projects and rank them based on their severities on time, cost, safety, and quality aspects of the onshore wind farm project. Accordingly, the following sections provide detailed steps for implementing hybrid fuzzy AHP and fuzzy TOPSIS for construction risk assessment.

In brief, the research methodology consists of two main components. The first component is data collection, where a careful literature review and analysis was carried out to explore and extract the construction risk factors affecting onshore wind farm projects. Then, the collected risk factors are evaluated by experts through a questionnaire survey. The second component analyzes the collected replies where weights of decision criteria are determined firstly using the Fuzzy AHP technique. Then Fuzzy TOPSIS is utilized to rank the risk factors. These two components are shown in Figure 2.2 and are further discussed in the following sub-sections.

2.3.1 Data Collection

2.3.1.1 Literature Survey

Relevant studies on risk management of wind farm projects were reviewed to develop a comprehensive list of risk factors that influence the construction phase of onshore wind farm projects. The literature review of risk factors included peer-reviewed journal articles, published reports by wind organizations, and conference papers. Scopus database and Google Scholar were used as search engines. All documents published between 2005 until the time of conducting this research in July 2020 were considered in the review. Journals related to civil engineering, construction and project management, and renewable energies were considered in the review.

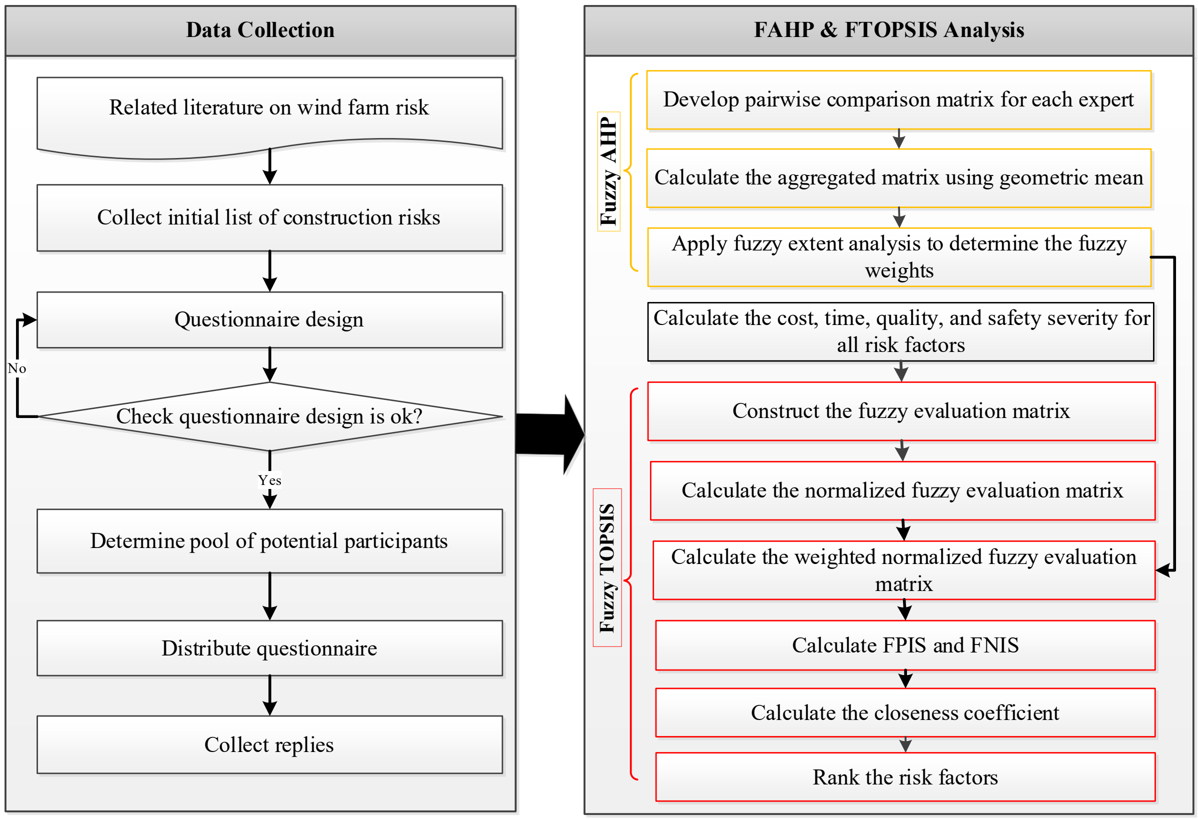


Figure 2.2. FAHP-FTOPSIS research methodology

The search was initiated using the following search terms: “risks in renewable energy infrastructure,” “risk factors in renewable energy project,” “construction risk factors in renewable energy projects,” “risk management in the construction of renewable energy projects.” Although the focus is on wind farm projects, the search started by examining all renewable energy projects, as many reports and articles addressing renewable energy projects include wind farms.

Then, more specific search terms were applied, including “risk factors in wind energy projects," "risk management in wind energy construction," "construction risk factors in wind farm projects." Similar to the first iteration, the search included all types of wind farm projects, as many reports address both onshore and offshore wind farm projects. The last search iteration included search terms such as "risk factors in onshore wind farm projects," "risk management in onshore wind farm construction," and "construction risk factors affecting onshore wind farm projects." A summery of the collected papers and reports is shown in Table 2.1 which showed that a total of 14 journal paper, 5 technical reports, and 2 conference papers were used. Risks identified from the collected papers and reports were classified to assist with documentation in this study. Risk factors were classified under two main categories: internal and external factors. Internal risk factors are related to the contractor and project characteristics, while the external risk factors are related to political, economic, and legal conditions. A summary of the risk factors is presented in Table 2.2. An initial list of 30 risk factors was identified and classified into the categories. A risk breakdown structure (RBS) of onshore wind farm project risks was established Figure 2.3.

Table 2.1: summary of references used

Reference type	**Count**
Journal paper	14
Technical report	5
Conference paper	2

Table 2.2: Identified risk factors from literature

No.	Factor	Reference	Referred frequency
R_1	Failure to keep up with recent innovative technology	(Gatzert and Kosub 2016b); (Waissbein et al. 2013); (Fera et al. 2017); (Montes and Martin 2007); (Rolik 2017a); (Xinyao et al. 2017)	6
R_2	Failure to establish a proper grid connection of a wind project to the electricity network	(Kucukali 2016); (Angelopoulos et al. 2016); (Waissbein et al. 2013); (Finlay-Jones 2007); (Noothout et al. 2016)	5
R_3	Material damage during construction	(Gatzert and Kosub 2016b); (Turner et al. 2013); (Montes and Martin 2007); (Ioannou 2017); (Zhou and Yang 2020)	5
R_4	Lack of financing	(Gatzert and Kosub 2016b); (Angelopoulos et al. 2016); (Prpich et al. 2014a); (Waissbein et al. 2013); (Fera et al. 2017); (Finlay-Jones 2007); (Noothout et al. 2016); (Xinyao et al. 2017)	8
R_5	Project cost overrun	(Enevoldsen 2016); (Fera et al. 2017), (Sovacool et al. 2017)	2
R_6	Unpredictable changes in the inflation rate	(Kucukali 2016); (Rolik 2017a); (Angelopoulos et al. 2016); (Waissbein et al. 2013); (Fera et al. 2017)	5
R_7	Fluctuation in prices of required materials	(Fera et al. 2014); (Waissbein et al. 2013); (Rolik 2017a)	3
R_8	Fluctuation in currency exchange rates	(Angelopoulos et al. 2016); (Waissbein et al. 2013); (Fera et al. 2014); (Rolik 2017a); (Noothout et al. 2016)	5

R_9	Poor economic development or economic instability	(Angelopoulos et al. 2016); (Fera et al. 2017); (Waissbein et al. 2013); (Noothout et al. 2016)	4
R_{10}	Level of corruption of the country	(Angelopoulos et al. 2016); (Noothout et al. 2016)	2
R_{11}	Lack of management expertise	(Gatzert and Kosub 2016b); (Angelopoulos et al. 2016); (Waissbein et al. 2013); (Noothout et al. 2016)	4
R_{12}	Delay in project completion	(Gatzert and Kosub 2016b); (Fera et al. 2014); (Enevoldsen 2016); (Fera et al. 2017); (Zhou and Yang 2020)	5
R_{13}	Shortage of resources required for project execution such as labour and equipment.	(Prpich et al. 2014a); (Waissbein et al. 2013); (Montes and Martin 2007); (Ioannou 2017); (Zhou and Yang 2020)	5
R_{14}	Relationship unreliability and complexity between project stakeholders	(Rolik 2017a); (Zhou and Yang 2020)	2
R_{15}	Poor cooperation to share technical expertise	(Gatzert and Kosub 2016b); (Fera et al. 2017)	2
R_{16}	Poor site geology: uncertainty in geotechnical properties of the construction site	(Kucukali 2016); (Enevoldsen 2016)	2
R_{17}	Poor access road to the site	(Kucukali 2016); (Waissbein et al. 2013)	2
R_{18}	Geopolitical instability between countries	(Prpich et al. 2014a); (Waissbein et al. 2013)	2
R_{19}	Changes in international energy agreements	(Prpich et al. 2014a); (Finlay-Jones 2007)	2
R_{20}	Unpredictable natural hazards	(Kucukali 2016); (Ioannou 2017)	2
R_{21}	Adverse environmental	(Gatzert and Kosub 2016b); (Kucukali 2016);	5

	impacts of the project	(Fera et al. 2017); (Prpich et al. 2014a); (Xinyao et al. 2017)	
R_{22}	Adverse weather	(Prpich et al. 2014a); (Gatzert and Kosub 2016b); (Atef et al. 2010); (Guo et al. 2017a)	4
R_{23}	Unstable political situation	(Kucukali 2016); (Angelopoulos et al. 2016); (Prpich et al. 2014a); (Waissbein et al. 2013); (Fera et al. 2017); (Noothout et al. 2016)	6
R_{24}	Market distortion such as high fossil fuel subsidies	(Waissbein et al. 2013); (Finlay-Jones 2007); (Prpich et al. 2014a)	3
R_{25}	Public obstruction to the project	(Gatzert and Kosub 2016b); (Kucukali 2016); (Enevoldsen 2016); (Angelopoulos et al. 2016); (Prpich et al. 2014a); (Michelez et al. 2011); (Waissbein et al. 2013); (Finlay-Jones 2007); (Noothout et al. 2016)	9
R_{26}	Insecurity and crime (theft, vandalism, or fraudulent practices)	(Gatzert and Kosub 2016b); (Turner et al. 2013)	2
R_{27}	Disturbances to public activities	(Waissbein et al. 2013); (Xinyao et al. 2017); (Zhou and Yang 2020)	3
R_{28}	Complexity and delays in permit approval	(Gatzert and Kosub 2016b); (Fera et al. 2014); (Kucukali 2016); (Angelopoulos et al. 2016); (Fera et al. 2011); (Michelez et al. 2011); (Waissbein et al. 2013); (Noothout et al. 2016); (Zhou and Yang 2020)	9
R_{29}	Land use and acquisition	(Kucukali 2016); (Enevoldsen 2016)	2
R_{30}	Regulatory and policy risks: Change of laws and regulations	(Gatzert and Kosub 2016b); (Kucukali 2016); (Angelopoulos et al. 2016); (Waissbein et al. 2013); (Finlay-Jones 2007); (Noothout et al. 2016); (Zhou and Yang 2020)	7

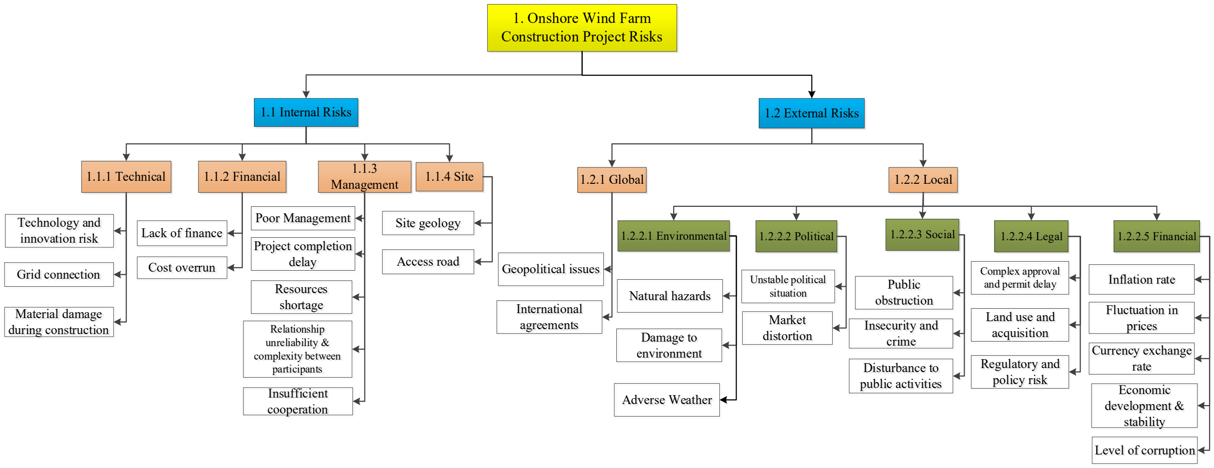


Figure 2.3. Risk breakdown structure of onshore wind farm risk factors

2.3.1.2 Questionnaire Design

The questionnaire survey (Survey Link n.d.) consisted of three parts: demographic information, pairwise comparison, and risk evaluation. The purpose of the first part (6 questions) was to collect information about the respondents, including the position/role of the respondent, level of education, years of experience in wind construction, installed capacity of involved projects, and the role of the respondent's company in wind projects construction. Respondents were given a pre-defined set of options for each question.

The second part was designed to collect the pairwise comparison evaluations of the project objectives criteria. A total of six questions were used to develop the pairwise comparison matrix between the criteria. Each of these six questions had nine options ranging from equally important to absolutely important, as per the scale illustrated in Figure 2.5. The pairwise comparison scale was explained to the respondents in this part of the questionnaire.

In the last part of the questionnaire, respondents were asked to evaluate each risk factor regarding its cost impact, time impact, quality impact, safety impact, and the probability of occurrence. Thus, five questions were asked for each risk factor. Respondents were given seven options to choose from for each question, in addition to one option for not applicable (N/A).

2.3.2 Fuzzy AHP And Fuzzy TOPSIS Analysis

In this step, fuzzy linguistic terms were utilized to evaluate the risk probability and impact of the risk factors that affect the construction wind farm projects. Then, these values were analyzed to determine the cost severity, time severity, quality severity, and safety severity for each risk factor. Next, risk factors were ranked using the fuzzy TOPSIS technique based on their evaluations in four criteria: cost severity, time severity, quality severity, and safety severity. As part of applying fuzzy TOPSIS ranking, the weights of these criteria needed to be determined. Fuzzy AHP was used in this research to calculate the weights of evaluation criteria. The details of implementing fuzzy AHP and fuzzy TOPSIS in the proposed risk assessment framework are provided in the following paragraphs.

Fuzzy logic was first introduced by Zadeh (Zadeh 1965) to model uncertain subjective knowledge. A Fuzzy set A is defined mathematically by a membership function $\mu_A(x)$, which assigns each element x in the universe of discourse X to a real number in the interval [0,1], referred to as a membership value (Fayek 2018). There are several types of membership functions for fuzzy sets, among which the triangular membership function is the most common type in engineering applications (Pedrycz and Gomide 2007). Triangular fuzzy numbers are commonly used (Wang and Elhag 2006) since they make calculations simple and interpretation straightforward (Ebrahimnejad et al. 2010). Other membership functions may increase the complexity of computations without considerable effect on the results (Ebrahimnejad et al.

2009). A triangular function is shown in Figure 2.4, and its mathematical description is presented in equation (2.1).

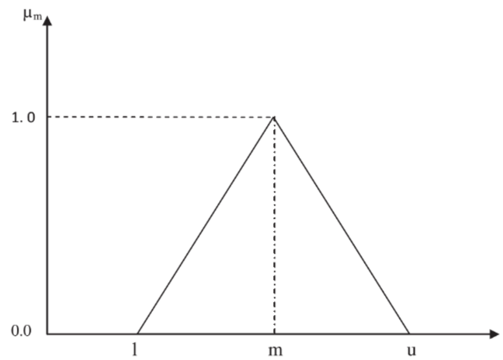


Figure 2.4. Triangular Fuzzy number

$$\mu_A(x) = \begin{cases} 0, & x < l \\ \dfrac{x-l}{m-l}, & l < x < m \\ \dfrac{u-x}{u-m}, & m < x < u \\ 0, & x > u \end{cases} \tag{2.1}$$

This study used the extent analysis method proposed by (Chang, 1996) to implement fuzzy AHP because it is easy to understand and apply, less time-consuming, and requires less computational effort than conventional fuzzy AHP (Lee 2009). The concept of the extent analysis method is based on the comparison between fuzzy triangular numbers to estimate the weight vectors. Based on the fuzzy values for the extent analysis of each criterion, a fuzzy synthetic degree value can be calculated. Fuzzy synthetic extents are values that are usually calculated based on other metrics. The fuzzy synthetic extents represent fuzzy weights of evaluation criteria. Experts were asked to compare every two criteria according to the pairwise comparison scale in Figure 2.5. For this purpose, the triangular fuzzy numbers scale proposed by Chan and Kumar (Chan and Kumar 2007) was adopted in this study to represent the pairwise comparison of decision criteria, as shown in Figure 2.5. Pairwise evaluations were collected and were represented using reciprocal matrices. The individual reciprocal matrices were then aggregated using the geometric mean, which remains a triangular fuzzy number. The aggregated matrix was analyzed using Chang's extent analysis (Chang 1996) on FAHP to determine each criterion's weights as follows.

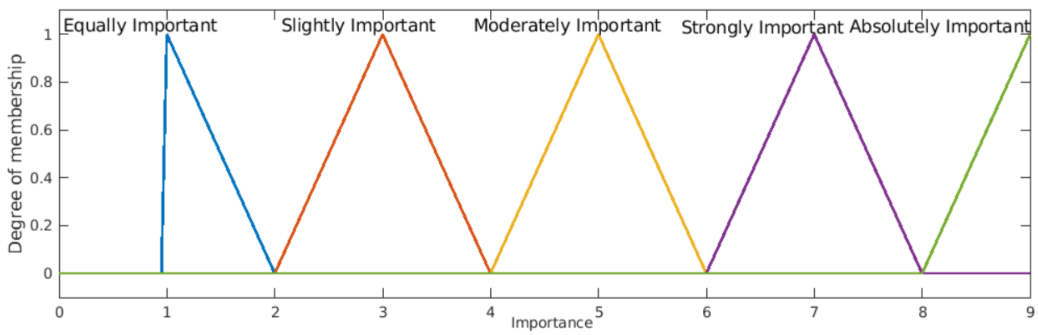


Figure 2.5. The membership functions of pairwise comparison (Chan and Kumar 2007)

Let C = $\{c_1, c_2, c_3, \ldots, c_n\}$ be the criteria set where n is the number of criteria. For each criterion c_i, the extent analysis was performed through the following steps:

Step 1: Extent analysis of j_{th} criterion M_i^j were obtained by performing a fuzzy addition operation for each row of the aggregated matrix, where subtotals were calculated for each criterion for the i_{th} boundary of the aggregated fuzzy number (i.e., lower, core, and upper values) for the j_{th} criterion as follows:

$$\sum_{j=1}^{n} M_i^j = \left(\sum_{j=1}^{n} l_j \,, \quad \sum_{j=1}^{n} m_j \,, \quad \sum_{j=1}^{n} u_j \right) \tag{2.2}$$

Where all the M_i^j (j=1, 2, ..., n) are fuzzy triangular numbers, l is the lower limit value, m is the core value, and u is the upper limit value.

Step 2: Fuzzy addition operation is then performed on all extent analysis values $M_i^j (j = 1, 2, 3, \ldots, n)$ of all criteria (j=1, 2, ..., m) as follows:

$$\sum_{j=1}^{m}\sum_{j=1}^{n} M_i^j = \left(\sum_{j=1}^{m}\sum_{j=1}^{n} l_j, \quad \sum_{j=1}^{m}\sum_{j=1}^{n} m_j, \quad \sum_{j=1}^{m}\sum_{j=1}^{n} u_j\right) \tag{2.3}$$

Step 3: The inverse of $\sum_{j=1}^{m}\sum_{j=1}^{n} M_i^j$ is calculated as per equation (2.4) as follows:

$$\left[\sum_{j=1}^{m}\sum_{j=1}^{n} M_i^j\right]^{-1} = \left(\frac{1}{\sum_{j=1}^{m}\sum_{j=1}^{n} u_j}, \quad \frac{1}{\sum_{j=1}^{m}\sum_{j=1}^{n} m_j}, \quad \frac{1}{\sum_{j=1}^{m}\sum_{j=1}^{n} l_j}\right) \tag{2.4}$$

Step 4: The last step is to calculate the value of fuzzy synthetic extent (S_i) for the *i*th criterion, which was used as the weight for the criteria defined in Equation (2.5) as follows:

$$S_i = \sum_{j=1}^{n} M_i^j \otimes \left[\sum_{j=1}^{m}\sum_{j=1}^{n} M_i^j\right]^{-1} \tag{2.5}$$

where $\otimes$ is fuzzy multiplication and is calculated according to (Sun 2010) as follows for two triangular fuzzy numbers K = (a_1, b_1, c_1) and L = (a_2, b_2, c_2); K $\otimes$ L = $(a_1a_2$, b_1b_2, $c_1c_2)$.

Fuzzy TOPSIS is an appropriate method for elucidating the group decision-making problem under subjective evaluation (Taylan et al. 2014). A risk factor is usually expressed as an event that could hinder the successful accomplishment of project objectives and is evaluated in terms of probability and impact (Taylan et al. 2014). Probability and impact for each risk factor were assessed based on expert judgment (Taylan et al. 2014). The scale used to evaluate the risk factors subjectively is seven linguistics triangular fuzzy numbers, as presented in Figure 2.6, adopted from similar studies (Wang and Elhag 2006) (KarimiAzari et al. 2011). The experts were explicitly asked to evaluate each risk factor's probability of occurrence and the cost, time, quality, and safety impacts. These values were used to assess the severity of each risk factor by multiplying each impact value by the probability of occurrence ($Severity = P \times I$). The resulting cost severity, time severity, quality severity, and safety severity were then used in the fuzzy TOPSIS calculations to rank the risk factors through the following steps:

Step 1: The decision matrix was developed for each expert, representing the severity of each risk for each of the four criteria. The aggregated matrix was generated by averaging all the experts' evaluations using the average operator (Zhao and Guo 2014). Risk factors (R_1, R_2, . . ., R_m) evaluated by a group of experts, based on *n* criteria (C_1, C_2, . . ., C_n), were represented by matrix D, as given in Equation (2.6). The elements x_{ij} of the matrix indicated the aggregated risk severity of the *i*th risk factor, R_i, with respect to the j^{th} criterion for all experts. Also, x_{ij} is a linguistic triangular Fuzzy number, so that it was represented as $x_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right)$.

$$\mathrm{D} = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ \cdots \\ R_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ x_{31} & x_{32} & \cdots & x_{3n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{2.6}$$

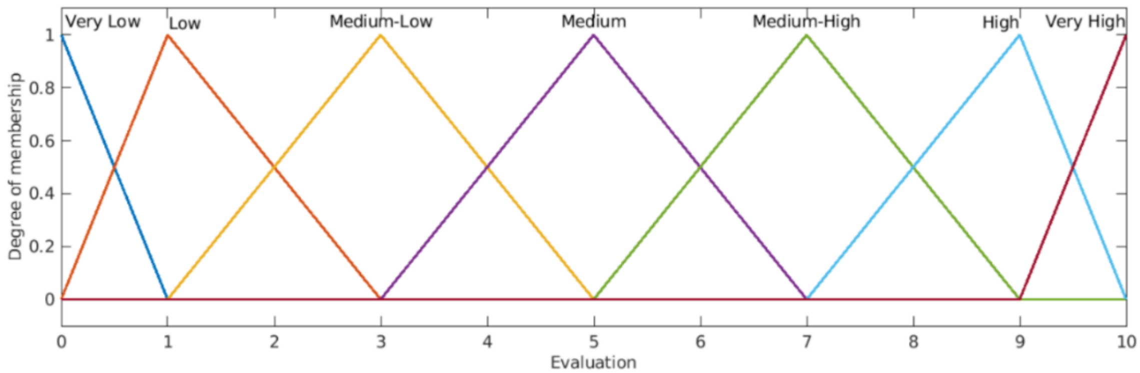


Figure 2.6. Linguistic scale used to evaluate the risk factors (Wang and Elhag 2006) (KarimiAzari et al. 2011)

Step 2: After constructing the fuzzy decision matrix, the normalization of matrix $\widetilde{D}$ was performed through a linear-scale transformation to convert the various criteria scales into a comparable scale for distance measurement using equations (2.7) and (2.8) for negative criteria (Chen 2000):

$$\widetilde{D} = [\tilde{r}_{ij}]_{m\times n} \qquad i = 1, 2, 3, \ldots, m; \text{ and } j = 1, 2, 3, \ldots, n \tag{2.7}$$

Where the fuzzy number $\tilde{r}_{ij}$ was normalized as follows:

$$\tilde{r} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \; a_j^- = \min_i\{a_{ij}\} \tag{2.8}$$

The normalization resulted in a matrix with fuzzy numbers which it's support is the crisp interval [0, 1].

Step 3: The weighted normalized fuzzy matrix $\tilde{V}$ was then calculated by multiplying the normalized matrix by the weight of criteria determined by the fuzzy synthetic extent in Equation (2.2), as shown in equations (2.9) and (2.10). The elements of the $\tilde{V}$ matrix are positive triangular fuzzy numbers, which their support is included in the crisp interval [0, 1].

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times n} \tag{2.9}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes w_j \tag{2.10}$$

where $\otimes$ represents the fuzzy multiplication operator.

Step 4: The positive ideal solution indicates the most favorable alternative, and the negative ideal solution indicates the least unfavorable alternative. The fuzzy positive ideal solution (A^+) and fuzzy negative ideal solution (A^-) were determined as follows:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \tilde{v}_3^+, \dots, \tilde{v}_n^+) \text{ where } \tilde{v}_j^+ = \max_i\{\tilde{v}_{ij}\} \tag{2.11}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \tilde{v}_3^-, \dots, \tilde{v}_n^-) \text{ where } \tilde{v}_j^- = \min_i\{\tilde{v}_{ij}\} \tag{2.12}$$

The elements $\tilde{v}_{ij}$ were normalized positive triangular fuzzy numbers with a support belonging to the closed interval [0, 1]. Thus, we can define $\tilde{v}_j^+$ = (1, 1, 1) and $\tilde{v}_j^-$ = (0, 0, 0) (Fouladgar et al. 2012) (Wang and Elhag 2006) (Ebrahimnejad et al. 2009) (Grassi et al. 2009).

Step 5: Then, the distance between each alternative (i.e. risk factor) and (A^+ and A^-) was computed as follows:

$$d_{j=1}^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+) \qquad i = 1;\ 2;\ \dots; m; \tag{2.13}$$

$$d_{j=1}^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \qquad i = 1;\ 2;\ \dots; m \tag{2.14}$$

Where $d_{j=1}^{+}$ and $d_{j=1}^{-}$ are two distances between two triangular fuzzy numbers. In this study, the Euclidean distance (Szmidt and Kacprzyk 2000) (Wang and Elhag 2006) (Chen 2000) was used to measure the distance between two fuzzy numbers, as shown in equations (2.15) and (16).

$$(\tilde{v}_{ij}, \tilde{v}_j^{+}) = \sqrt{\frac{1}{3}\left[\left(\tilde{v}_{ij_{lower}} - 1\right)^2 + \left(\tilde{v}_{ij_{core}} - 1\right)^2 + \left(\tilde{v}_{ij_{upper}} - 1\right)^2\right]} \quad (2.15)$$

$$d(\tilde{v}_{ij}, \tilde{v}_j^{-}) = \sqrt{\frac{1}{3}\left[\left(\tilde{v}_{ij_{lower}} - 0\right)^2 + \left(\tilde{v}_{ij_{core}} - 0\right)^2 + \left(\tilde{v}_{ij_{upper}} - 0\right)^2\right]} \quad (2.16)$$

Step 6: Finally, the closeness coefficient addressing the ranking order of the alternatives was computed as per equation (2.17):

$$CC_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}} \quad (2.17)$$

The authors wanted to explore and identify the critical risk factors; therefore, risk factors with the lowest closeness coefficient were considered the most critical risk factors because they were too close to the negative ideal solution. Thus, Equation (2.18) was used to calculate the closeness coefficient instead of equation (2.17).

$$CC_i = \frac{d_i^{+}}{d_i^{+} + d_i^{-}} \quad (2.18)$$

2.4 Model Application and Results

2.4.1 Data Collection

In this section, the collected risk factors presented in Table 2.2 were evaluated by a group of experts working on the construction and development of onshore wind farm projects in Canada. A structured questionnaire was prepared and distributed online using the SurveyMonkey® platform to collect experts' evaluations of the risk factors affecting Canada's construction of an onshore wind project. A total of 150 questionnaire invitations were distributed to experts who were specialized in wind project construction in Canada. In addition, invitations were circulated to the Canadian wind energy association (CanWEA) and the wind energy institute of Canada (WEICAN). The responses were collected over 15 months, spanning January 2020 through March 2021. A minimum statistical sample size for the study was determined using the formula introduced by (Cochran 1977) for scaled variables as shown in Equation (2.19):

$$n = \frac{t^2 * s^2}{d^2} \tag{2.19}$$

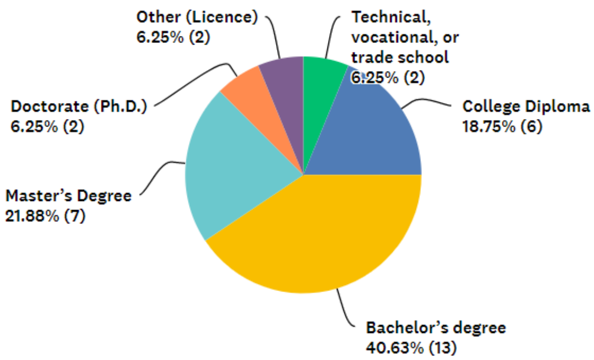
Where: n = sample size; t = corresponding value for selected significance; s = estimate of variance deviation for the scale used for data collection, which was calculated by dividing the inclusive range of the scale by the number of standard deviations that include almost all possible values in the range (Barlett et al. 2001); and d = number of points on the primary scale multiplied by the acceptable margin of error (Barlett et al. 2001).

The significance adopted in this research is 95% (therefore, t =1.96), and the margin of error is 0.05%. Because a Likert scale was used in the questionnaire to evaluate the risk factors, the values of (s) and (d) were determined according to the explanation given by (Barlett et al. 2001). The estimated variance (s) can be calculated by dividing the questionnaire scale (i.e., 7) by the standard variation (7), yielding a value of 1. Accordingly, the minimum sample size was calculated to be 32 participants, as follows:

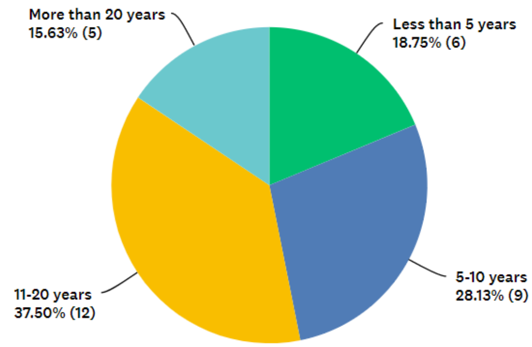
$$n = \frac{(1.96)^2 * (1)^2}{(7 * 0.05)^2} = 32$$

The authors secured 40 responses out of 150 invitations, resulting in a response rate of 26.6%. After reviewing the collected responses, eight were incomplete resulting in 32 complete responses—meeting the minimum required sample size. It is common in construction research studies to obtain a low response rate (20% – 30%), which is expected in this research area (Akintoye 2000). Many risk management research studies have reported similar or lower response rates, such as Hlaing et al. (Hlaing et al. 2008) reported 19.5%, Zhao et al. (Zhao et al. 2016) reported 11.2%, Wang et al. (Wang et al. 2004) reported 7.5%, Adams (Adams 2006) reported 18%, and Lindhard et al. (Lindhard et al. 2020) reported 19%. Low response rates in construction research have been was attributed to: the comprehensive nature of the research instrument (Hlaing et al. 2008; Wang et al. 2004); the busy schedules of project managers and engineers (Adams 2006; Lindhard et al. 2020; Zhao et al. 2016); confidentiality of information that companies were reluctant to disclose (Hlaing et al. 2008; Mu et al. 2014; Zhao et al. 2016). In this paper, the survey included 30 risk factors with five questions about each risk factor, which gives a total of 150 questions in addition to the pairwise comparison, making the survey too long for industry experts. Also, the authors believed that the current circumstances of anxiety and stress due to Covid-19 contributed to the low response rate. Also, studies that applied the same methodology (i.e. fuzzy AHP and fuzzy TOPSIS) have used lower numbers of experts such as: Ebrahimnejad et al. (Ebrahimnejad et al. 2009) used 15 experts; Fouladgar et al. (Fouladgar et al. 2012) and Taylan et al. (Taylan et al. 2014) used seven experts; Liu and Wei (Liu and Wei 2018) used four experts; KarimiAzari (KarimiAzari et al. 2011) and Makui et al. (Makui et al. 2010) used three experts.

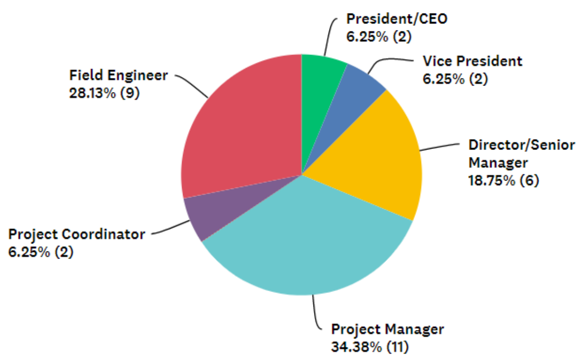
Morton et al. (2012) asserted that characteristics of study respondents should be detailed explicitly to allow full consideration of study validity. Therefore, the demographics of the respondents were collected and analyzed to show the configuration of the respondents. The education levels were shown in Figure 2.7 (a), with approximately 87 % of the respondents having a university degree. Years of experience is illustrated in Figure 2.7 (b), where approximately 81 % of the respondents have more than five years of experience in onshore wind projects. Figure 2.7 (c) shows the respondents' positions, where around 65 % of the respondents have senior managerial positions in onshore wind projects. The sizes of experts' projects were shown in Figure 2.7 (d), where more than 66% of the respondents worked in large and very large onshore wind projects. The locations of experts' involvement projects were shown in Figure 2.7 (e), where most projects were located in Alberta and Ontario. Lastly, the role of the respondents' organizations in constructing onshore wind projects were shown in Figure 2.7 (f), where the majority are either the primary contractor or specialty contractor, followed by consultants and owners. Visser et al. (Visser et al. 1996) concluded that a low response rate does not entail low accuracy of the findings. Therefore, following the above discussion, the authors believe that the findings from this study based on the collected data are reliable—particularly when considering that onshore wind projects are a relatively novel type of infrastructure (i.e. onshore wind projects) that is characterized by a lack of relevant literature and a scarcity of historical data, especially in the Canadian energy sector (Somi et al. 2020) (Mohamed et al. 2020b).



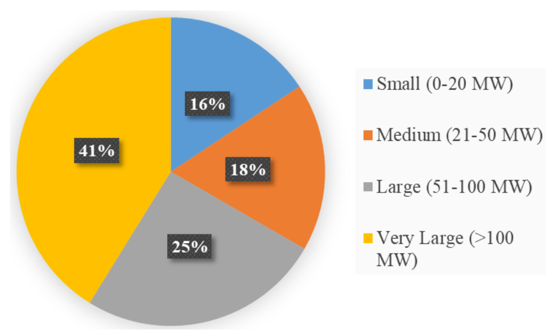
(a) Education level of respondents



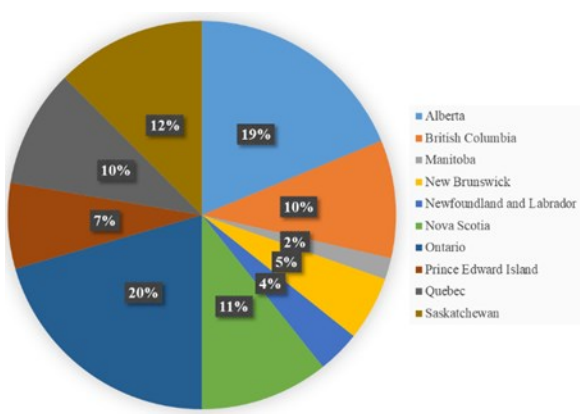
(b) Years of experience of respondents



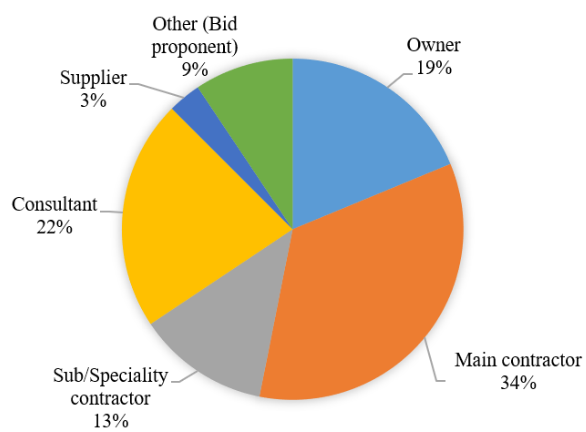
(c) Roles of respondents



(d) Sizes of projects in which respondents participated



(e) Locations of projects in which experts participated



(f) Role of expert's organization

Figure 2.7. Demographic information of respondents

2.4.2 Data Analysis

The collected responses were analyzed using the methodology discussed in Section 2.3.2. First, the weights of the criteria were calculated using the FAHP method. Here, a pairwise comparison matrix was constructed for the evaluation of each expert. Then, an aggregated matrix was obtained by calculating the geometric mean of all pairwise comparisons of experts' evaluation, as shown in Table 2.3.

Table 2.3: Fuzzy geometric mean matrix of pairwise comparisons

Criteria	Cost severity	Quality severity	Time severity	Safety severity
Cost severity	(1, 1, 1)	(1.35, 1.64, 2.32)	(1.46, 1.76, 2.49)	(0.16, 0.18, 0.22)
Quality severity	(0.43, 0.61, 0.74)	(1, 1, 1)	(1.32, 1.57, 2.11)	(0.22, 0.24, 0.32)
Time severity	(0.40, 0.57, 0.68)	(0.47, 0.64, 0.76)	(1, 1, 1)	(0.20, 0.22, 0.27)
Safety severity	(4.58, 5.71, 6.12)	(3.14, 4.24, 4.51)	(3.67, 4.58, 4.89)	(1, 1, 1)

The calculations for the extent value $\sum_{j=1}^{n} M_i^j$ of the cost severity are detailed as follows, with the extent value for each of remaining criteria calculated using the same approach:

$$\sum_{j=1}^{4} M_1^4 = 1 + 0.75 + 1.13 + 0.15 = 3.03$$

$$\sum_{j=1}^{4} M_2^4 = 1 + 0.87 + 1.37 + 0.16 = 3.40$$

$$\sum_{j=1}^{4} M_3^4 = 1 + 1.26 + 1.99 + 0.2 = 4.45$$

Then, the value of $\sum_{j=1}^{m}\sum_{j=1}^{n} M_i^j$ was calculated as follows:

$$\sum_{j=1}^{m}\sum_{j=1}^{n} M_i^j = (22.70, 27.30, 30.64)$$

And $\left[\sum_{j=1}^{m}\sum_{j=1}^{n} M_i^j\right]^{-1}$was calculated as follows:

$$\left[\sum_{j=1}^{m}\sum_{j=1}^{n} M_i^j\right]^{-1} = \left(\frac{1}{30.64}, \frac{1}{27.30}, \frac{1}{22.70}\right) = (0.032, 0.036, 0.044)$$

The final step was to calculate the value of fuzzy synthetic extent (S_i) with respect to *j*th criterion (*j* =1, 2, 3, 4) as follows:

$$S_{cost\ severity} = (3.03, 3.40, 4.45) \otimes (0.032, 0.036, 0.044) = (0.097, 0.122, 0.196)$$

$$S_{time\ severity} = (2.03, 2.38, 2.66) \otimes (0.032, 0.036, 0.044) = (0.065, 0.086, 0.117)$$

$$S_{quality\ severity} = (3.76, 4.45, 5.37) \otimes (0.032, 0.036, 0.044) = (0.12, 0.16, 0.236)$$

$$S_{safety\ severity} = (13.87, 17.03, 18.16) \otimes (0.032, 0.036, 0.044) = (0.44, 0.613, 0.8)$$

These synthesis extents are fuzzy weights of the evaluation criteria used in the fuzzy TOPSIS method to rank the risks. After developing the weights for criteria, the experts were asked to evaluate the cost impact, time impact, quality impact, safety impact, and probability of each risk factor using the scale presented in Figure 2.6. A sample of experts' replies was presented in Table 2.4.

Table 2.4**:** Linguistic evaluation of risk factors by experts according to evaluation criteria

Risk factor	Evaluation criteria	Expert 1	Expert 2	Expert 3	………..	Expert 32
Failure to keep up with recent innovative technology	Cost impact	MH	VL	MH	………..	H
	Time impact	ML	VL	MH	………..	ML
	Quality impact	H	N/A	MH	………..	ML
	Safety impact	M	N/A	H	………..	ML
	Probability of occurrence	M	VL	H	………..	ML
Failure to establish a proper grid connection of a wind project to the electricity network	Cost impact	H	VH	H	………..	VH
	Time impact	H	VH	M	………..	VH
	Quality impact	H	N/A	M	………..	VL
	Safety impact	N/A	N/A	ML	………..	VL
	Probability of occurrence	ML	VL	MH	………..	ML
………..	……………	……..	……..	………	……….	……….
Regulatory and policy risks: Change of laws and regulations	Cost impact	H	ML	VH	……….	ML
	Time impact	H	ML	VH	……….	ML
	Quality impact	H	N/A	M	……….	N/A
	Safety impact	ML	N/A	ML	……….	N/A
	Probability of occurrence	L	VL	MH	……….	VL

Note: VL= very low, L= low, ML= medium-low, M= medium, MH= medium-high, H= High, and VH= very high

Some experts did not evaluate some of the criteria of specific risk factors; therefore, they were not included when aggregating all of the experts' evaluations for that particular risk. Once the individual responses were collected, the severity of each risk was calculated as shown in Table 2.5 and then the aggregated decision matrix (D) was developed as follows:

$$
\mathrm{D} = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ \cdots \\ R_{29} \\ R_{30} \end{array}
\begin{array}{c}
\begin{array}{cccc} \textit{Cost severity} & \textit{Time severity} & \textit{Quality severity} & \textit{Safety severity} \end{array} \\
\begin{bmatrix}
(12.8, 29.3, 51.8) & (11.4, 26.4, 47.1) & (12.5, 27.7, 48.6) & (12.6, 26.6, 45.1) \\
(15.0, 30.3, 48.8) & (10.78, 24.5, 43.5) & (6.5, 16.4, 31.6) & (5.7, 12.8, 25) \\
(18.2, 35.8, 55.45) & (20.4, 38.3, 57.8) & (16.8, 32.7, 51.5) & (15.0, 29.9, 48.3) \\
\cdots & \cdots & \cdots & \cdots \\
(14.8, 28.5, 45.7) & (15.8, 29.3, 46.3) & (8.12, 14.2, 24.2) & (6.4, 10.5, 18.9) \\
(11.3, 22.5, 38.8) & (11.1, 21.9, 38.1) & (8.7, 16.1, 27.3) & (7.7, 13.9, 24.3)
\end{bmatrix}
\end{array}
$$

Table 2.5: calculated severity of each risk factor based on individual experts' evaluations

Risk factor	Risk severity	Expert 1	Expert 2	Expert 3	………..	Expert 32
Risk 1	Cost impact	(15, 35, 63)	(0, 0, 1)	(35, 63, 90)	………..	(21, 45, 70)
	Time impact	(3, 15, 35)	(0, 0, 1)	(35, 63, 90)	………..	(3, 15, 35)
	Quality impact	(21, 45, 70)	N/A	(35, 63, 90)	………..	(3, 15, 35)
	Safety severity	(9, 25, 49)	N/A	(49, 81, 100)	………..	(3, 15, 35)
Risk 2	Cost impact	(7, 27, 50)	(0, 0, 10)	(35, 63, 90)	………..	(9, 30, 50)
	Time impact	(7, 27, 50)	(0, 0, 10)	(15, 35, 63)	………..	(9, 30, 50)
	Quality impact	(7, 27, 50)	N/A	(15, 35, 63)	………..	(0, 0, 5)
	Safety severity	N/A	N/A	(5, 21, 45)	………..	(0, 0, 5)
………..	……………	……..	……..	………	……….	……….
Risk 30	Cost impact	(0, 9, 30)	(0, 0, 5)	(45, 70, 90)	……….	(0, 0, 5)
	Time impact	(0, 9, 30)	(0, 0, 5)	(45, 70, 90)	……….	(0, 0, 5)
	Quality impact	(0, 9, 30)	N/A	(15, 35, 63)	……….	N/A
	Safety severity	(0, 3, 15)	N/A	(5, 21, 45)	……….	N/A

Then, a normalized matrix $\widetilde{D}$ is obtained using equations (2.7) and (2.8).

$$\widetilde{D} = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ \cdots \\ R_{29} \\ R_{30} \end{array} \begin{array}{c} \begin{array}{cccc} \textit{Cost severity} & \textit{Time severity} & \textit{Quality severity} & \textit{Safety severity} \end{array} \\ \begin{bmatrix} (0.09, 0.17, 0.38) & (0.1, 0.18, 0.43) & (0.056, 0.099, 0.2) & (0.06, 0.108, 0.22) \\ (0.10, 0.16, 0.33) & (0.11, 0.2, 0.45) & (0.08, 0.16, 0.42) & (0.11, 0.22, 0.5) \\ (0.09, 0.14, 0.27) & (0.08, 0.12, 0.24) & (0.05, 0.08, 0.16) & (0.06, 0.09, 0.19) \\ \cdots & \cdots & \cdots & \cdots \\ (0.1, 0.17, 0.33) & (0.1, 0.16, 0.31) & (0.11, 0.19, 0.33) & (0.15, 0.27, 0.44) \\ (0.13, 0.22, 0.44) & (0.13, 0.09, 0.44) & (0.1, 0.17, 0.31) & (0.11, 0.2, 0.37) \end{bmatrix} \end{array}$$

Once the normalized matrix was developed, the weighted normalized matrix $\tilde{V}$ was obtained using the weights obtained from the fuzzy AHP method (i.e., S_1, S_2, S_3, and S_4) for the evaluation criteria by applying equations (2.9) and (2.10).

$$\tilde{V} = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ \cdots \\ R_{29} \\ R_{30} \end{array} \begin{array}{c} \begin{array}{cccc} \textit{Cost severity} & \textit{Time severity} & \textit{Quality severity} & \textit{Safety severity} \end{array} \\ \begin{bmatrix} (0.009, 0.021, 0.07) & (0.006, 0.016, 0.05) & (0.006, 0.016, 0.052) & (0.028, 0.067, 0.18) \\ (0.01, 0.02, 0.065) & (0.007, 0.017, 0.053) & (0.01, 0.027, 0.099) & (0.052, 0.14, 0.4) \\ (0.008, 0.017, 0.053) & (0.005, 0.011, 0.028) & (0.006, 0.013, 0.038) & (0.027, 0.06, 0.15) \\ \cdots & \cdots & \cdots & \cdots \\ (0.01, 0.021, 0.066) & (0.007, 0.014, 0.036) & (0.014, 0.031, 0.08) & (0.068, 0.17, 0.36) \\ (0.01, 0.027, 0.087) & (0.0085, 0.008, 0.052) & (0.012, 0.027, 0.074) & (0.053, 0.13, 0.29) \end{bmatrix} \end{array}$$

Then, the distances $d_{j=1}^{+}$ and $d_{j=1}^{-}$ from the fuzzy positive ideal solution and fuzzy negative ideal solution were computed using equations (2.13) and (2.14), respectively. A sample of the calculated Euclidean between each risk factor evaluation and the $\tilde{v}_j^{+}$ and $\tilde{v}_j^{-}$ was presented in Table 2.6 and Table 2.7 respectively.

Table 2.6**:** Distance between $\boldsymbol{R_i}$ evaluation and $\tilde{\boldsymbol{v}}_{\boldsymbol{j}}^{+}$ for each criterion

Risk severity	Cost severity	Time severity	Quality severity	Safety severity	$d_{j=1}^{+}$
R_1	0.964	0.975	0.975	0.909	3.824
R_2	0.968	0.974	0.954	0.815	3.712
R_3	0.973	0.984	0.980	0.921	3.86
……………	……………	……………	……………	……………	……………
……………	……………	……………	……………	……………	……………
R_{29}	0.967	0.980	0.958	0.809	3.715
R_{30}	0.958	0.977	0.962	0.845	3.743

Table 2.7**:** Distance between $\boldsymbol{R_i}$ evaluation and $\tilde{\boldsymbol{v}}_{\boldsymbol{j}}^{-}$ for each criterion

Risk severity	Cost severity	Time severity	Quality severity	Safety severity	$d_{j=1}^{-}$
R_1	0.046	0.0309	0.0317	0.1138	0.2225
R_2	0.0399	0.0327	0.0597	0.2473	0.3798
R_3	0.0330	0.0178	0.0239	0.0961	0.1710
……………	……………	……………	……………	……………	……………
……………	……………	……………	……………	……………	……………
R_{29}	0.0407	0.0230	0.0504	0.2333	0.3475
R_{30}	0.0531	0.0307	0.0463	0.0190	0.3203

Then, the closeness coefficient was calculated according to Equation (2.18) for each risk factor, as presented in Table 2.8. A complete ranking of the risk factors was presented in Figure 2.8.

Table 2.8**:** Calculation of CC and ranking of risk factors

	d^{-}	d^{+}	$d^{-} + d^{+}$	CC	Rank
R_1	0.2225	3.9327	4.04723	0.94501	5
R_2	0.3798	3.8727	4.09280	0.90719	20
R_3	0.1710	3.9371	4.03151	0.95757	4
……………	……………	……………	……………	……………	……………
……………	……………	……………	……………	……………	……………
R_{29}	0.3475	3.715	4.06312	0.91446	19
R_{30}	0.3203	3.743	4.06403	0.92116	16

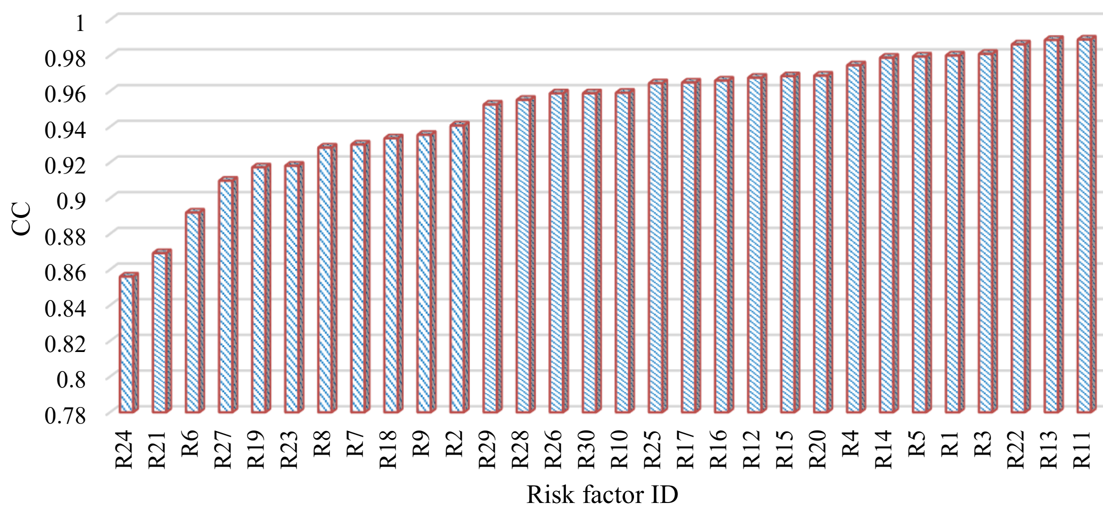


Figure 2.8: Ranking of risk factors affecting wind farm projects

2.5 Results and Discussion

This study employed a hybrid methodology of fuzzy AHP and fuzzy TOPSIS for onshore wind project risk assessment. Fuzzy AHP method was used to evaluate the weights for the evaluation criteria. The fuzzy synthetic extents for the criteria weights were then determined by Equations (2.2) to (2.5). Risk factors evaluation and ranking is a multi-criteria decision-making problem. Each risk has to be evaluated according to four criteria (i.e., cost severity, time severity, quality severity, safety severity). Therefore, the fuzzy TOPSIS method is employed to assess and rank the risk factors based on subjective evaluations of a group of experts in onshore wind construction. Expert evaluations were collected using an online questionnaire tool and were analyzed using a fuzzy AHP and fuzzy TOPSIS methodology. The final output of the method is a prioritized list of critical risk factors affecting onshore wind farm projects, as presented in Figure 2.8. It was concluded that the top 10 critical risk factors were (1) Lack of management expertise, (2) Shortage of resources required for project delivery, (3) Adverse weather, (4) Material damage during construction, (5) Failure to keep up with recent innovative technology, (6) Project cost overrun, (7) Relationship unreliability and complexity between project participants, (8) Lack of financing, (9 Unpredictable natural hazards, and (10) Poor cooperation to share technical expertise.

Table 2.9 details the top 10 risk factors. It was concluded that almost all risk factors were internal risk factors directly related to the project characteristics. Exceptions included adverse weather and natural hazard risks, which were external risk factors. Interestingly, the CC value and percentage of deviation from the most severe risk factor (i.e. lack of management expertise) for the top 10 critical risk factors were comparable to each other (Figure 2.8 and Table 2.9), indicating that the criticality of those risks was close, and they all should be addressed adequately.

Managerial risks refer to the availability of knowledge and experience to successfully develop and construct a renewable energy project (Noothout et al. 2016). Lack of management experience is a common risk factor in most construction projects; however, the specialized nature and technology used in constructing wind farm projects make the management of such projects a challenge. Lack of technical and managerial experience with renewable energy projects results in high technical and managerial risks (Angelopoulos et al. 2016). Therefore, selecting an experienced team, reviewing lessons learned, and providing training for personnel in onshore wind farm projects will help mitigate such risk (Gatzert and Kosub 2016b).

Table 2.9: Top 10 risk factors affecting wind farm projects

Risk ID	Description	Category	CC	Deviation (%)	Rank
R_{11}	Lack of management expertise	Internal - Management	0.9710	0	1
R_{13}	Shortage of resources required for project delivery	Internal - Management	0.9642	0.68	2
R_{22}	Adverse weather	External - Environmental	0.9635	0.75	3
R_3	Material damage during construction	Internal - Technical	0.9575	1.35	4
R_1	Failure to keep up with recent innovative technology	Internal - Technical	0.9450	2.6	5
R_5	Project cost overrun	Internal - Financial	0.9431	2.79	6
R_{14}	Relationship unreliability and complexity between project participants	Internal - Management	0.9424	2.86	7
R_4	Lack of financing	Internal - Financial	0.9419	2.91	8
R_{20}	Unpredictable natural hazards	External - Environmental	0.9406	3.04	9
R_{15}	Poor cooperation to share technical expertise	Internal - Management	0.9381	3.29	10

Shortage in required resources for executing the project may lead to bottlenecks in construction, leading to delays in the implementation of wind farm projects (Prpich et al. 2014a). An increase in the investment and number of projects across the country can lead to a shortage of skilled staff and equipment needed to implement onshore wind farm projects (Prpich et al. 2014a). Accordingly, the Canadian energy sector must ensure that sufficient resources exist to support the expected increase in the number of onshore wind energy projects.

Adverse weather during construction has always been a concern for contractors of wind farm projects due to the location bias of these projects to high wind speed. Consistent and moderate to moderate-high wind speed is favourable for the operation phase of the project; however, it represents a challenge for the construction phase when segments of the turbines must be lifted with specialized cranes. To reduce the harmful effects of the weather on construction activities, Gatzert and Kosub (Gatzert and Kosub 2016b) suggested the following mitigations: effective project management and careful contracting; development of contingency and recovery plans for relevant "what if" scenarios; lastly, weather monitoring before construction is vital to evaluate the best timing for construction.

Onshore wind farm projects are a capital-intensive type of renewable projects; therefore, damage to assets can significantly impact project costs (Turner et al. 2013) (Gatzert and Kosub 2016b). In addition to the cost, safety issues during the construction of wind farm projects that may occur during the lifting of tower segments were highlighted as a consequence of damage during construction (Aneziris et al. 2016). Therefore, proper planning for the transportation of materials, storage, and installation should be effectively-prepared. Adhering to best practices during the construction and installation of wind towers and turbines allows for the mitigation of potential consequences. Also, a contractor can seek insurance coverage for accidental damage (Gatzert and Kosub 2016b).

Failure to keep up with recent innovative technologies in construction methods and wind turbines themselves is a critical factor. Obsolete technology implies lower efficiency than newer and more efficient ones (Gatzert and Kosub 2016b). Contractors and developers must review and consider the impact of emerging innovative technology, such as self-rising-towers, which does not require large cranes for lifting segments. New materials for towers and support structures should be reviewed (Watson et al. 2019).

Cost overrun presents a challenging risk parameter for onshore wind farm projects

(Enevoldsen 2016). Sovacool et al. (Sovacool et al. 2017) investigated 35 wind farms to test the potential cost overrun pattern for wind farm projects. They concluded that a mean cost overrun of 0.8% exists for the studied projects. Sovacool et al. (Sovacool et al. 2017) discovered no relationship between the installed capacity of a wind project (MW) and the percentage of cost overruns. However, other factors that contribute to the cost overrun of wind farm projects that are not well-addressed must be investigated through research studies together with the subsequent development of improved control strategies.

Different stakeholders have different levels and types of investments and interests in the projects they are involved in. Therefore, managing multiple stakeholders and maintaining an acceptable balance between their interests is crucial to successful project delivery (Yang and Shen 2015). The complexity of the relationship with a negative attitude between project stakeholders can severely obstruct its implementation (Jha and Iyer 2006) (Yang and Shen 2015). Thus, to avoid such complexities and deliver projects successfully, stakeholder management should be carried out in construction projects (Yang and Shen 2015). An effective stakeholder management process depends on understanding the critical success factors for stakeholder management in construction projects early at the project start. This will enable the project team to successfully carry out stakeholder management and achieve project success (Molwus et al. 2017).

Onshore wind farm projects are similar to other energy infrastructures requiring substantial development costs (Prpich et al. 2014a). The construction phase accounts for the most significant cost accumulation in developing a wind farm due to the high costs of the turbine, foundation, and transmission assets. Private companies, banks, and investors represent the primary source of finance for these types of projects (Prpich et al. 2014a). Developing an innovative and creative finance structure will promote growth in onshore wind farm projects. Governments can help reduce the financing risk through their involvement in the financial market (e.g. through government or public/private investment funds and loan guarantees) (Noothout et al. 2016).

Natural hazards, such as earthquakes, flooding, and landslides, can cause widespread damage during the execution of the project (Gatzert and Kosub 2016b) (Kucukali 2016). The probability and impact of the natural hazards vary based on the characteristics of the project location; therefore, a detailed analysis of the project study area can help determine the severity of such risks. While natural hazards can affect the construction phase, these can also extend to the operation phase of the project.

Sharing knowledge and information is a crucial element to project success (Fong 2005) (McDermott et al. 2004). A collaborative environment is required to facilitate high levels of information sharing (Bond-Barnard et al. 2018). Social capital can be achieved in construction projects by promoting collaborative practices to encourage sharing common knowledge between team members performing nonroutine tasks (Dietrich et al. 2010). Trust between team members must exist so that information can flow between members, allowing knowledge exchange to occur (Bond-Barnard et al. 2018). Sharing knowledge between project teams enhances project work and organizational learning and enables tasks to be performed faster (Jafari Navimipour and Charband 2016).

2.6 Conclusions

Risk and uncertainty hinder the investment and development of onshore wind farm projects. The construction phase was recognized as the riskiest phase of the project life cycle. Therefore, to identify the critical risk factors affecting the construction of onshore wind farm projects, this study applied fuzzy AHP and fuzzy TOPSIS to analyze experts' evaluations. Experts from the Canadian energy sector who worked in various locations across Canada with different roles and years of experience were interviewed to evaluate the risk factors. The proposed assessment model utilizes a MCDM framework that enables risk assessment based on various criteria, including cost severity, time severity, quality severity, and safety severity, which allows the capturing of all aspects of risks inherent in onshore wind energy projects. Results of this study provided a ranking for 30 risk factors, which were identified through an extensive literature review. The top 10 critical risk factors were: lack of management experience, shortage of resources, adverse weather, material damage during construction, failure to keep up with recent innovative technology, project cost overrun, relationship unreliability and complexity between project participants, lack of financing, unpredictable natural hazards, and poor cooperation to share technical expertise. Eight of the top 10 risks were internal risk factors related to technical, financial, and management aspects. The other two risk factors were related to external environmental aspects. Future work will include developing models to quantitatively address the effects of the critical risks on project objectives. Also, critical risks of other phases of onshore wind farm projects will be investigated in future research.

2.7 Acknowledgment

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Chapter 3 : Context-Driven Ontology-Based Risk Identification for On-shore Wind Farm Projects

3.1 Introduction

By 2050, approximately 35% of worldwide electricity demands are anticipated to be supplied by onshore and offshore wind farms (IRENA 2019). Expanding the capacity of wind energy to meet this demand will require the construction of turbines and grid systems. An important step in the pre-construction stage of wind farm projects is risk management. The construction phase of wind projects can be hindered by various types of risks (Somi et al. 2020), which must be appropriately managed to ensure project objectives are completed on time, within budget, and in adherence to environmental and safety regulations (Gatzert and Kosub 2016a; Somi et al. 2020). The first step of the risk management process is risk identification. Here, various aspects of a project, including financial, environmental, social, regulatory, and/or political considerations (De Zoysa and Russell 2003), are reviewed to identify factors that may result in schedule delays, cost overruns, or other safety or environmental concerns. Risk analysts often review similar historical projects and risk registers curated for a particular type of project to identify potential risks for a new project. Usually, knowledge of construction risk factors is obtained from different and detached sources (e.g., expert experience, historical project information, construction plans, and other project-related documentation).

As a relatively new type of construction, available historical data and reference materials for wind farm projects are either scarce or of low quality (Somi et al. 2020). As such, existing risk registers for onshore wind farm construction are board, encompassing risks that may not be applicable to all projects while omitting contextual or project-specific risks. Current risk identification methods, therefore, lack the capacity to map specific project characteristics to identified risk factors. This limitation prevents the contextualization of historical data, requiring risk analysts to manually evaluate the similarity between previous and current projects. This is a time-intensive process that involves the review of data across multiple, fragmented databases and the tedious mapping of risk factors to the specific characteristics of a new project (Somi et al. 2020).

Traditional risk identification in construction is often performed using time-consuming manual approaches that are prone-to-error because of its dependence on expert recall. In attempt to address this limitation, several advanced risk identification techniques have been proposed in literature. However, existing techniques (e.g., case-based reasoning) are limited by their inability to consider specific project details and contexts or, if capable of considering project specifics, are limited by the need to create lengthy lists of mapping rules for each new project (e.g., knowledge-based models).

Although models (e.g., case-based reasoning and knowledge-based) for automating the mapping of risk factors with project characteristics have been developed, they focus on mapping risks at a high-level and cannot consider the specific, contextual characteristics of individual projects. This is particularly important in wind farm construction, as the specific regulatory, environmental, social, and geographical context of a project can substantially impact the types and severity of risks on project outcomes. For example, a risk factor of damage to existing infrastructure that was identified in previous risk register of an onshore wind project may not apply to another onshore wind project until the context of that project is defined and information about existing infrastructure is determined. Recently, risk ontologies were shown to rapidly map safety risks to specific projects in construction. Although promising, these studies were limited to specific risk factors (e.g., safety risks) and, therefore, cannot be used to compile a comprehensive list of all risk factors (e.g., financial, environmental, etc.) present during the construction phase of wind farm projects.

Building upon the current-state-of-the-art, this study has developed a unified, ontology-based model to automate the context-driven identification of risk factors in onshore wind farm construction. A generic risk ontology model, which functions as a knowledge base for the storage, reuse, sharing, and recall of risk information, was built from historical project data and was validated by a group of subject matter experts. Once validated and verified, the model was used to develop a context-driven risk identification ontology. This study contributes to the body of knowledge by (1) extending the application of ontology to the identification of risk factors associated with the construction of onshore wind projects, (2) enhancing risk knowledge management by improving the storage, reuse, and recall of risk-related knowledge, and (3) reducing the time and effort required to map risks to specific project contexts by automating the risk identification process.

3.2 Literature Review

3.2.1 Risk Identification in Onshore Wind Farm Projects

A risk factor is defined by the Project Management Institute (PMI) (PMBOK® Guide

2008) as “an uncertain event or condition that, if it occurs, has a positive or negative effect on a project’s objectives”. Risk identification is the process of systematically and continuously identifying, categorizing, and assessing the initial significance of risk factors associated with a construction project (Al-Bahar and Crandall 1990). Risk identification is considered the most important step in the risk management process (Chapman 1998; Rostami 2016), as unidentified risk factors cannot be controlled or mitigated (Chapman 2001; Siraj and Robinson Fayek 2019) and, therefore, impose unassessed threats to project objectives (Chapman 2001).

Numerous research studies have focused on identifying the risk factors affecting the entire lifecycle of a wind farm project, including design, construction, operation, maintenance, and/or decommissioning. Many of these studies have relied on published literature and/or questionnaire surveys. For example, Gatzert and Kosub (Gatzert and Kosub 2016a) presented the risk factors affecting onshore and offshore wind farm projects in Europe, including risk factors at different phases of the project lifecycle and risk mitigation strategies for the proposed risks. In a similar study, Angelopoulos and colleagues (Angelopoulos et al. 2016) investigated the risk factors affecting the planning, construction, and operation of onshore wind energy projects in Europe. Another study identified and presented the risks and challenges that face the design, planning, construction, and control of small wind turbine projects in Italy with respect to time, cost, and quality (Fera et al. 2014). Other studies have reviewed the risk factors affecting the entire lifecycle of onshore wind farm projects in Northern Europe (Enevoldsen 2016), risk factors in implementing wind energy projects along with proposed mitigation strategies for those risks (Rolik 2017b), and risks facing solar and wind energy projects along with the available risk mitigation strategies that can contribute to the sector's growth and long-term sustainability (Turner et al. 2013).

Much of the risk identification literature in onshore wind farm construction has focused on the identification of risks, as opposed to the development of advanced methods for identifying risks. As such, these studies have not addressed the challenges associated with the management and representation of knowledge for risk identification. The importance of project context and knowledge representation in risk identification is detailed in the following section.

3.2.2 Project Context and Knowledge Representation

Context is defined by Dey (Dey 2001) as "any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves". With respect to risk identification problem, entities are risk factors, and the information used to identify the risk factors is the project context. From a construction perspective, Boukamp and Ergen (2008) defined context as specific project conditions on site (such as the project components that are built), activities performed, and resources used. Dey (2001) further outlined three important features of context-aware modelling techniques, specifically (1) the system has the ability to present information and services to the user; (2) the system can automatically execute services for a user; and (3) the system can link context and information together to enable reasoning and retrieval.

Consideration of project context can be achieved through knowledge representation, which is the process of recording and coding real-word domain knowledge using communicative media to allow reasoning (Levesque 1986; Stephan et al. 2007). The five main categories of representation techniques include object-, network-, frame-, logic-, and semantic web-oriented (Kapauan and Fernandez 2002) representation. Object-oriented representation allows information to be organized as objects that communicate with each other (Kapauan and Fernandez 2002). Each object is defined by private properties (i.e., attributes) and methods (i.e., procedures) (Kapauan and Fernandez 2002). Objects can only communicate with each other through messages (Kapauan and Fernandez 2002). Network-oriented representation allows knowledge to be represented visually through a network of interconnected nodes, each representing different entities that have various relationships (Kapauan and Fernandez 2002). Frame-oriented representation, which is often used in natural language processing, allows all information relevant to an entity to be arranged together in one structure associated with that entity (Kapauan and Fernandez 2002). Logic-oriented representation makes use of rules that deal with propositions, where a conclusion can be drawn based on different conditions. Lastly, semantic web was developed to represent generic knowledge, such as concepts, their relationships, and how they are semantically associated (Stephan et al. 2007).

Risk management is often complicated in construction by the fragmented nature of construction data, where various data are stored in isolated data islands. As such, risk management in construction requires a systematic model for risk management that allows the consideration of complex risk sources and their causation mechanisms (Cao et al. 2020). A change in project context can significantly influence the risk factors of a project (Leung et al. 1998). Incorporating project context with risk factors allows risk analysts to identify contextoriented risk factors, instead of relying on a generic list that may not apply to the current situation (De Zoysa et al. 2005; De Zoysa and Russell 2003). Considering context descriptors is beneficial for accurate recognition and for determining potential relationships between risk factors and their sources (Cao et al. 2020). Ignoring project context information increases the burden on analysts due to the effort required to select the risk factors that are more relevant to the current project (De Zoysa et al. 2005; De Zoysa and Russell 2003). Furthermore, the use of knowledge acquired from previously-executed projects is often limited without an explanation by the practitioners involved in these projects regarding the context and relationships between data (Scherer and Reul 2000).

Recent work by Kifokeris and Xendis (2019) suggested that risk factors and sources should be contextually and methodologically integrated with other technical project information. Context modelling approaches were classified by Wang and colleagues (Wang et al. 2004) into formal and informal modelling. Formal context modelling adopts formal approaches for manipulating contexts to enable reasoning about contextual knowledge. Conversely, informal context modelling is often based on proprietary representation schemes that do not permit reasoning about contexts in a single system (Wang et al. 2011) or share understanding about context easily between different systems (Wang et al. 2004). Although a majority of context models employ classification systems to structure contextual information, only a few allow association relationships between contextual information without considering the semantic relationships (Wang et al. 2011). Existing methods for identifying risks in construction are detailed as follows.

3.2.3 Risk Identification Techniques in Construction

Risk identification techniques can be classified as either traditional methods or advanced methods. Generally, traditional methods implement the risk identification process manually without any support from information and communications technology (ICT) techniques (Zhang and Zhong 2014), while advanced techniques tend to automate the risk identification process using some form of ICT techniques (Ding et al. 2012). Brief descriptions of both traditional and advanced methods, as well as promising developments in each category, are provided.

3.2.3.1 Traditional Techniques

Manual documentation review, where risk factors are identified through a review of documents from the current or similar projects, is one of the most common traditional risk identification approaches (Rostami 2016; Siraj and Robinson Fayek 2019). Time consuming and laborious, documentation review relies heavily on the quality of the documentation and expert judgment for identifying risk factors and on the ability of experts to discover relationships between knowledge that exists in the same or different documents.

Other common traditional techniques rely solely on expert judgment for risk identification (Siraj and Robinson Fayek 2019). In the Delphi technique, a group of experts are asked individually about the relevance of each potential risk factor to the project; then, their opinions are aggregated and recirculated among the participants until a consensus is reached (Barati and Mohammadi 2008; Garrido et al. 2011). The brainstorming technique can also be applied. This technique begins with the presentation of the overall objectives, followed by a free and open dialogue to encourage the identification of risk factors (Garrido et al. 2011; Goh et al.

2013; Tavakolan and Mohammadi 2018). Another common technique is one-to-one interviews. Here, interactive dialogue is used to elicit risk factors directly from interviewees (Chapman 2001), where experts are interviewed directly about the risk factors in a project. Although the Delphi technique, brainstorming, and interviews do not rely on project documents for risk identification, these techniques depend on expert recollection of previous experiences and comparing them to the project under study. Depending on expert recall can result in certain risk factors being unintentionally omitted. Notably, Goh et al. (Goh et al. 2013) have recommended the implementation of a database interface between project team members to streamline communications during brainstorming sessions.

Using checklists developed from previous projects (AbouRizk 2009) or lessons learned (Barati and Mohammadi 2008) as a memory aid is another traditional technique for risk identification. Often used as a starting point in the risk identification process (Rostami 2016), checklists alone cannot link risk factors to specific project contexts. Risk registers, which use recorded data from previous projects—including information about the risk factors, response strategies, required resources, risk impact, and risk allocation (De Zoysa and Russell 2003; Willams 1994)—to identify risk factors in new project (Siraj and Robinson Fayek 2019), may also be used for risk identification. Although risk registers provide more information compared to other traditional techniques, risk registers, much like checklists, lack the capacity to automatically map risk data to each other. Lastly, diagramming or graphical techniques, including cause-and-effect diagrams, system or process flow charts, and influence diagrams, have been used to identify risks in construction projects (Rostami 2016; Siraj and Robinson

Fayek 2019). These techniques are used relatively infrequently in construction (Garrido et al. 2011; Siraj and Robinson Fayek 2019), and similarly to other traditional identification techniques, the accuracy of diagramming techniques relies on the recall accuracy of experts.

Traditional risk identification techniques are limited by several barriers, including (1) requiring experts to review a significant volume of project documents, (2) inability to automatically discover and map relations between risk knowledge that exists in the same or in different documents, and (3) dependency of output quality on the recall accuracy of experts.

3.2.3.2 Advanced Techniques

A number of a studies have attempted to address the limitations of traditional risk identification techniques through the development of advanced risk identification methods. De Zoysa and Russel (2003) suggested the use of project context to identify the risk factors of a construction project using a knowledge-based system (De Zoysa 2006; De Zoysa et al. 2005; De Zoysa and Russell 2003). Their risk identification framework consists of three primary components: a standard library (standard templates), current project context, and rule sets. The standard library allows the user to define the project context for sources of risk factors, including financial, social, environmental, political, and regulatory aspects. The current project context allows the user to define the attributes and parameters of the current project. The rule sets allow communication between the current project context and the standard library.

Although able to consider the specific context of a particular project, the rule sets that link the current project to the standard library must be defined manually for each new project. Requiring considerable time and effort, existing knowledge-based approaches do not represent a considerable improvement in terms of laboriousness and time.

Other researchers have suggested the use of case-based reasoning for risk identification. For example, Somi et al. (Somi et al. 2020, 2021) proposed a fuzzy case-based reasoning model to support risk identification in onshore wind projects. However, the first study (Somi et al. 2020) focused only on s specific component of the project (i.e., tower assembly). Moreover, both studies (Somi et al. 2020, 2021) lack the ability to represent risk knowledge and project context information. Zou et al. (Zou et al. 2017) proposed case-based reasoning and natural language processing to retrieve similar cases from previous projects. Although able to more rapidly identify project risks, these methods are unable to consider the detailed context of project during the identification process.

Recently, evidence demonstrating the potential of ontology-based approaches to address these gaps has been reported, with several studies demonstrating promising results in other application areas. For example, Xing et al. (Xing et al. 2019) developed an ontology model to identify risks in a metro construction project. Aziz et al. (Aziz et al. 2019) proposed an ontology model to represent the knowledge of safety hazards during petrochemical operations. Cao et al. (Cao et al. 2020) presented an ontology model to support the identification of accidents during railway operations. (Osorio-Gómez et al. 2019) proposed an ontology approach for risk identification of operational risk management in a supply chain with third party logistics providers. Although promising, these studies were limited to a specific set of risk factors in other application areas. The ability of these existing approaches to identify and assess a comprehensive set of all risk factors present during construction, therefore, remains considerably limited.

Although still in its infancy, the development of more generalized ontology-based risk assessment approaches has been described in a few studies. A description of ontological modelling in construction and for risk identification is detailed as follows.

3.2.4 Ontological Modelling in Construction

A fundamental key to proper and successful risk management is the ability to share information between different technical and management teams in a project (Aziz et al. 2019)—a process requiring a unified language, terminology, and information (Aziz et al. 2019). Ontology, as a means for information storage and transfer, is a widely-used approach for knowledge representation and modeling, especially when knowledge is highly interconnected and linked (Munir and Sheraz Anjum 2018). Key objectives that can be achieved by the development of ontologies have been described by Noy and McGuinness (2001). These include (1) to share a common understanding of the structure of information between people or software agents, (2) to enable the reuse of domain knowledge, and (3) to analyze domain knowledge.

Ontology represents domain knowledge as a set of concepts along with the connections (i.e., relationships) between them (El-Diraby et al. 2005; El-Diraby 2013). Compared to traditional database schema (Xing et al. 2019), ontologies enable the presentation of knowledge with explicit and rich semantics. As such, ontology goes beyond the listing of all concepts within specific domain; rather, it represent an abstract philosophical conceptualization of the essence of knowledge in a domain (El-Diraby 2013). Ontology development typically begins as meta-ontology, which describes the main components of knowledge to be considered (Aguilar et al. 2018). Then, a taxonomy is used to organize sub-concepts contained within each of the main components (Niu and Issa 2015). A taxonomy allows for the organization of concepts into concept schemes through a hierarchy of classes and subclasses (Niu and Issa 2015). A class is a collection of instances that can encompass sub-classes within its taxonomy. Relationships are used to describe the connections amongst the classes and sub-classes of the ontology. The various features and attributes of the classes and sub-classes are defined by properties. Instances are the basic component of an ontology, which fill the defined properties of the classes and subclasses (2001). Ontology-based approaches have two advantages over traditional knowledge representation techniques, specifically (1) they are able to model context variables and semantic relationships in one unified framework and (2) they can be used for reasoning purposes to infer the characteristics of a system with new conditions.

Ontology has been widely applied in construction management to model the domain knowledge of construction concepts. Leading research in this area was originated by El-Diraby et al. (2005), who proposed a domain taxonomy of construction knowledge that provided a foundation for the development of domain ontologies of urban civil infrastructure (El-Diraby and Osman 2011), highway infrastructure (El-Diraby and Kashif 2005), and generic construction domain knowledge (El-Diraby 2013). Existing ontology-based approaches to model risk knowledge in construction are limited by one of two barriers. The first set of studies have limited their scope to a specific set of risks. A comprehensive set of project risks, therefore, can not be identified using these methods. Examples include the use of ontologies to identify safety hazards related to specific construction methods, such as metro construction (Xing et al. 2019; Zhong and Li 2015) or to model the safety requirements and standards for active fall safety hazards (Guo and Goh 2017). Similarly, other researchers have attempted to link building information modeling (BIM) to ontology for identifying safety hazards in construction projects (Ding et al. 2016; Zhang et al. 2015). However, these studies primarily focused on modelling knowledge of safety hazards related to a specific construction method at the activity level. Although an ontology-based approach was used in the aforementioned studies, risk knowledge at the project level was not modeled. Moreover, studies focused on safety risk factors, while overlooking cost, time, quality, and environmental risk factors.

The second set of studies have focused on improving knowledge management and transfer between different phases of the risk management process at the project level. For example, Tserng and colleagues (Tserng et al. 2009) proposed an ontology-based risk management (ORM) model for representing risk factors' knowledge to enhance information flow in both the identification and assessment phase of the risk management process. Importantly, however, their model did not consider the specific context of a project, limiting the ability of their model to support context-driven risk identification in practice. Meditskos and colleagues (Meditskos et al. 2012) and Angelides and colleagues (Angelides et al. 2012) proposed an ontology model to facilitate the integration of risk assessment practices from various domains and to provide unified terminologies for managing risks in industrial projects. Similarly to the study of Tserng and colleagues, the coverage and comprehensiveness of Meditskos and colleague's model were limited: only a high-level ontology model, with few details regarding the taxonomies in each sub-ontology, was presented. Therefore, existing models are limited due to their inability to consider the semantics of the contextual information required for proper identification of risk factors. Nevertheless, these previous models laid the foundation for the current study by suggesting that ontology-based modelling may represent a potential approach capable of addressing the challenges related to context and semantic modelling in risk identification (Wang et al. 2011).

Although no single ontology can fully cover all domains, nor can a single ontology satisfy the needs and preferences of all users (El-Diraby and Kashif 2005; El-Gohary and El-Diraby 2010), generic ontologies for application to a certain project type can be designed. An ontology for improving knowledge management during risk identification in onshore wind projects, however, has yet to be developed.

3.2.5 Research Gaps

Several limitations of advanced risk identification techniques that must be addressed to progress the state-of-the-art have been recognized in the literature:

1. While existing knowledge-based models (De Zoysa 2006; De Zoysa et al. 2005; De Zoysa and Russell 2003) are capable of integrating risk factors with specific project contexts, the modelling approaches proposed require practitioners to expend a considerable amount of time and effort to develop the rules that map risk factors to their context.
2. Although less laborious, existing case-based reasoning models (Somi et al. 2020, 2021; Zou et al. 2017) lack the capacity to consider detailed project contexts and, when mapping to corresponding risk factors, prevent automated reasoning and identification of related risk factors.
3. Existing ontology models developed to support risk identification in construction focus on only:
   a. a specific set of risk factors (Angelides et al. 2012; Aziz et al. 2019; Cao et al.

2020; Meditskos et al. 2012; Osorio-Gómez et al. 2019; Tserng et al. 2009; Xing et al. 2019) or

b. risks at the activity-level (Ding et al. 2016; Zhang et al. 2015).

4. Ontologies designed to support risk identification in onshore wind projects have not yet been developed.

3.3 Proposed Framework

To address the aforementioned gaps, this study has developed a generic risk ontology for onshore wind farm projects that is capable of identifying a context-driven list of project risks during the execution phase of construction projects. The risk ontology was then incorporated into a framework designed to enable the rapid, automatic identification of various risks in consideration of detailed project contexts. The proposed framework consists of three steps, (1) ontology population, (2) current project data collection and input, and (3) risk factor identification, as shown in Figure 3.1. The methodology used to develop the ontology as well as a description of the proposed framework are detailed in Sections 3.1 and 3.2, respectively.

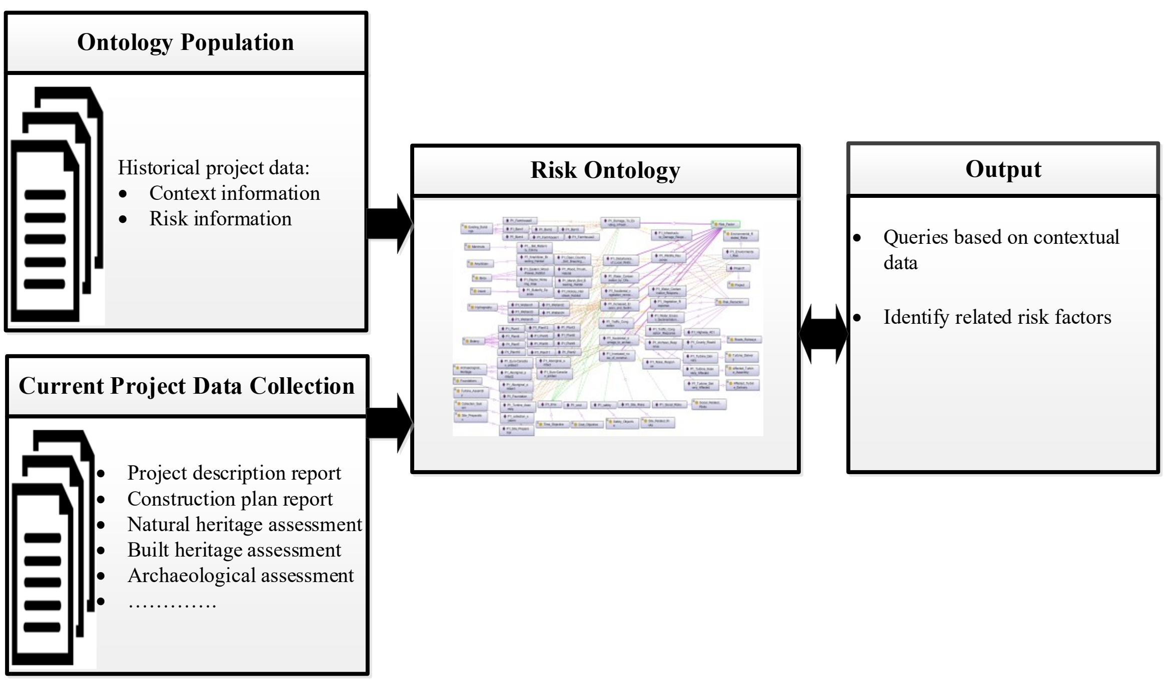

Figure 3.1. Proposed ontology-based framework for risk identification.

3.3.1 Ontology Development

First, the generic risk ontology that is incorporated into the framework was developed using the method proposed by Noy and McGuinness (2001). The methodology consisted of a conceptual formulation stage and an implementation stage. The conceptual formulation stage included six steps. The first was a knowledge extraction step, where (1) the domain and scope of the ontology was determined. This was followed by ontological preparation steps, where (2) important terms were enumerated and (3) classes and class hierarchy, (4) relationships between classes, (5) properties of classes, and (6) instances within classes were defined. Conversely, the implementation stage consisted of two steps, specifically ontology (7) implementation and (8) evaluation. An overview of the methodology used to develop the ontology is presented in Figure 3.2.

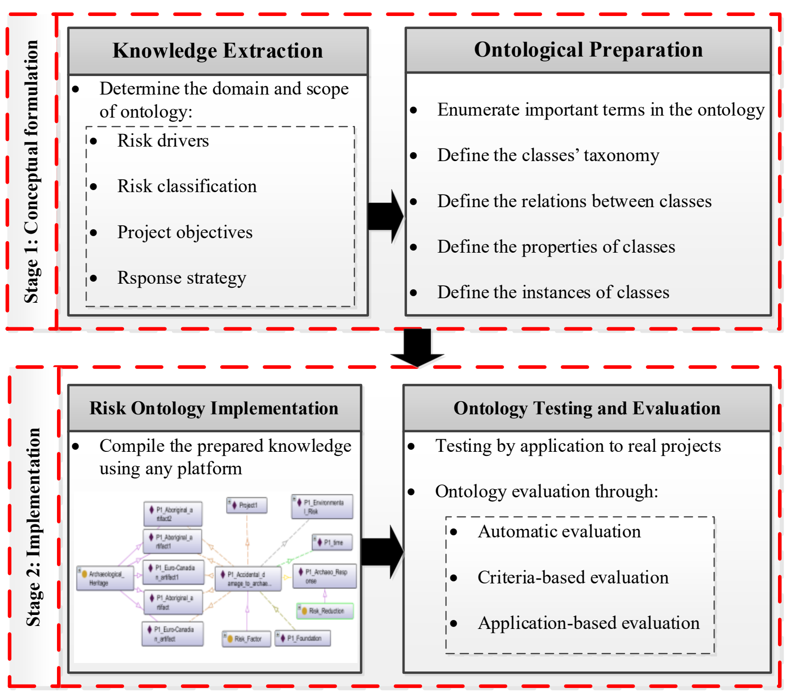

Figure 3.2. Ontology development methodology.

3.3.1.1 Knowledge Extraction

In the knowledge extraction step, competency questions that focus on determining the purpose, scope, level of formality, intended uses, and end-users of the risk ontology were established based on those recommended in literature (El-Diraby and Kashif 2005; El-Diraby and Osman 2011). Questions in this study included “What is (are) the purpose(s) of the ontology?”, “What parts of the risk management process should be covered by the ontology?”, “What information should be captured in the ontology?”, and “Who are the end-users of the ontology?”.

It was determined by the authors that the ontology should focus on the identification stage of the risk management process to support project planners, project managers, and decision makers who are involved in the risk identification of onshore wind projects. As such, information related the drivers or sources of the risk factor, the response strategy developed to mitigate the impacts of risk factors if they occurred, and their effect on the project and objectives of the project were included as classes of this particular ontology.

Once the scope was defined, a meta-model of the ontology was developed to support knowledge extraction and modelling. The meta-model was developed based on a review of previous research related to knowledge-based risk identification (De Zoysa and Russell 2003; Leung et al. 1998; Meditskos et al. 2012; Osorio-Gómez et al. 2019). Common classes found across multiple studies, or classes used in previous studies that were well-suited to onshore wind farm construction were identified, as summarized in Table 3.1. Based on these findings, seven key classes, (1) risk factors, (2) project, (3) risk drivers, (4) risk classification, (5) project objectives, (6) project work packages, and (7) response strategy, were used to establish the meta-model illustrated in Figure 3.3.

Table 3.1: Summary of classes in previous studies.

Reference	**Primary Classes Used**
(De Zoysa and Russell 2003)	Risk factors, risk factor classification, response strategies, and physical components
(Leung et al. 1998)	Risk factors, risk factor classification, work breakdown structure of affected project components
(Meditskos et al. 2012)	Case study, risk case, risk, risk variable, category, and impact category
(Osorio-Gómez et al. 2019)	Risks, sources of risk, frequency, impact, managerial strategies, and logistic companies

It is also common practice for domain experts (groups of 3–10 experts) to be involved in the iterative development and evaluation of ontologies (in contrast to using a mass survey approach) (El-Diraby and Kashif 2005). Here, a focus group consisting of six experts in risk management, as detailed in Table 3.2, evaluated the meta-ontology and confirmed that the content analysis was complete, and that ontology development could begin.

Table 3.2: Demographic information of focus group experts.

No.	Position	Industry Experience	Education
1	Vice President	20	M.Sc.
2	Project Manager	18	B.Sc.
3	Project Manager	15	B.Sc.
4	Risk Analyst	12	B.Sc.
5	Wind Turbine Engineer	10	Ph.D.
6	Project Coordinator	7	B.Sc.

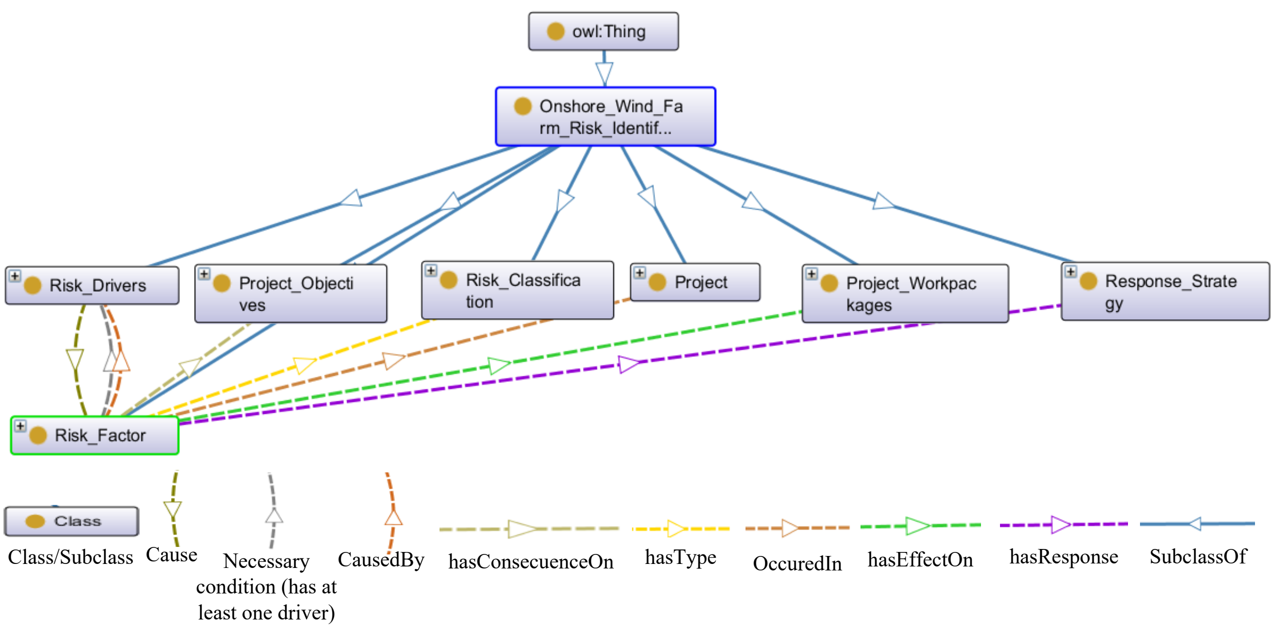

Figure 3.3. Meta-model of onshore wind farm risk knowledge in Protégé®.

3.3.1.2 Ontological Preparation

After establishing the meta-model and the main classes that should be modeled in the risk ontology, detailed descriptions of the classes, relationships, and properties were developed.

Content analysis was applied to discover the existence of classes within texts, to understand their meanings, and to analyze the relationships between the classes (Niu and Issa 2015). Following a content analysis of related project records, historical data, and project documents, the defined classes were detailed using a knowledge taxonomy format. Consultations with domain experts were used to periodically evaluate the representativeness of the developing taxonomies. In the following sub-sections, each taxonomy is defined; then, semantic relationships between the classes of the meta-model are detailed. Finally, data properties of the classes and sub-classes are described.

3.3.1.2.1 Development of Class Taxonomy

The taxonomy development process typically includes varying degrees of judgments regarding classification and the balance between depth and coverage (El-Diraby et al. 2005). A review of existing literature provided the foundation for taxonomy development. Moreover, ontology development best practices proposed by El-Diraby et al. (El-Diraby et al. 2005), specifically (1) iterative development and (2) involvement of domain experts, were used to support this process. After the first set of expert interviews (i.e., held after the development of the meta-model), a set of preliminary taxonomies, based on available literature, was developed. Then, a second set of interviews with the domain experts listed in Table 3.2 were held. Subject experts reviewed and evaluated the proposed taxonomy. Their feedback was incorporated, ultimately resulting in the final taxonomies illustrated in Figure 3.4. The development process of each class is detailed as follows.

- Risk drivers' taxonomy

Understanding the relationships between the risk factors and their drivers is crucial for effective risk identification. The taxonomy of the risk drivers class was developed based on previous research (De Zoysa et al. 2005; De Zoysa and Russell 2003; Leung et al. 1998; Xing et al. 2019), which proposed that risk identification can be classified into external and internal project contexts. This sub-classification was applied to the risk drivers' class of the current ontology, as illustrated in Figure 3.4.

Here, the external project context class represents the characteristics surrounding a project, including physical, economic, social, political, and regulatory contexts (De Zoysa 2006; De Zoysa and Russell 2003). The first external project context sub-class is the physical class, which represents both the natural and artificial objects surrounding a project. The physical sub-class is further divided into the natural objects sub-class, which includes living organisms and inorganic objects, such as geological features and natural resources (De Zoysa 2006; De Zoysa and Russell 2003), as well as the artificial objects sub-class, which represents man-made objects, including existing structures such as buildings, utilities, and other infrastructure. The second external project context sub-class is the economic sub-class, which refers to financial conditions such as inflation, exchange rate, and labor market. The third sub-class is the political context sub-class, which represents federal, state (or provincial), and municipal government characteristics. The fourth sub-class, the regulatory class, refers to the various regulations imposed by the federal, state (or provincial), and municipal governments on project execution, such as environment protection laws, labour and safety regulations, and other municipal by-laws. The final sub-class, the social class, refers to the demographic profile of the project, in terms of cultural characteristics of local and First Nations communities.

The internal project context class contains two sub-classes, the process sub-class and the organizational structure sub-class, as detailed in Figure 3.4. The process sub-class refers to the various work packages executed during the construction phase of the project that are represented in a typical work breakdown structure. The organizational structure sub-class represents the different stakeholders involved in the project and, importantly, the relationships between them (De Zoysa Sanjaya et al. 2005; Zoysa and Russell 2003).

- Risk classification taxonomy

Risk factors in onshore wind farm projects can be classified into a number of risk categories. The risk factor classification taxonomy developed here, and illustrated in Figure 3.4, was adopted from the generic taxonomy for risk factors in construction projects proposed by Siraj and Fayek (Siraj and Robinson Fayek 2019). Risk factors themselves are instances of the risk factor class and are linked to the risk classification class through a "hasType" relationship, as detailed in Section 3.1.2.2 below.

- Project objectives taxonomy

The aim of all construction projects is to execute the project with a high level of quality, within planned budgets and schedules, with zero incidents, and with little, if any, harm to the environment (De Zoysa and Russell 2003). When a risk factor occurs, it has the potential to impact one or more of these five objectives. As such, five sub-classes, namely cost, time, quality, safety, and environmental objectives, were included in the taxonomy of the project objectives class, as illustrated in Figure 3.4.

- Project work packages taxonomy

In certain conditions, risk factors are known to affect select portions of the project. Based on the work breakdown structures of onshore wind farm projects developed by Hao et al. (2019) and Mohamed et al. (Mohamed et al. 2021), the construction activities of onshore wind farm projects were represented in the current ontology by eight primary work package sub-classes, as shown in Figure 3.4.

- Risk response strategy taxonomy

Risk response strategies in construction projects are commonly-grouped under five categories (Baker et al. 1999). Accordingly, risk acceptance, risk elimination, risk transfer, risk retention, and risk reduction sub-classes for the risk response strategy class were developed in the ontology, as shown in Figure 3.4.

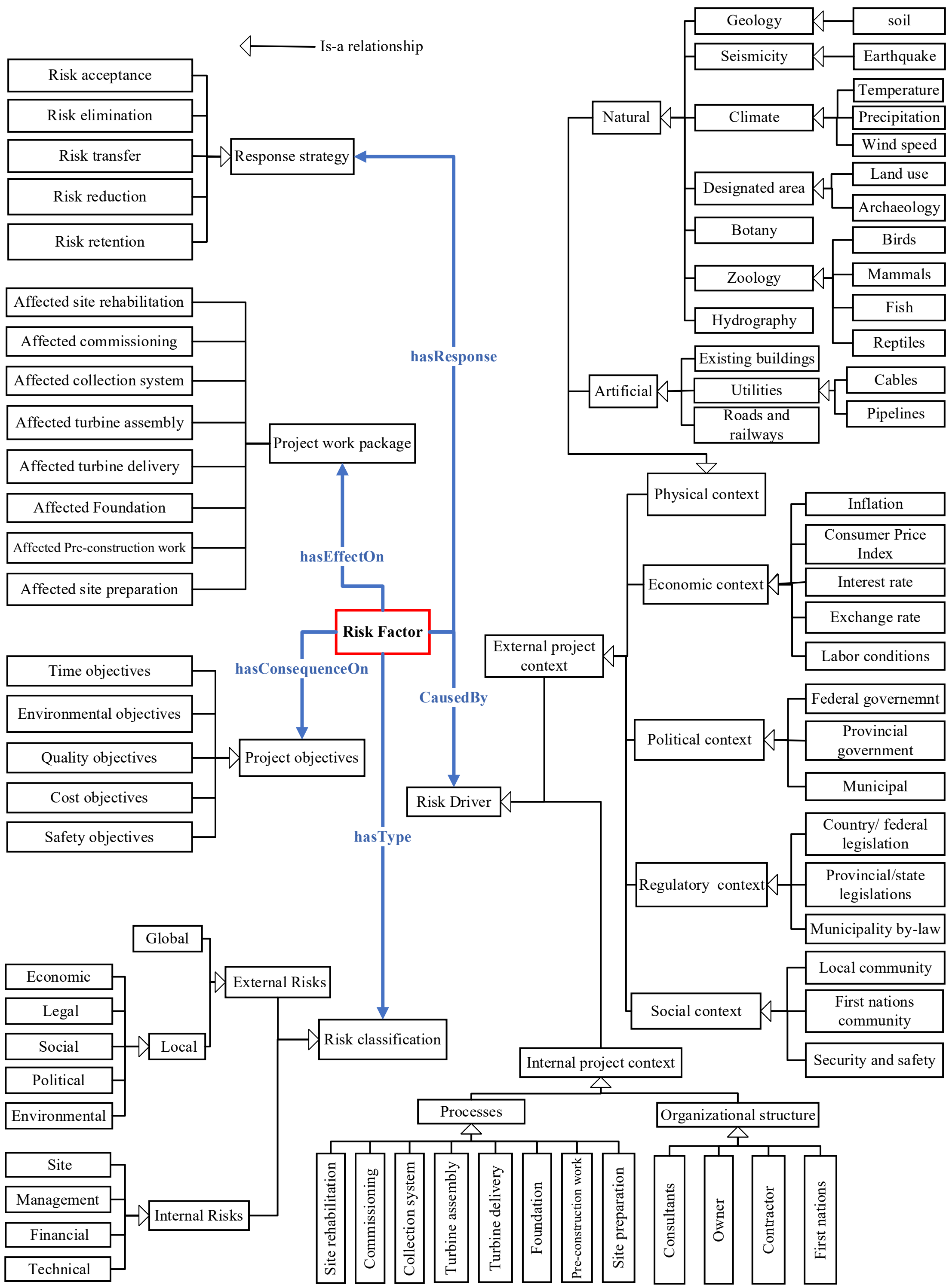

Figure 3.4. Class taxonomy of risk ontology.

3.3.1.2.2 Relationship Establishment

Semantic relationships emulate how two or more concepts are associated (Guo and Goh 2017). Relationships are often defined by a verb-containing phrase that describes the semantics of the relationship (Guo and Goh 2017) to enable their reasoning (Wang et al. 2011). Two of the five methods proposed by El-Diraby et al. (El-Diraby et al. 2005) were applied to identify relationships in the current ontology, specifically (1) a review of related ontologies and their approaches to build relationships and (2) expert review during the development phase of the research. All of the relationships defined between classes, in addition to the domain and range for each, are illustrated in Figure 3.4. Details of this process are described as follows.

In this research, relationships between classes and associated sub-classes were established using Hyponym–Hyperonym relationships. Hyponym–Hyperonym relationships, which have been referred to by a number of alternate terms including IS-A (is-a), a-kind-of, genus-species, and class-subclass relationships, are commonly-used to establish relationships (Khoo and Na 2006). Here, classes (i.e., hyperonym) are related to sub-classes (i.e., hyponym) using verb-containing phrases. For example, the risk drivers are divided into internal and external risk drivers, thus “internal risk drivers are a-kind-of risk drivers”. Cause-and-effect relationships between concepts were described by a number of causative verbs, such as Cause, hasConsequenceOn, hasEffectOn, hasType, and hasMitigation (Figure 3.4). For example, “risk drivers cause risk factors”. Finally, concept-object relationships were used to specify relationships between classes and their instances. As an example, “accidental damage of archaeological finds is-instance-of risk factor”.

3.3.1.2.3 Properties Identification

Although the taxonomy of different classes discussed above provides a description of the domain ontology, it does not provide detailed information about the classes, sub-classes, and their instances. As such, properties were used to represent the detailed characteristics of the predefined classes (El-Gohary and El-Diraby 2010), as defined in Table 3.3. The inclusion of properties is particularly important for the project context class, as the associated risk factors depend on the specific characteristics (i.e., properties) of the project context.

3.3.1.2.4 Expert Review of Risk Ontology

Once the class taxonomy, relationships, and properties were established, a second focus group meeting was organized to collect feedback from domain experts. Experts were asked to indicate whether or not they believed that the ontology was being developed in a manner that was representative of real operations and was capable of fulfilling the intended purpose. Each taxonomy was discussed in depth with the focus group, along with the associated relationships and properties. Questions that were asked in this meeting included, “Do you think the taxonomy depth comprehensively covers the knowledge in this class?”, “Do you think the relationships are logical and capture the association between classes?”, and “Is the hierarchy of the taxonomy reasonable?”

Table 3.3: Data properties defined for the risk driver class.

Class (Domain)	Data Property	Data Type	Units
Project	Project name	String	–
	Project location	String	–
	Project size	Float	MW
	Project duration	Float	months
Roads and railways	Road category	String	–
	Average daily traffic	Float	vehicle/day
Existing buildings	Heritage significance	Boolean	–
	Closest construction activity	String	–
	Distance to closest activity	Float	m
Utilities (pipelines /cables)	Closest construction activity	String	–
	Distance to closest activity	Float	m
Botany	Name	String	–
	Closest construction activity	String	–
	Distance to closest activity	Float	m
Temperature	Minimum winter temperature (5 year average)	Float	°C
	Maximum winter temperature (5 year average)	Float	°C
	Average winter temperature (5 year average)	Float	°C
Precipitation	Average snowfall (5 year average)	Float	cm
	Maximum snowfall (5 year average)	Float	cm
	Average rainfall (5 year average)	Float	mm
	Maximum rainfall (5 year average)	Float	mm
Wind	Maximum wind speed (5 year average)	Float	m/s
	Average wind speed (5 year average)	Float	m/s
Archaeological heritage	Closest construction activity	String	–
	Distance to closest activity	Float	m
	Heritage significance	Boolean	–
Land use	Purpose	String	
	Affected area size	Float	m^2
Soil	Type	String	–
	Groundwater level	Float	m
Hydrography	Closest construction activity	String	–
	Distance to closest activity	Float	m
Earthquake	Return period	Integer	years
	Magnitude	Float	Richter
Zoology	Closest construction activity	String	–
	Distance to closest activity	Float	m
	Breed in the area	Boolean	–

	Animal name	String	–
Political	Overall stability	Boolean	–
	Support for the project	Boolean	–
Regulatory	Responsible agency	String	–
	Approval status	Boolean	–
Social	Attitude toward project	String	–
	Participation in public consultation	Boolean	–
Organizational	Cooperation level	String	–
	Risk attitude	String	–
	Clear responsibility	Boolean	–
Response strategy	Description	String	–
Risk factor	Probability	String	–
	Impact	String	–

3.3.1.3 Ontology Implementation

Following the review by domain experts, the ontology was modeled using a knowledge-domain modelling platform to transform the ontology from a conceptual model to an implementable format for testing and application. Designed to facilitate the development, navigation, and visualization of knowledge-domain models, the free, widely-used, and open-source ontology platform, Protégé, was applied to implement the risk identification ontology in the present study (Rubin et al. 2007). Notably, other ontology platforms may also be used.

3.3.1.4 Ontology Verification

Two evaluation methods were used in this study to verify the implementable version of the risk ontology. First, an automated consistency check was applied to ensure that the ontology was free from contradicting facts (Gómez-Pérez 1996), which can result inconsistencies and, ultimately, in incorrect conclusions. Second, criteria-based evaluation was used to verify the content of the ontology using a predefined set of criteria proposed for ontology evaluation in previous research (Guo and Goh 2017; Xing et al. 2019). The verification processes are detailed as follows.

3.3.1.4.1 Automated Consistency Check

The Pellet reasoner (Sirin et al. 2007) in Protégé was used to perform an automated consistency check. This reasoner has been applied to many applications in construction research, where is has been shown to be stable. Here, the Pellet reasoner reviewed the ontology for inconsistent, disjointed class assertions, domains, and ranges of relationships. An automated consistency check was performed routinely at each step in the development process of the ontology. A final check was conducted after ontology was completed. Results of the final consistency check are shown in Figure 3.5. The "owl: Nothing" of Figure 3.5 indicates that inconsistencies in the ontology were not found.

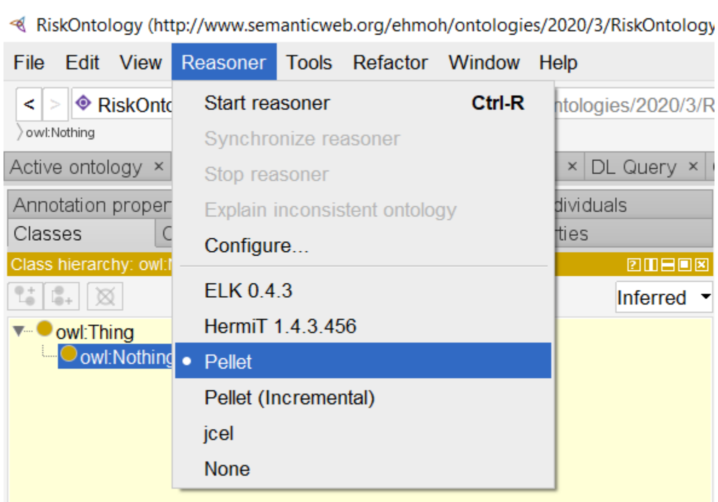

Figure 3.5. Consistency check in Protégé.

3.3.1.4.2 A Criteria-Based Evaluation

Criteria-based evaluation was conducted through interview with domain experts using a focus group approach. Experts were selected based on the following criteria: (1) years of experience in the risk management of construction projects and (2) familiarity with risk identification in wind farm projects. To reduce bias, experts that were not interviewed during the ontology development process performed the evaluation. Three experts were selected: a project manager, estimator, and risk analyst with an average of 15 years of experience in industry.

The goal of the criteria-based evaluation was to test the adequacy of the semantics and the ease of use of the ontology (El-Diraby and Osman 2011). Once selected, experts were asked to rate their satisfaction with the proposed risk ontology across several criteria using a 5-point Likert scale. An open-ended question asking the experts to indicate other areas of the ontology that may require further investigation was also included. Results of the criteria-based evaluation are summarized in Table 3.4 and are described below.

Table 3.4: Overall evaluation by experts.

Criteria	Sub-Criteria	Average	Std. Dev.
Coverage	Core concepts are incorporated	4.33	0.57
	All relationships are incorporated	4.00	1.00
Completeness	Definitions of classes, taxonomy, and relationships are complete	4.33	0.57
	The ontology explicitly includes all that should be included	4.67	0.57
Clarity	All concepts in the ontology are clear	5.00	0
	Concepts are in agreement with literature	4.33	0.57
Conciseness	The ontology does not contain unnecessary concepts	4.67	0.57
	The ontology does not contain explicit redundancy between concepts	5.00	0

- Coverage

Coverage assesses whether the ontology incorporates the main concepts and relationships within the domain or lacks certain classes and relationships (El-Gohary and El-Diraby 2010). This criterion was also examined throughout the conceptual formulation stage as the taxonomies and relationships of the meta-ontology were established. Based on the results of the evaluation, subject experts "agreed" that core concepts and all relationships are incorporated in the developed wind farm risk ontology. The overall average evaluation of this criterion was 4.16, with a standard deviation of less than one, indicating that the evaluation was consistent amongst the experts. The experts proposed that other concepts could be added to benefit the risk quantification stage.

- Completeness

Completeness determines if the classes, taxonomies, and relationships defined in the ontology are complete and appropriate for use in the application stage (Gómez-Pérez 1996). The ontology is considered complete if two conditions are satisfied: (1) each definition is complete and (2) the ontology explicitly includes all that should be included (Gómez-Pérez 1996). To achieve this, a top-down approach is used to assess if each top class is complete with respect to its subclasses (taxonomy) and if the domain and range for each relationship is defined. The overall average evaluation of this criterion was 4.50, indicating that the experts "agreed to strongly-agreed" that the classes, taxonomies, domain, and range of the relationships were complete. There were no open-ended comments regarding completeness.

- Clarity

Clarity of ontology indicates if an ontology can clearly exhibit the intended meanings of the developed classes and their taxonomies without ambiguity. This criterion was also examined throughout the conceptualization stage as concepts and standards for defining and setting the meaning of each concept/class were extracted from literature. The clarity criterion was evaluated based on the two items: (1) concepts are clear and (2) intended concept definition was consistent with definitions from literature and practice. The overall average evaluation of this criterion was 4.67, indicating that the experts "agreed to strongly-agreed" that all concepts and their intended meanings were consistent with definitions from literature and practice. There were no open-ended comments regarding clarity.

- Conciseness

Conciseness assesses if the information collected in the ontology is useful and precise (Gómez-Pérez 1996). Gómez-Pérez (1996) indicated that an ontology is concise if the following two conditions are met: (1) it does not contain unnecessary and useless concepts and (2) explicit redundancy does not exist between concepts. The overall average evaluation of this criterion was 4.84, indicating that the experts "agreed to strongly-agreed" that the ontology did not contain redundancies or unnecessary concepts. There were no open-ended comments regarding conciseness.

3.3.2 Proposed Framework

After development, the generic risk ontology was integrated into the proposed framework. Application of the framework involves three primary steps: (1) ontology population, (2) current project data collection and input, and (3) risk factor identification, as shown in Figure

3.1.

3.3.2.1 Ontology Population

Historical data of previous projects are input into the generic risk ontology to establish instances of each class in a process known as a ontology population or instance extraction (Danger and Berlanga 2009; Petasis et al. 2011). The contextual information of previous historical projects, together with the risk information of these projects, are then used to extract the instances of the developed risk ontology. Instance extraction can be performed either manually or automatically using various machine learning approaches (Danger and Berlanga 2009; Petasis et al. 2011). Notably, companies should continuously enrich the ontology contextual information from related projects to improve the identification of risks for new projects.

3.3.2.2 Current Project Data Collection

After inserting the instances into related classes, the ontology—now enriched with knowledge—can be used to fetch information for risk identification purposes. Current project data is then input into the populated ontology. Required inputs for this process include the contextual information about the project for which risk factors must be identified. This information can be collected once the context of the project is established (i.e., scope of the project and surrounding environment) from various project documents, such as construction plan reports, financial reports, built heritage assessments, and environmental assessments. Examples of input data collection are described in section 4.2 of the case study.

3.3.2.3 Risk Factor Identification

Once the current project data is collected, the contextual information is fed, using queries, into the ontology. The queries that input the contextual project information are responsible for fetching and retrieving specific project risk factors for the project under study. The ontology can be accessed through Description Logic (DL) queries or through SPARQL queries to fetch and identify context-based risk factors, as shown in Figure 3.6. The DL query language, supported by a user-friendly syntax plug-in for OWL DL, is designed to collect all information about a particular class, property, or individual ("DLQueryTab - Protege Wiki" n.d.). SPARQL queries, in contrast, have greater flexibility and applicability than DL queries. Readers are referred to the online SPARQL reference site ("SPARQL 1.1 Query Language" n.d.) for a detailed explanation of SPARQL queries. Various risk-related information can be retrieved based on the structures of the queries and descriptors of the project context. Examples of these queries are presented in Section 4.3.

Once risk factors for the new project have been identified, risks can be further analyzed by determining their impacts, probabilities, and proposing appropriate response strategies. Risk management literature includes a large body of work; readers are referred to the work of Somi et al. (Somi et al. 2020), Mohamed et al. (Mohamed et al. 2021), and Mohamed et al. (Mohamed et al. 2020b) for a review of current risk management approaches in onshore wind farm construction.

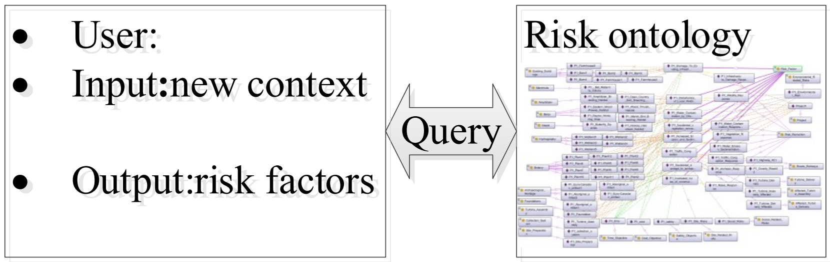

Figure 3.6. Fetching the ontology.

3.4 Case Study

Publicly-available data from seven real wind farm projects were used to demonstrate the functionality and applicability of the proposed framework. The onshore wind project, Settlers Landing ("Settlers Landing Wind Park" 2017), was chosen as the study project to which the proposed risk identification framework was applied. Historical projects used to develop the class instance representations and populate the ontology are listed in Table 3.5. Protégé, a free, widely used, and open-source ontology platform, was used to implement the risk identification ontology. The reader is referred to the user guide (Horridge et al. 2004) of Protégé for a detailed overview of the development steps.

3.4.1 Ontology Population

A dataset of six onshore wind farm projects located in Ontario, Canada, was collected and used to fill and build the instances of the proposed ontology. A description of these projects is provided in Table 3.5; all are onshore wind farms. Project documents that were available included project descriptions, construction plans, cultural heritage assessments, natural heritage assessments, and noise assessments.

Instances for each class were extracted from these documents, including the risk factors, context of the project (i.e., risk drivers), risk response strategies, and attributes of the instances. Public disclosure of project documents is often limited to risks pertinent to the public. As such, the majority of extracted information was related to environmental or social risk factors. These included environmental risk factors with the potential to cause damage or harm to the surrounding environment of the projects or social risk factors, such as traffic congestion and noise disturbances due to construction activities. A manual approach instance representation approach was adopted in the current case study. First, related documents from different sources were reviewed; then, instances were extracted and input into the related class in the ontology. Historical risk knowledge was implemented and coded in Protégé platform (Musen 2015), as shown in Figure 3.7. The extracted risk concepts and taxonomies were modeled as "classes" (Figure 3.7; red box); relationships between concepts were modeled as "object properties" (Figure 3.7; blue box); and attributes of the classes were modeled as "data properties" (Figure 3.7; green box).

Table 3.5: Details of the projects used for ontology population.

No.	Project	Project Size (MW)	No. of Risk Factors
1	Belle River Wind Project ("Belle River Wind :: Documents" 2016)	73.5	8
2	Bornish Wind Energy Centre ("NextEra Energy Canada - Bornish" 2013)	72.9	8
3	Grey Highlands Clean Energy ("Grey Highlands Clean Energy: Project Documents" 2015)	18.5	7
4	Grey Highlands Zero Emission ("Grey Highlands Zero Emission: Project Documents" 2015)	10.0	6
5	K2 Wind Project ("K2 Wind: Project Documents" 2014)	270	6
6	Port Ryerse Wind Power ("Port Ryerse" 2016)	10.0	4

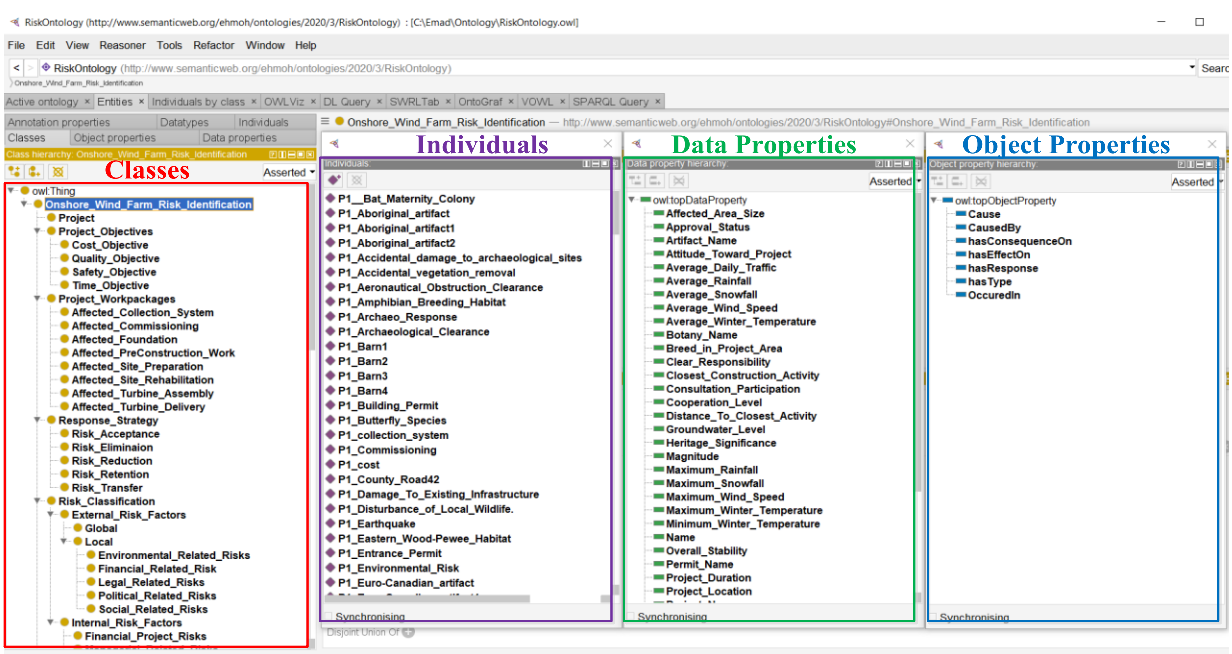

Figure 3.7. Screenshot of the risk ontology in Protégé®.

Examples of the populated instances for one risk factor, as well as an example of populated instances of the risk factors for an entire project are provided as Figure 3.8 and Figure 3.9, respectively. The semantic structure of the risk factor "Accidental Damage of Archaeological Finds" from the Belle River Wind Project is shown in Figure 3.8. This risk factor has six drivers (CausedBy, Cause), which are the foundation excavation activity and the presence of five archaeological artefacts near the construction activities. This risk factor is classified (hasType) as an environmental risk factor (P1_Environmental_Risk) and is an instance of the class "Risk_Factor". This risk factor can impact (hasConsequenceOn) the project time objective (P1_time) because regulations require that work must stop immediately. This risk factor occurred in (OccuredIn) the Belle River Wind Project, or Project 1. The attributes of the archaeological finds in the project study area are provided in Table 3.6. The example provided in Figure 3.8 illustrates the advantages of using ontologies to model risk information, specifically (1) the ability to model information at the risk-level precisely and (2) the elegance and simplicity of the resulting visualization.

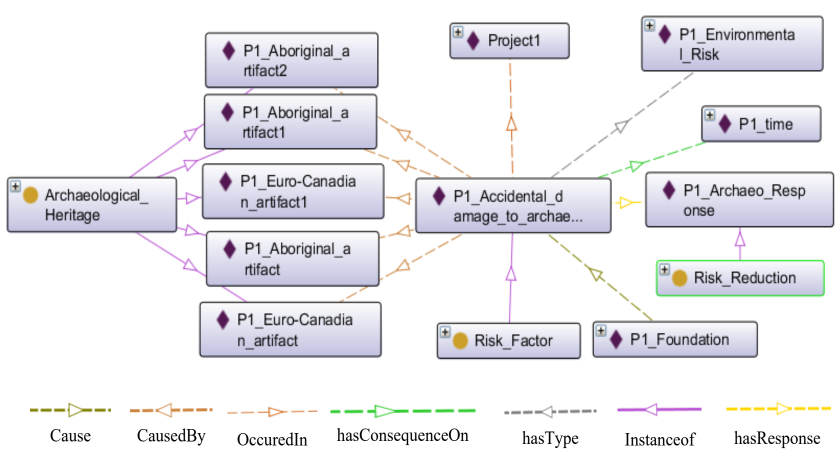

Figure 3.8. Semantic structure of archaeological damage risk in Protégé®.

Table 3.6: Data properties of archaeological finds.

Artifact Name	**Closest Activity**	**Distance to Activity (m)**	**Heritage Significance**
Aboriginal Artifact	Turbine 1	200	Yes
Aboriginal Artifact 1	Turbine 2	285	Yes
Aboriginal Artifact 2	Turbine 3	30	Yes
Euro-Canadian Artifact	Turbine 1	131	Yes
Euro-Canadian Artifact 1	Turbine 3	140	Yes

All remaining risk factors in the Belle River Wind Project were modeled and implemented using an approach similar to the detailed risk example. Figure 3.9 illustrates the semantic structure, risk drivers (context), and the response strategies of the eight risk factors identified in Project 1. The other five projects were modeled and added to Protégé using a similar approach.

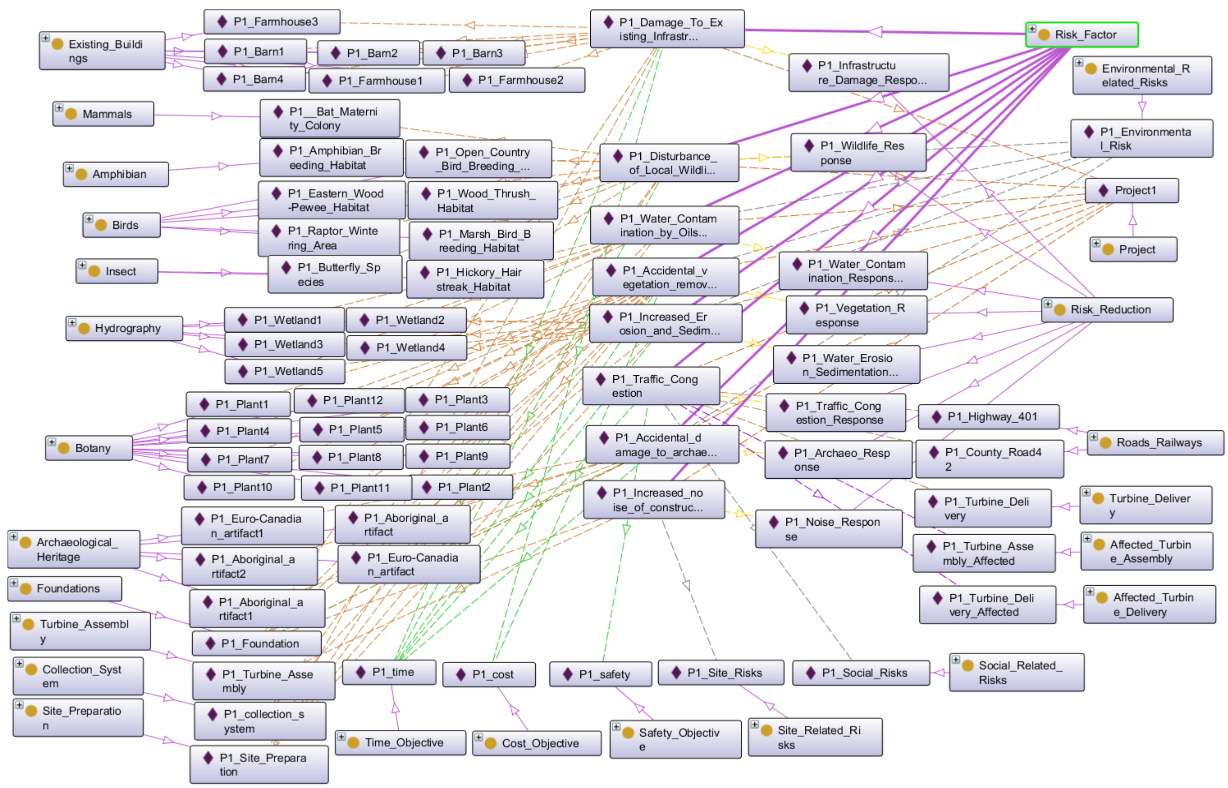

Figure 3.9. Semantic structure of Project 1 risk factors along with their context in Protégé®.

3.4.2 Current Project Data Collection

Then, contextual project information from the project under study (i.e., risk identification project) was collected and prepared for input into the ontology. Information was retrieved from project data available in the Settlers Landing project repository ("Settlers Landing Wind Park" 2017) and summarized as shown Table 3.7.

Table 3.7: Project context information.

Item	Class	Data Property (Attributes)	Data Value	Unit
New wind project	Project	Project name	Project A	–
		Project location	Ontario, Canada	–
		Project size	8	MW
		Project duration	5	months
Stone farmhouse	Existing buildings	Heritage significance	Yes	–
		Closest construction activity	Access Road	–
		Distance to closest activity	750	m
Plant 1	Botany	Name	Sugar Maple	–
		Closest construction activity	Turbine 3	–
		Distance to closest activity	33	m
Plant 2	Botany	Name	White Oak	–
		Closest construction activity	Turbine 3	–
		Distance to closest activity	33	m
Plant 3	Botany	Name	White Birch	–
		Closest construction activity	Turbine 3	–
		Distance to closest activity	33	m
Amphibian 1	Amphibian	Animal name	Amphibian Breed. Habitat	–
		Closest construction activity	Underground Cable	–
		Distance to closest activity	230	m
		Breed in the area	Yes	–
Reptile 1	Reptiles	Animal name	Snake Hibernacula	
		Closest construction activity	Underground Cable	–
		Distance to closest activity	46	m
		Breed in the area	Yes	–
Mammal 1	Mammals	Animal name	Bat Maternity Colony	–
		Closest construction activity	Access Road	–
		Distance to closest activity	18	m
		Breed in the area	Yes	–

3.4.3 Risk Factor Identification

Seven separate SPARQL queries were designed for each of the defined project contexts provided in Table 3.7.Queries were directly expressed and written in the separate SPARQL tab in Protégé. The query itself was written in the top part of the tab while the query results were shown at the bottom part of the tab as shown in Figure 3.10, Figure 3.11, and Figure 3.12. Query 1 extracted the risk factors and their response strategies that could be implemented to mitigate risks resulting from the presence of existing buildings surrounding the project. The results of the query are shown in Figure 3.10. Here, one risk factor, "Damage to Existing Infrastructure" was identified and recalled based on the similarity of the current project (i.e., Settlers Landing) to historical Project 1. Project 1 (i.e., Belle River) had three existing buildings (Farmhouses 1-3) located within the project area within varying distances of construction activity. Using the context of the current project, which also is characterized by the presence of a farmhouse, the framework was able to automatically recall and identify the risk factor "Damage to Existing Infrastructure" as well as the associated response strategies.

Query 2 was designed to search the ontology for risk factors associated with the existence of sugar maple trees in the project area based on the contextual information specified in Table 3.7. Figure 3.11 shows the results of the query. Here, two risk factors "Accidental Vegetation Damage/Removal" were recalled from Projects 2 and 5 based on their contextual similarity to the current project (i.e., Settlers Landing).

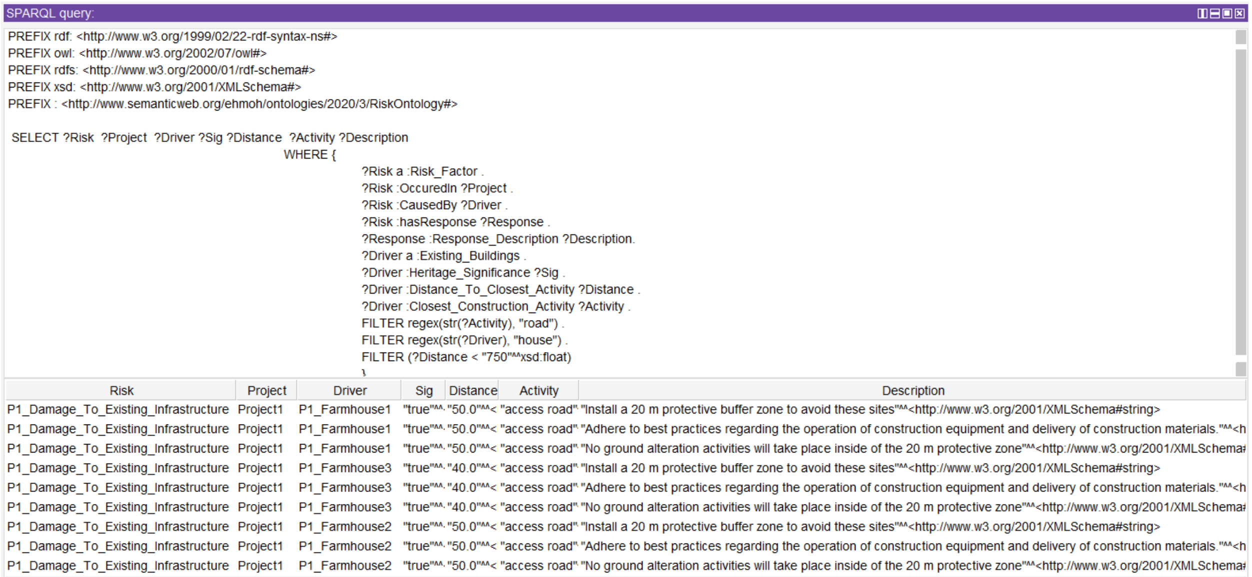

Figure 3.10. SPARQL query of existing buildings related risk factors.

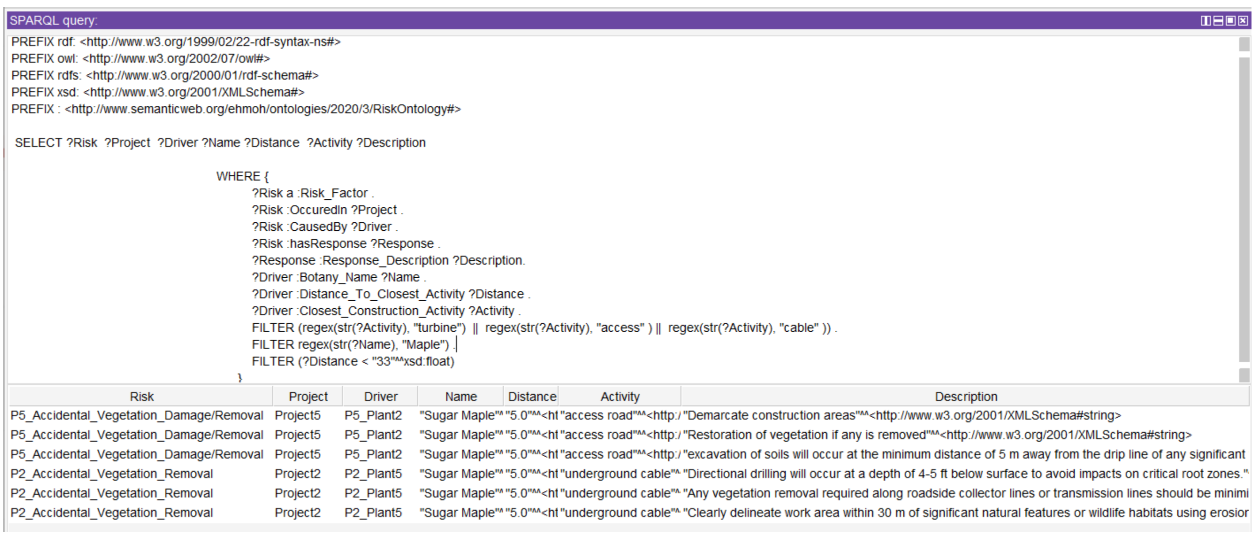

Figure 3.11. SPARQL query of sugar maple tree related risks.

Similarly, Queries 3 and 4 were designed to identify risks associated with white oak and white birch trees in the project area by entering the associated contextual information (e.g., botany name, closest construction activity, and the distance to the closest activity). Queries 5 through 7 were also developed to identify risk factors resulting from the existence of amphibians, snakes, and bats. Implementation of Query 5 is illustrated in Figure 3.12. Queries 6 and 7 were implemented using a similar approach, with the animal name, closest construction activity, and distance to activity changed as applicable. The six risk factors recalled and identified using the proposed framework for the construction of the Settlers Landing onshore wind project are detailed in Table 3.8.

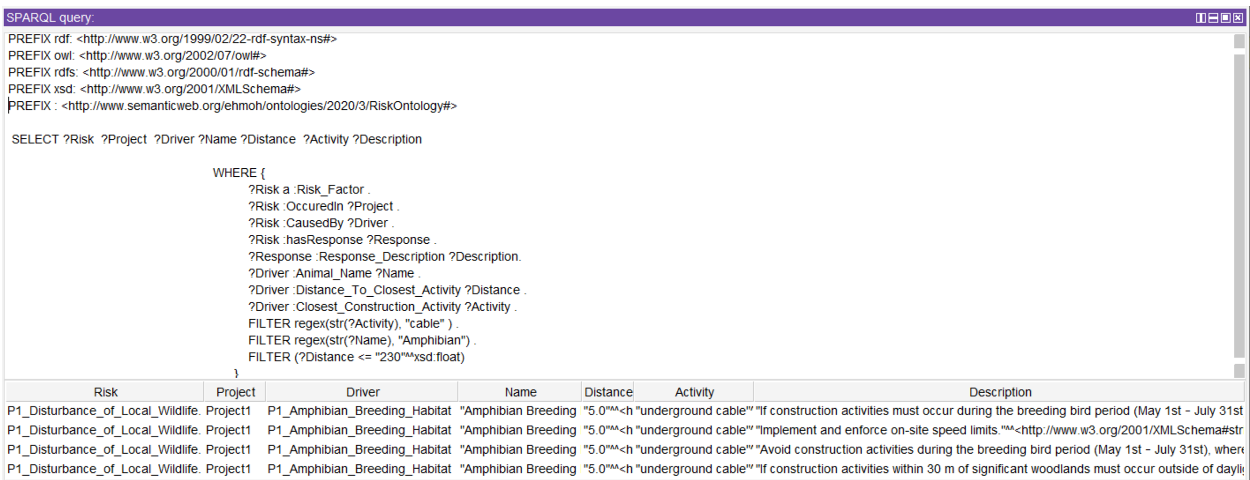

Figure 3.12. SPARQL query of amphibian related risks.

Table 3.8. Identified risks of the Settlers Landing wind project.

No.	Risk factors	Retrieved from	Response description
1	Damage to existing buildings	Project1	Install a 20 m protective buffer zone to avoid these sites
			No ground alteration activities will take place inside of the 20 m protective zone
			Adhere to best practices regarding the operation of construction equipment and delivery of construction materials.
2	Accidental damage to Sugar Maple trees	Project 2 and 5	Directional drilling will occur at a depth of 4-5 ft below surface to avoid impacts on critical root zones.
			Any vegetation removal required along roadside collector lines or transmission lines should be minimized and occur completely within the road right of way.
			Clearly delineate work area within 30 m of significant natural features or wildlife habitats using erosion fencing, or similar barrier, to avoid accidental damage to species to be retained.
			Demarcate construction areas
			Restoration of vegetation if any is removed
			Excavation of soils will occur at the minimum distance of 5 m away from the drip line of any significant woodland
3	Accidental damage to White Birch trees	Project 5	Excavation of soils will occur at the minimum distance of 5 m away from the drip line of any significant woodland
			Restoration of vegetation if any is removed
			Demarcate construction areas
4	Accidental damage/mortality of Amphibian	Project 1	If construction activities must occur during the breeding bird period (May 1–July 31), a biologist will conduct nest searches, in areas where natural vegetation will be removed, to ensure there

			will be no impact to breeding birds.
			Implement and enforce on-site speed limits.
			If construction activities within 30 m of significant woodlands must occur outside of daylight hours, spotlights will be directed downward and/or away from the woodland to limit potential light disturbance to breeding birds.
5	Mortality of snake and damage of Hibernaculum	Project 3	Construction personnel will be educated about the location and significance of these features
			Flag and demarcate the 30 m area around each hibernaculum
6	Disturbance and/or mortality of bat	Project 2	Propose a lighting scheme to that will minimize potential risk to bat collisions while fulfilling Transport Canada requirements
			Clearly delineate work area using erosion fencing, or similar barrier, to avoid accidental damage to potentially significant bat roosting trees

The results show the benefits of using context and mapping to risk factors; it was effortless to retrieve the risk factors based on their context. Ontology allowed the modelling of risk information easily and accurately, which made the knowledge sharing, reuse, and retrieval undemanding for risk analysts. Risk ontology represents a unified knowledgebase of risk information where risk analysts can and share use the same concepts and terminologies related to the risk factors, project context, and response strategies. No risk factors were identified related to the existence of white oak trees in the project area because of no similar context was detected. Therefore, the more available context information, the more accurate risk identification results.

3.4.4 Framework Evaluation and Anticipated Benefits

The risk factors identified by the proposed framework (Table 3.8)were compared with risks extracted from the publicly-available project documentation on which the case study was based ("Settlers Landing Wind Park" 2017). All of the risk factors discussed in the documentation were identified by the proposed framework, demonstrating the ability of the proposed framework to generate comprehensive, representative results.

The proposed framework was compared to the traditional risk identification techniques. To perform a traditional risk identification, a risk analyst would have needed to review project documents for four historical projects with similar contexts and review the documents for the project under study. This laborious process was easily and rapidly performed using the proposed framework. The framework was also compared to the fuzzy case-based reasoning method for risk identification in onshore wind projects proposed by Somi et al. (Somi et al. 2020, 2021). The case-based reasoning approach makes use of two project characteristics—project type and project work packages—to retrieve similar projects. Risk factors are then extracted based on the calculated similarity between two projects. Notably, the fuzzy case-based reasoning approach could not consider and model the specific project context—a major advantage of the proposed methodology.

Risk ontology represents a unified knowledgebase of risk information where risk analysts can share and use concepts and terminologies related to risk factors, project context, and response strategies. The benefits of considering project context and contextual information during risk identification was demonstrated in the case study presented here. The proposed framework considerably reduced the effort and time required to identify risk factors for a new project. Furthermore, the ability of the ontology to identify risk factors based on historical information rather than expert recall is anticipated to increase the accuracy of risk identification results, thereby improving risk management efforts for both the current and future projects.

3.5 Discussion

Risk identification in onshore wind farm projects is a burdensome task for risk analysts in construction companies because (1) risk factors have multi-source drivers that must be defined accurately, (2) information related to risk factors, risk drivers, and response strategies are fragmented across various documents, increasing the time and effort required to review these documents, and (3) for the information to be useful in future projects, data related to the risk factors must be saved in a manner than can be easily shared and reused. Indeed, as the risk knowledge maintained by risk analysts increases, so too does the accuracy of risk identification processes.

Current risk identification practice still relies on spreadsheets and text documents, limiting the communication of risk knowledge in practice. A knowledge model that can overcome these challenges can represent a real benefit to risk experts and analysts. Ontology and semantic web technology has been applied successfully to solve a wide range of knowledge modelling problems. Building on these findings, an ontology-based approach to address existing risk identification knowledge limitations was developed. The ontology was evaluated by domain experts who agreed with the validity and practicality of the model.

The following limitations should be considered in parallel with the findings of the study.

First, the ontology model was developed based on project data from the Canadian wind energy sector. While it is expected that the model can be successfully applied to any onshore wind project using the proposed methodology, the adaptability of the approach was not directly tested in this study. Second, the quality of output results is highly dependent on the quality of the input data. In the case study, risk factors related to the presence of white oak tress in the project area were not detected, as similar contexts were not identified within the five historical projects used to populated the ontology. Third, with the current development, the ontology included only risk knowledge related to environmental risk factors, which was the only information available in publicly-available project documents. In practice, however, there is not limit to the amount of information that construction companies can input into the ontology (i.e., as instances) to enrich the ontology. In the future, the onshore risk knowledge stored the model should be expanded. Application of the framework to additional onshore wind farm projects will assist in further validating the model. Future work can also focus on the development of methods capable of automating ontology population and insertion of instances.

3.6 Conclusion

Risk identification is an important yet challenging task. While unidentified risks must be identified, analyzed, and managed, the abundance of fragmented information that must be considered for risk identification renders this process time-consuming, prone-to-error, and challenging. Accordingly, this research has developed an ontology-based approach to overcome the limitations in the risk identification process. Identification-related information—which includes risk factors, risk drivers, risk response strategies, consequence on project objectives, and effect on project work-packages—are modeled semantically using ontologies. The proposed approach was validated using an automated consistency check, criteria-based evaluation, and application-based evaluation of a real project. The evaluation demonstrated that the proposed methodology was beneficial and valuable for risk identification in onshore wind farm projects by decreasing the burden on risk analysts. Risk analysts can use the proposed ontology-based approach to easily and accurately save, communicate, and reuse the knowledge required for risk identification. Reuse of the ontology also allows identification of context-based risk factors when a new project is defined.

Acknowledgments

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Chapter 4 : Fuzzy-Based Multivariate Analysis for Input Modelling of Risk Assessment in Wind Farm Projects

4.1 Introduction

Wind and solar energy are expected to lead the future transformation of the global electricity sector, with onshore and offshore wind predicted to produce about 35% of total electricity demands by 2050 (IRENA 2019). To reach the targeted installation capacity, considerable investments in the construction of renewable energy infrastructure are being made (IRENA 2019). In Alberta, Canada, $3.6 billion will be invested through the Renewable Electricity Program (REP) to add 5000 megawatts of renewable energy by 2030 ("Renewable Electricity Program" n.d.),("Wind energy in Alberta" n.d.).

As a relatively novel type of infrastructure, wind farm construction is characterized by a lack of relevant literature and a scarcity of historical data. The development of risk management plans for these types of projects, therefore, are highly dependent on the collection of expert knowledge (Somi et al. 2020). While the boom in the wind energy industry has encouraged new contractors to engage in the construction of these projects, a lack of data represents a challenge for new contractors when conducting risk management. Inadequate risk identification and assessment can have a detrimental impact on these large-scale projects, resulting in negative effects on cost, time, quality, and safety, while simultaneously discouraging contractors from engaging in wind farm construction.

Risk assessment is necessary during all phases of a wind farm project, including design, construction, operation, maintenance, and life cycle planning (Leimeister and Kolios 2018).

Although there are several types of qualitative and quantitative methods for reliability-based risk assessment, determining which approach to apply in each phase of the project's life cycle will depend on the amount and/or type of data available at a particular phase (Leimeister and Kolios 2018). Qualitative approaches (e.g., failure mode and effect analysis (FMEA), fault tree analysis (FTA), event tree analysis (EVA), and risk matrices), are better suited to the planning and early construction phases of a project when data are limited (Leimeister and Kolios 2018). However, as projects progress and as more data are gathered, quantitative methods (e.g., analytical methods, stochastic methods, and Bayesian approaches) are favored due to their comprehensive capabilities (Leimeister and Kolios 2018).

Monte Carlo simulation (MCS) is a widely applied stochastic quantitative approach for risk assessment. It is an extremely powerful tool used for understanding and quantifying the potential effects of uncertainty on a project (Kwak and Ingall 2007), and has been widely applied to simulate cost and time in construction (Kwak and Ingall 2009). As with many quantitative methods, however, the application of MCS is constrained by the need for variables to be input as probability density functions, limiting its use in the planning and early construction phases of a project. Currently, there are two primary approaches for developing the probability density functions that are input into MCS-based risk assessment models (Figure 4.1).

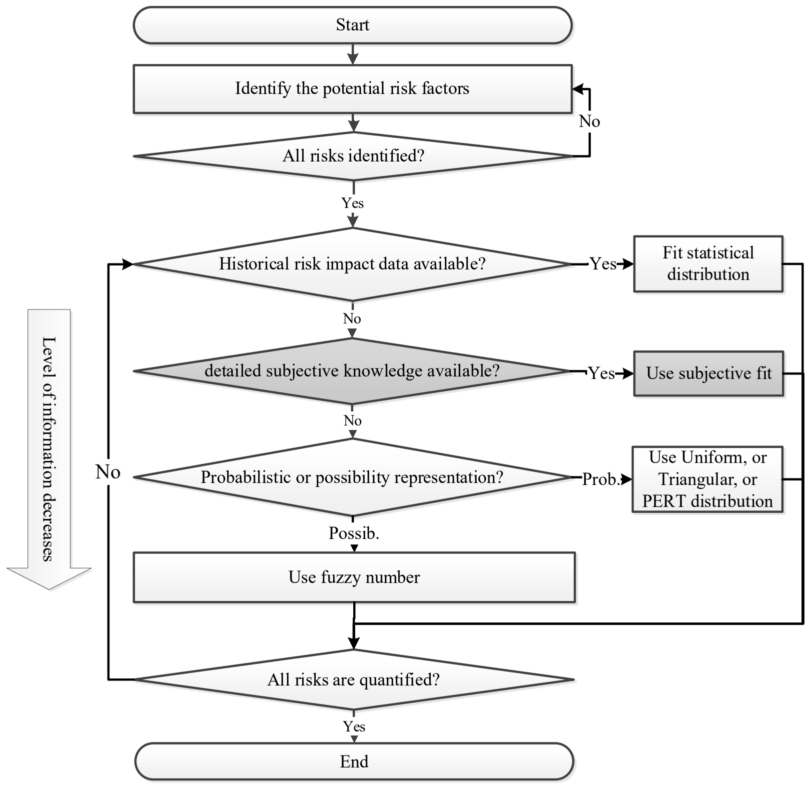


Figure 4.1. Levels of data available and accompanying methods used for input modelling.

As classified by Biller and Gunes (Biller and Gunes 2010), the two approaches are categorized based on data availability. The first approach can be adopted when there is sufficient historical data available for a particular variable (Biller and Gunes 2010). In this case, a probability distribution is fit to the data and is then input into the risk assessment model. The second approach is adopted when there is an absence of data. This approach uses elicitation methods to construct the input distribution (Biller and Gunes 2010), where the risk analyst can decide to use either (1) a probabilistic approach by choosing either triangular, uniform, or PERT distributions (Abou Rizk 2013),(Smith et al. 2006), or (2) a possibility approach, where fuzzy numbers are used to represent the impact of a risk factor (Sadeghi et al. 2010).

Wind farm construction does not have sufficient historical data available to complete a risk assessment using the first approach. Nevertheless, there is a substantial amount of detailed subjective knowledge available (Somi et al. 2020). The second approach, however, cannot make use of this knowledge, thereby missing an opportunity to enhance the reliability of risk assessment results. Indeed, the current state-of-the-art lacks methods that can derive an appropriate probability distribution function from detailed subjective expert knowledge.

An additional difficulty experienced when conducting risk assessment modelling in wind farm construction is the consideration of risk factors affecting schedule and cost as independent. Delays in project schedule will often result in increased project costs, where impacts on cost are generally accompanied by project delays (Hulett et al. 2019). Treating these cost and schedule impacts as dependent during risk assessment modelling will help generate more realistic results. Methods for modelling the dependence of a risk factor's impact on cost and schedule, however, remain relatively unexplored.

To address these limitations, this paper is proposing a methodology that is designed to enhance risk assessment outcomes by (1) assisting risk analysts in fitting appropriate distributions for detailed subjective knowledge of the cost and schedule impacts of risk factors (see dark grey area, Figure 4.1) and (2) adapting existing methods to model the dependence between the cost and schedule impact of a risk factor in a Monte Carlo simulation (MCS)-based risk assessment model. Fuzzy logic is used to process and quantify subjective knowledge, which is then fit to a probabilistic distribution function that represents the marginal distribution for the impact on either cost or schedule. Then, copula-based modelling of multivariate distributions

(Yan 2007) is used to model the dependence between the cost and schedule impact of a risk factor. The remaining sections of this paper are organized as follows: MCS in risk assessment, input modelling for MCS, and correlation and dependence between input distributions are first discussed in a literature review section. Then, the research methodology is explained. Next, an illustrative case study is presented to demonstrate the functionality of the proposed method, and a sensitivity analysis is performed to establish its validity. The final section summarizes conclusions and future research directions.

4.2 Literature Review

4.2.1 MCS for Risk Assessment and Input Modelling

Risk assessment is conducted by evaluating the probability of occurrence and the impact of risk factors to determine their severity on project outcomes. Mathematically, this is accomplished by multiplying probability of occurrence (*P*) by impact (*I*) (Zavadska et al. 2010)(Banaitiene and Banaitis 2012) and summing the results to obtain an overall effect of risk factor, *n*, on project cost and time, as per Equation 4.1:

$$\mathrm{S} = \sum_{i=1}^{n} P_i * I_i \tag{4.1}$$

Monte Carlo simulation is a probabilistic technique for the quantitative analysis of risks in the construction industry (Molenaar et al. 2013). MCS makes use of probability distributions rather than deterministic values to model the uncertainty associated with a particular input (Abou Rizk 2013). In a MCS risk analysis experiment, the term I_i in Equation 4.1 is replaced with a probability distribution function representing the impact on cost or schedule.

A Monte Carlo simulation experiment for assessing project risks is performed as follows. First, the baseline cost and schedule of the individual activities is prepared (Abou Rizk 2013). Then, risk factors affecting the project are identified, and the cost impact, schedule impact, probability of occurrence, and affected work-packages are determined for each individual risk factor (Abou Rizk 2013). If a risk occurs while running the simulation experiment, the cost and schedule impacts are added to the affected activities. An example project, consisting of three activities (A, B, C) and one risk factor affecting Activity A, is presented in Figure 4.2.

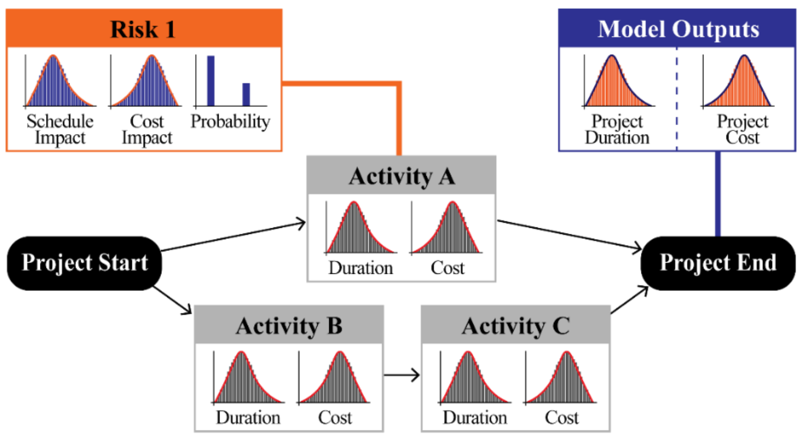


Figure 4.2. MC simulation experiment for risk assessment.

A key limitation for the practical application of MCS in risk assessment is the development of risk impact probability distributions that are not readily available due to insufficient historical data. These distributions, therefore, must be derived from other existing information and knowledge (Duracz 2006),(Yoe 2016). The development of such distributions, known as input modelling, is widely discussed in literature due to its impact on simulation outputs and, consequently, on the quality of decisions made based on the simulation results (Law 2013). Input modelling in the case of absent data is known as an elicitation process. Here, expert judgment, recognized as a type of scientific data (O'Hagan 2019), is elicited and used to construct probability distributions (Morris et al. 2014). Elicitation of expert judgment can take three forms, where experts are asked to specify (1) the cumulative distribution function, (2) the density distribution function, or (3) to provide partial information about the distribution such as mean, standard deviation, or several quintiles of the distribution (Cooke and Goossens 2004). The elicitation process typically involves the elicitation of the most likely, maximum, and minimum values, or estimating the mean and variance from experts (Galway 2004). Several studies have provided a review and guidelines of the statistical methods used to elicit probability distributions (Cooke and Goossens 2004),(Nasir et al. 2003),(van Dorp and Duffey 1999). For example, Galway (Galway 2007) concluded that multiple experts should be asked to provide upper, lower, and most likely values for an uncertain quantity, which can then be fitted to a triangular distribution. In contrast, Morris et al. (Morris et al. 2014) developed a web-based tool that has five optional methods for the elicitation process, including a roulette method, quartile method, tertile method, probability method, and hybrid method.

Another challenge of elicitation for risk assessment is the introduction of biases arising from the inherent subjectivity of risk evaluation. Although experts are considered to be knowledgeable and experienced, their judgment may, as a result of biases, be inaccurate—especially when judging probability (Meyer et al. 2011). There are two major types of biases: cognitive and motivational. Cognitive biases are defined as "systematic deviations [of expert evaluation] from logic, probability, or rational choice theory" (Dikmen et al. 2018) and are often associated with heuristic judgment processes (Tversky and Kahneman 1974). Examples of cognitive biases include overconfidence (i.e., excessive confidence in one's own answers to questions), anchoring (i.e., the tendency to rely too heavily on one piece of information when making decisions), and availability bias (i.e., the tendency to overestimate the likelihood of events with greater availability in memory). Various debiasing methods, such as decomposition, multiple experts, and exploration of the extremes of a target variable, can be applied to reduce cognitive biases (Dikmen et al. 2018).

Motivational biases are defined as "those in which judgments are influenced by the desirability or undesirability of events, consequences, outcomes, or choices" (Montibeller and Winterfeldt 2015). One example of motivational bias is the underestimation of project costs to provide more competitive bids. A strategy for overcoming motivational biases, proposed by Montibeller and Winterfeldt (Montibeller and Winterfeldt 2015), is the decomposition of a target variable into component variables and events (i.e., root causes). It is expected that the evaluation of a specific root cause by an expert will be more precise than the evaluation of a risk factor as a whole. As such, analysts are encouraged to adopt a decomposition strategy when eliciting subjective risk evaluations from experts.

While recommendations for successfully inputting uniform, triangular, or PERT distributions into Monte Carlo risk assessment models have been proposed in literature, other forms of input modelling remain limited by a need for a large number of experts or by an inability to integrate their detailed knowledge (Abou Rizk 2013),(Smith et al. 2006). The fitting of expert opinion regarding the impact and probability of occurrence of risks into a probability distribution has been proposed by Li et al. (Li et al. 2016). However, their approach requires a large number of experts to be involved in the assessment, which is not feasible for novel projects, such as onshore wind farms, where the number of experts at a construction company is limited. Furthermore, their approach does not allow experts to express their detailed knowledge about a risk factor, potentially limiting the accuracy and representativeness of the risk assessment results. In 2003, Nasir et al. (Nasir et al. 2003) proposed a methodology to enhance the input modelling of Monte Carlo risk assessment using belief networks to estimate the boundaries (i.e., minimum and maximum) of Beta-Pert distributions for activity durations. In their method, they assumed that, while experts can estimate the most-likely activity duration, the boundaries are more difficult to estimate using traditional methods (Nasir et al. 2003). The Bayesian belief network was, therefore, applied to integrate the risk factors affecting activity duration when calculating the optimistic and pessimistic boundaries of Beta-Pert. However, their model did not distinguish between the variability in activity duration and the risk impact. Furthermore, their model was built using multiple questionnaires, making it difficult for construction companies to implement this approach because of the number of experts and time required to complete the questionnaires.

4.2.2 Correlation and Dependence in Risk Assessment

A common source of error in MCS is the assumption of independence between the input variables of a model (Touran and Wiser 1992). If two random variables are modeled as independent probability distributions in a simulation model, the sampled random variates of the two distributions will exhibit one of the following: (1) one variable is high, while the other is low, (2) both are high, or (3) both are low (van Dorp and Duffey 1999). Disregarding the dependence or correlation in large risk models can result in estimation errors through under- or overestimation (van Dorp and Duffey 1999). To improve risk analysis and subsequent decision-making, relationships between random variables must be considered (Clemen and Reilly 1999).

Multiple research studies investigating the effect of correlation in Monte Carlo risk assessment models have been conducted. Touran and Wiser (Touran and Wiser 1992) presented a methodology that can account for the correlation between cost components in probabilistic cost estimation models. It is important to note, however, that their model only considered variability in the cost of and correlation between project work packages without considering external risk factors in their model. Touran (Touran 1993) later extended the methodology by proposing a method that can account for subjective correlation between cost components by experts when historical data are absent.

van Dorp and Duffey (1999) proposed a method that can account for dependencies between activity durations when developing a project schedule network. The authors suggested that activities affected by the same external risk factor should be dependent and, therefore, that correlations between project activities can be determined from common risk factors that are shared. However, the correlation between cost and time impact of a risk factor was not considered in their model. Ökmen and Öztaş (2008) developed a heuristic method for correlating schedule-risk analysis in construction schedule planning. Their model considered correlations between activities that are affected by the same risk factors, as well as correlations between the risk factors themselves. However, only the impact of risks on the schedule were modeled. Moret and Einstein (2012) presented a model that considers correlations between the costs of activities in rail line construction when calculating the cost of a rail project. They then extended this by developing a comprehensive MCS model that considers (1) variability in activity duration and cost, (2) correlations between the cost of the activities, and (3) external risk factors affecting the project (Moret and Einstein 2016). However, their model did not consider the correlation between the cost and schedule impact of a risk factor. Other research studies have attempted to use multivariate distributions for presenting the output of a simulation model for integrated cost and schedule-risk analysis (Mawlana and Hammad 2015),(Covert and COVARUS 2013). While certain commercial software, such as @risk developed by the Palisade Group (Palisade n.d.), have correlations implemented, dependencies between the cost and schedule impact of a risk factor have not been addressed by these previously-developed models.

Copulas have been used in many applications to model dependencies between random variables. A copula-based joint distribution can be constructed using assessed rank-order correlations and marginal distributions, thereby reducing the effort required for assessments and to search for conditional independence (Clemen and Reilly 1999). Copulas are a flexible method, as they do not have any restrictions on the type of marginal distributions that can be used (Embrechts et al. 2003). Using copulas to "couple" the marginal distribution requires two steps, namely (1) modelling the marginal distributions and (2) modelling dependencies between random variables (Clemen and Reilly 1999). Copulas have been used in risk management literature to successfully model the dependencies between variables that can affect the decision to purchase a used aircraft (Clemen and Reilly 1999), in turn determining if the purchase of a used aircraft would generate more profit than using funds for other investments. Copulas have also been used to model dependencies between the activities of a project during the construction and scheduling of a project network (van Dorp and Duffey 1999).

4.2.3 Construction Risk Assessment in Onshore Wind Project and its Challenges

Installing a wind turbine onto its foundation and completing final assembly appears on the surface to be straightforward. However, constructing a wind farm involves a long list of civil engineering and electrical work that require high levels of project management and coordination (Rajgor 2011). Once permits, approvals, and project finance are secured, the rigorous management of a complex series of engineering, logistical, and electrical processes must occur to reduce uncertainties and risks (Rajgor 2011). While many studies have been conducted to enhance risk management in wind projects, most of these studies have focused on the exploration and identification of risk factors affecting onshore wind projects. For example, while several studies have investigated which risk factors affected the planning, construction, and operation phases of wind projects (Turner et al. 2013), (Finlay-Jones 2007), few studies have focused on methods for *assessing* risk factors. Kucukali (Kucukali 2016) developed a methodology for assessing the overall risk severity in wind projects based on a linguistic subjective scale. Rolik (Rolik 2017b) proposed a Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis approach to assess the risk level in wind energy projects. Mohamed and colleagues (Mohamed et al. 2020a) proposed a simulation-based approach to assess the severity of risk factors on the cost and time of onshore wind projects. Due to a lack of historical data, triangular and uniform distributions were used to depict the cost and schedule impact of the identified risk factors (Mohamed et al. 2020a). Notably, none of the aforementioned studies were capable of (1) incorporating large amounts of expert knowledge into simulation-appropriate input distributions and (2) considering the dependency between cost and schedule.

4.2.4 Fuzzy Logic

Fuzzy logic is often used to solve problems characterized by subjective uncertainty, ambiguity, and vagueness (Fayek 2020). It has been widely applied by researchers in construction to incorporate the influence of factors that are linguistically assessed into an uncertain variable quantity (Smith and Hancher 1989)(Budayan et al. 2018). The application of fuzzy logic provides a means of quantifying subjective evaluations and converting this information into a probability distribution function for input into MCS-based risk assessment models. The application of fuzzy logic for the linguistic assessment of root causes of risk factors in onshore wind projects, however, remains relatively unexplored.

4.3 Proposed Method

This research proposes a method that is capable of addressing the current input modelling limitations of MCS risk assessment (Figure 4.3). The methodology has three main components, namely input data, data processing, and multivariate representation, which are detailed as follows.

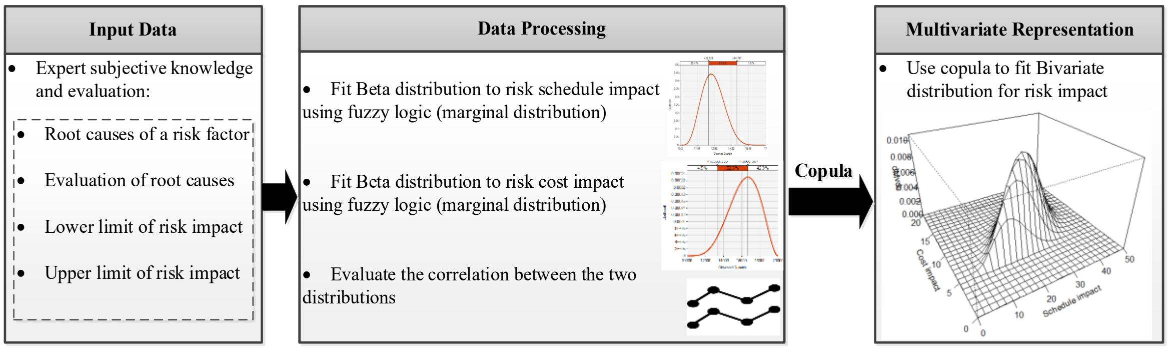


Figure 4.3. Fuzzy multi-variate research methodology.

4.3.1 Input Data

The input data component details the information required from the expert to successfully apply the methodology. Here, an expert provides detailed information about the impact of risks on schedule or cost, including (1) the minimum potential value of the risk impact (lower limit, A), (2) the maximum potential value of the risk impact (upper limit, B), and (3) root causes of the risk factor along with their evaluation.

To obtain this information, a root cause analysis, defined as “a structured investigation that aims to identify the true cause of a problem and actions necessary to eliminate it” (Andersen and Fagerhaug 2006), is performed to identify the potential root causes of different risk events (Ayyub 2014), (Abdelgawad and Fayek 2010) . Root cause analysis consists of five steps (Andersen and Fagerhaug 2006): problem understanding, problem-cause brainstorming, data gathering, data analysis, and root-cause identification. Several tools and techniques can be applied for the identification of root causes, such as cause-and-effect charts, matrix diagrams, five whys, fault tree analysis, and failure mode and effect analysis. Here, the analyst may choose any root cause analysis method, provided that it is suited to their application.

After the comprehensive identification of the root causes, possible scenarios that may occur as a result of these root causes are then defined, ensuring that all possible combinations that can lead to the primary risk factor are captured. All defined root causes/scenarios are assessed in terms of frequency and adverse consequences on the overall schedule or cost. This is often described in subjective terms, such as "*if the root cause 1 is very severe, it will significantly impact total schedule or cost, and this is very likely.*" As discussed previously, because of the subjectivity of the problem domain, current methods are not able to consider root causes when deriving a probability distribution for the impact.

4.3.2 Data Processing

4.3.2.1 Marginal Distributions

Fuzzy set theory is then used to scientifically quantify the combined influence of the root causes to derive the marginal probability distribution functions that will be input into the MCS models. The workflow for deriving the marginal distributions is illustrated in Figure 4.4, and a step-by-step procedure of the proposed method is detailed.

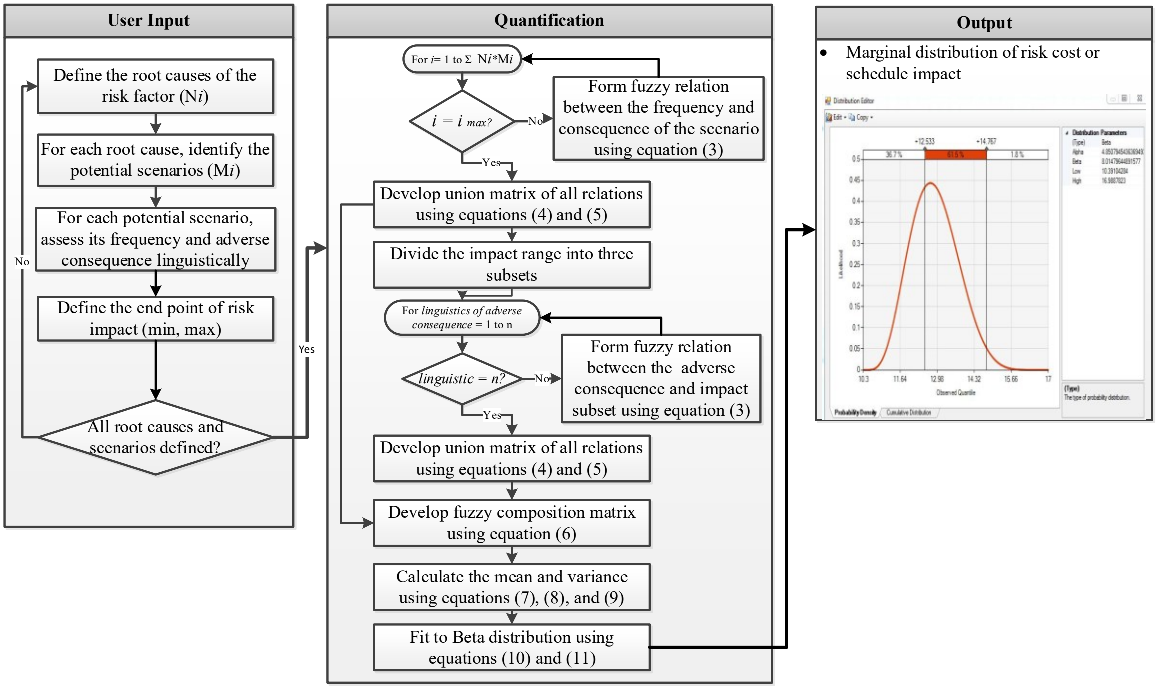


Figure 4.4. Quantification steps for marginal distribution.

This study has chosen a Beta distribution to represent the marginal distribution of schedule or cost impact. A Beta distribution was selected because (1) its specialized form, the PERT distribution, is commonly applied in risk assessment studies (Johnson 2002), (2) it is a bounded distribution with finite limits, making it intuitively plausible to many decision-makers in risk analysis (Johnson 2002), (3) it is flexible, taking any shape according to its shape parameters (i.e., ß and α) (AbouRizk et al. 1994), (AbouRizk et al. 1991), and (4) it is frequently used to describe variability or uncertainty over a fixed (i.e., bounded) range (Yoe 2016). The steps for integrating subjective knowledge into the Beta distributions are detailed as follows.

A membership function is usually used in fuzzy sets to represent the relationship between a range of possible values and a linguistic term (Fayek and Lourenzutti 2018). The membership function assigns a membership degree, in which the relation of these values to the linguistic term is defined within the interval [0, 1], representing no and full membership, respectively. In general, the membership of a fuzzy set, A, in the case of a discrete universe of discourse, X, is usually expressed as follows:

$$A = \sum_{1=1}^{n} {}^{\mu_i}/_{x_i} = {}^{\mu_1}/_{x_1} + {}^{\mu_2}/_{x_2} + \ldots\ldots + {}^{\mu_n}/_{x_n} = \sum \mu_A(x)/x, \quad (4.2)$$

where $\mu_i = \mu_i(x_i)$ is the degree of belonging of element x_i to set A, and n = the number of elements in set A. In construction applications, triangular and trapezoidal fuzzy numbers are usually used to represent the membership function. The development of the membership function, including the selection of linguistic terms and the range of values that a linguistic term represent, is determined by the analyst.

Once root causes are identified and assessed linguistically, the quantification analysis can be conducted. The fuzzy logic quantification algorithm combines the adverse consequence (C) (i.e., the contribution of the root cause to the overall cost or schedule-risk impact as a percentage) and the frequency of occurrence (F) for each root cause scenario. This is accomplished by calculating a fuzzy relation matrix between (F) and (C), resulting in R (F, C), which is the Cartesian product F × C. The elements of R (F, C) are computed as follows:

$$\mu_R(x_i, y_i) = min[\mu_F(x_i), \mu_C(y_i)], \quad (4.3)$$

where x_i = an element of universe X; y_i= an element of universe Y; $\mu_R(x_i, y_i)$ = the membership value of element (x_i, y_i) in the fuzzy relation R; *min* = the minimum values of both elements x_i andy_i; $\mu_F(x_i)$ = the membership value of element x_i in fuzzy set F; and $\mu_C(y_i)$ = the membership value of element y_i in fuzzy set C.

Once all of the fuzzy relation matrices have been calculated, the fuzzy logic quantification algorithm calculates the union matrix of all the fuzzy relation matrices, thereby representing the combined effect of all root cause scenarios. The union of two fuzzy relations, for example S and Z, is denoted by S ∪ Z, and the membership function is calculated as follows:

$$\mu_{S\cup Z}(x_i, y_i) = max[\mu_s(x_i, y_i), \mu_z(x_i, y_i)] \quad (4.4)$$

where *max* = the maximum value of both relations s and z.

Union **U**, between the fuzzy relation matrices R (F, C), is then computed as:

$$U = max\ [(F_1 \times\ C_1) \cup (F_2 \times\ C_2) \cup (F_3 \times\ C_3)\ \dots\dots\dots\dots.. \cup (F_k \times\ C_k)], \quad (4.5)$$

where *max* = the maximum value of the two relations.

The next step uses expert knowledge to subjectively assess the relationship between the adverse consequence of a root cause and the overall cost or schedule impact of a risk factor. For example, "*if the adverse consequence of root 1 is large, then the overall risk impact is medium*." The range of a risk factor impact (i.e., between minimum and maximum) is then calibrated by mapping the range to a predefined scale using the concept of membership values. The mapping values represent the confidence level with which the expert believes that a particular value belongs to the set (AbouRizk and Sawhney 1993) and that the impact will be in a certain range. To facilitate the mapping, the risk impact range is divided into three equidistant subsets. Notably, Beta distributions can take multiple shapes, of which three cases, as shown in Figure 4.5, are of interest for calibration. These are shapes that are (1) skewed to the upper limit, (2) skewed to the lower limit, or (3) symmetric. Cases where the distribution is skewed toward the lower limit are mapped to the small impact range; cases where the distribution is symmetric are mapped to the medium impact range; while cases where the distribution is skewed toward the upper limit are mapped to the large impact range.

Once all of the adverse consequences of root causes are related to the overall risk impact, a fuzzy relation Q (C, *I*), which is the Cartesian product $C \times I$ between fuzzy subset C, representing the adverse consequence, and fuzzy subset I, representing the overall risk impact as per Equation (4.3), is computed. After forming all fuzzy relations matrices, a union matrix, V, of all relations is calculated using Equation (4.5)

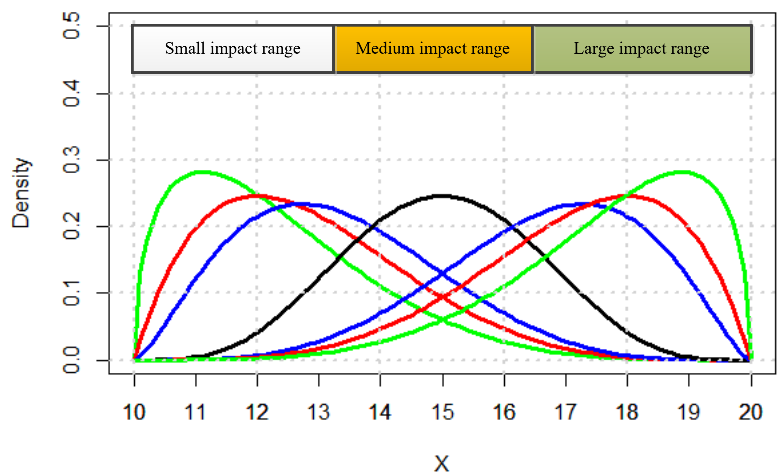


Figure 4.5. Quantification steps for marginal distribution.

Finally, a fuzzy composition of the union matrices U and V is calculated to assess the overall combined impact of all root causes. The composition is defined by Equation (4.6), which is the standard max-min composition as follows:

$$\boldsymbol{U}\circ\boldsymbol{V}(x_i, z_k) = \max_{y_j}\{min[\mu_U(x_i, y_i), \mu_V(y_j, z_k)]\}, \tag{4.6}$$

where $U\circ V(x_i, z_k)$ = membership value of element (x_i, z_k) in composition matrix between U and V; $\mu_U(x_i, y_i)$ = membership value of element (x_i, y_i) in union matrix U; and $\mu_V(y_j, z_k)$= membership value of element (y_j, z_k) in union matrix V.

A fuzzy subset from the composition matrix is used to represent the overall uncertain variable under study [46]. A fuzzy subset (e.g., subset = O), or one row from the matrix, will be selected such that the product of the row summation and the corresponding frequency of occurrence is the maximum. Then, the selected fuzzy subset (e.g., subset = O) will be used to calculate the mean, μ_I, and the variance, $\sigma^2{}_I$, of the marginal risk impact according to the following equations derived from (Ayyub and Haldar 1984), (Oliveros and Fayek 2005), (Corona-Suárez et al. 2014), and (Budayan et al. 2018):

$$\boldsymbol{P(R_I = z_k)} = \frac{\mu_o(z_k)}{\sum_1^m \mu_o(z_k)}, \tag{4.7}$$

$$\boldsymbol{\mu_I} = \sum_{k=1}^{m} (z_k) * P(R_I = z_k), \tag{4.8}$$

$$\boldsymbol{\sigma^2{}_I} = [\sum_{k=1}^{m} (z_k)^2 * P(R_I = z_k)] - \mu_I{}^2, \tag{4.9}$$

where R_I = risk impact; z_k = element of the risk impact; $P(R_I = z_k)$ = probability of occurrence of the risk impact to be element z_k; $\mu_o(z_k)$ = membership value of element z_k in subset O; and m = number of risk impact elements in subset O.

Once the mean and variance are calculated, they are used, along with the minimum (A) and the maximum (B), to derive a generalized Beta distribution. Equations (4.8) and (4.9) together with terms A and B are used to estimate the shape parameters, α and ß, of the generalized Beta distribution as follows (AbouRizk et al. 1994).

$$\boldsymbol{\alpha} = \frac{\mu_I - A}{B - A}\left[\frac{(\mu_I - A)(B - \mu_I)}{\sigma^2{}_I} - 1\right] \; and, \tag{4.10}$$

$$\boldsymbol{ß} = \alpha\left[\frac{B - \mu_I}{\mu_I - A}\right], \tag{4.11}$$

The probability density function is then visualized using shape parameters α and ß together with the end points of distributions A and B.

4.3.2.2 Correlation of Dependent Variables

Using copula-based multivariate modelling requires the correlation between dependent variables to be evaluated. When historical data are lacking, a subjective evaluation of the correlation from experts is acquired. Here, the Spearman correlation (ρ) is used to measure the association between random variables because of its ability to capture relationships through a pairwise measure of dependence (van Dorp and Duffey 1999), (Clemen and Reilly 1999). While the Spearman correlation coefficient varies between -1 and +1, most correlations between cost and schedule in construction are positive, limiting the values in this application to between 0 and 1 (Touran 1993). Correlations are classified into three categories, as proposed by Touran (Touran 1993), to reflect the linguistic representation of correlations often used by experts, namely weak (0 - 0.3), moderate (0.3 - 0.6), and strong (0.6 - 1). The midpoint of each interval is chosen to represent the interval (i.e., 0.15 for weak, 0.45 for moderate, and 0.8 for strong). Consequently, the correlation matrix (R) will take one of the following forms.

$$\boldsymbol{R}_{\boldsymbol{weak}} = \begin{bmatrix} 1 & 0.15 \\ 0.15 & 1 \end{bmatrix}, \tag{4.12}$$

$$\boldsymbol{R}_{\boldsymbol{moderate}} = \begin{bmatrix} 1 & 0.45 \\ 0.45 & 1 \end{bmatrix}, \mathit{and,} \tag{4.13}$$

$$\boldsymbol{R}_{\boldsymbol{strong}} = \begin{bmatrix} 1 & 0.8 \\ 0.8 & 1 \end{bmatrix}. \tag{4.14}$$

4.3.3 Multivariate Representation

The last component of the methodology is the multivariate representation of the marginal distributions of the schedule- and cost-risk impacts that is achieved using copulas (Yan 2007). There are many classes of copulas, including elliptical, Archimedean, and Marshall-Olkin (Embrechts et al. 2003). Selection criteria for specific classes of copulas have yet to be established (Moret and Einstein 2012); therefore, the class of copula selected is up to the discretion of the analyst.

4.4 Application and Results

An illustrative case study is presented to demonstrate the functionality of the proposed approach. The example risk factor chosen for illustration is public obstruction during the construction phase of the project, which is a critical risk factor that is known to cause project delays and financial losses (Diógenes et al. 2019).

4.4.1 Input Data

Four root causes were identified, namely noise due to construction activities, harm to business and farming activities of the local community, traffic disturbance due to logistic and supply chain to the construction site, and poor communication with the local community. Scenarios/root causes that may occur are detailed in Table 4.1.

Table 4.1: Root causes of risk factors with accompanying scenarios and assessment

No.	Root Cause/Scenario	Frequency of Occurrence (F)	Adverse Consequence (C)
1	Construction noise is low	Likely	Very small
2	Construction noise is medium	Likely	Large
3	Construction noise is high	Unlikely	Large
4	Harm to activities is low	Unlikely	Small
5	Harm to activities is medium	Somewhat likely	Large
6	Harm to activities is high	Unlikely	Very large
7	Traffic disturbance is low	Very likely	Very small
8	Traffic disturbance is medium	Somewhat likely	Large
9	Traffic disturbance is high	Unlikely	Very large
10	Poor communication	Unlikely	Medium

4.4.2 Data Processing

4.4.2.1 Marginal Distributions

The assessment (Table 4.1) includes the frequency of occurrence (F) and adverse consequence (C) of the scenario/root cause in linguistic terms. The linguistic terms were then represented using a membership function chosen by the analyst. In this example, the following membership functions, adopted from (AbouRizk and Sawhney 1993), were used to represent (F) and (C), as shown in Table 4.2 and Table 4.3 respectively:

Table 4.2: Membership function for frequency of occurrence (F).

Element of Linguistic Variable	**Frequency of Occurrence (F)**				
	Very Unlikely	Unlikely	Somewhat Likely	Likely	Very Likely
0	1	0	0	0	0
0.1	0.8	0.8	0	0	0
0.2	0.2	1.0	0	0	0
0.3	0	0.8	0.5	0	0
0.4	0	0	0.8	0	0
0.5	0	0	1	0.5	0
0.6	0	0	0.8	0.8	0
0.7	0	0	0.5	1.0	0.5
0.8	0	0	0	0.8	0.8
0.9	0	0	0	0.6	0.9
1.0	0	0	0	0	1

Table 4.3: Membership function for adverse consequence (C).

Element of Linguistic Variable	**Adverse Consequence (C)**				
	Very Small	**Small**	**Medium**	**Large**	**Very Large**
0	1	1	0	0	0
0.1	0.81	0.9	0	0	0
0.2	0.25	0.5	0	0	0
0.3	0	0	0.2	0	0
0.4	0	0	0.8	0	0
0.5	0	0	1	0	0
0.6	0	0	0.8	0	0
0.7	0	0	0.2	0	0
0.8	0	0	0	0.5	0.25
0.9	0	0	0	0.9	0.81
1.0	0	0	0	1	1

Once the linguistic assessment was conducted for all scenarios, fuzzy relations were constructed using Equation (4.3). Table 4.4 shows the fuzzy relation of the first scenario (i.e., construction noise is low). Remaining scenarios were represented similarly (data not shown):

Table 4.4: Fuzzy relation R (F, C).

Frequency of Occurrence (F)	**Adverse Consequence (C)**		
	0	0.1	0.2
0.5	0.5	0.5	0.25
0.6	0.8	0.8	0.25
0.7	1.0	0.81	0.25
0.8	0.8	0.8	0.25
0.9	0.6	0.6	0.25

After all relations were determined, a fuzzy union matrix U of all relations was established using Equations (4.4) and (4.5). Table 4.5 shows the fuzzy union matrix of all relations.

Table 4.5: Fuzzy union matrix (U) of all relations of the scenarios.

Frequency of Occurrence (F)	**Adverse Consequence (C)**										
	0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**
0	0	0	0	0	0	0	0	0	0	0	0
0.1	0.8	0.8	0.5	0.2	0.8	0.8	0.8	0.2	0.5	0.8	0.8
0.2	1.0	0.9	0.5	0.2	0.8	1.0	0.8	0.2	0.5	0.9	1
0.3	0.8	0.8	0.5	0.2	0.8	0.8	0.8	0.2	0.5	0.8	0.8
0.4	0	0	0	0	0	0	0	0	0.5	0.8	0.8
0.5	0	0	0	0	0	0	0	0	0.5	0.9	1
0.6	0	0	0	0	0	0	0	0	0.5	0.8	0.8
0.7	1.0	0.81	0.25	0	0	0	0	0	0.5	0.9	1
0.8	0.8	0.8	0.25	0	0	0	0	0	0.5	0.8	0.8
0.9	0.9	0.81	0.25	0	0	0	0	0	0.5	0.5	0.5
1.0	1	0.81	0.25	0	0	0	0	0	0	0	0

Then, the end points of the cost-risk impact distribution were identified by the analyst as minimum = $ 10,000 and maximum = $ 40,000. The range was divided into three equidistant sections, each with value of $ 10,000. Then, at the analyst's discretion, each range impact was divided into 5 elements. A membership degree for each element in each impact range was assigned by the analyst. The elements in each range along with the membership degrees are provided in Figure 4.6.

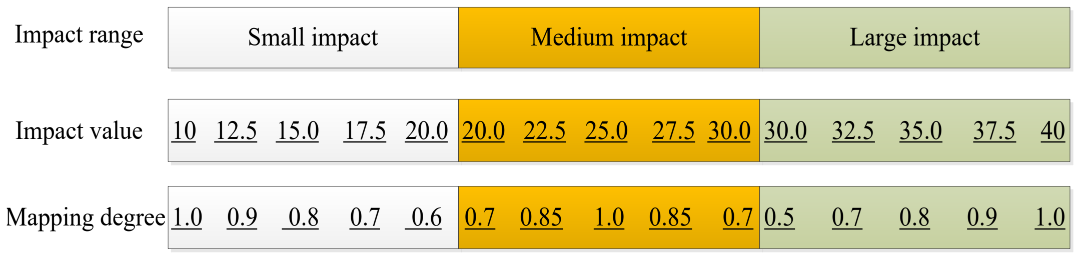


Figure 4.6. Ranges of risk impact along with values and their membership degree.

The adverse consequence of root causes was related to the overall risk impact subjectively (i.e., if the consequence is very small, the impact will be small) by the expert, as shown in Table 4.6.

Table 4.6: Relationships between adverse consequence (C) and impact (I).

No.	**Adverse Consequence (C)**	**Impact (I)**
1	Very small	Small
2	Small	Small
3	Medium	Medium
4	Large	Large
5	Very large	Large

Once assessed, each relationship was represented using a fuzzy relation matrix as per Equation (4.3). An example of fuzzy relation for row No. 3, Q (C_{medium}, I_{medium}), is provided in Table 4.7.

Table 4.7: Fuzzy relation Q (C, I) between medium adverse consequence (C) and medium impact (I).

Adverse Consequence (C)	**Impact (I)**				
	20.0	**22.5**	**25.0**	**27.5**	**30.0**
0.3	0.2	0.2	0.2	0.2	0.2
0.4	0.7	0.8	0.8	0.8	0.7
0.5	0.7	0.85	1	0.85	0.7
0.6	0.7	0.8	0.8	0.8	0.7
0.7	0.2	0.2	0.2	0.2	0.2

After establishing all relations, a fuzzy union matrix, V, between all relations was established, as detailed in Table 4.8, using Equations (4.4) and (4.5).

Table 4.8: Fuzzy union matrix V of all relationships between adverse consequence (C) and impact (I).

Adverse Conseq.	Impact*$\mathbf{10^3}$												
	10	12.5	15	17.5	20	22.5	25	27.5	30	32.5	35	37.5	40
0	1.0	0.9	0.8	0.7	0.6	0	0	0	0	0	0	0	0
0.1	0.9	0.9	0.8	0.7	0.6	0	0	0	0	0	0	0	0
0.2	0.5	0.5	0.5	0.5	0.5	0	0	0	0	0	0	0	0
0.3	0	0	0	0	0.2	0.2	0.2	0.2	0.2	0	0	0	0
0.4	0	0	0	0	0.7	0.8	0.8	0.8	0.7	0	0	0	0
0.5	0	0	0	0	0.7	0.85	1.0	0.85	0.7	0	0	0	0
0.6	0	0	0	0	0.7	0.8	0.8	0.8	0.7	0	0	0	0
0.7	0	0	0	0	0.2	0.2	0.2	0.2	0.2	0	0	0	0
0.8	0	0	0	0	0	0	0	0	0.5	0.5	0.5	0.5	0.5
0.9	0	0	0	0	0	0	0	0	0.5	0.7	0.8	0.9	0.9
1.0	0	0	0	0	0	0	0	0	0.5	0.7	0.8	0.9	1.0

Fuzzy composition matrix $U \circ V(x_i, z_k)$ of the union matrices U and V (Table 4.5 and Table 4.8 respectively) was calculated using Equation (4.6). The resulting matrix is provided as Table 4.9. The multiplication of the rows' summation and frequency of occurrence is provided. Row No. 9 (Table 4.9, grey) was selected, as it provided the maximum value for the product.

Table 4.9: Fuzzy union matrix V of all relationships between adverse consequence (C) and impact (I).

Frequency of Occurrence	Impact*10^3													Row Sum	Multiplication
	10.0	12.5	15.0	17.5	20.0	22.5	25.0	27.5	30.0	32.5	35.0	37.5	40.0		
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.1	0.8	0.8	0.8	0.7	0.7	0.8	0.8	0.8	0.7	0.7	0.8	0.8	0.8	10.0	1.00
0.2	1.0	0.9	0.8	0.7	0.7	0.85	1	0.85	0.7	0.7	0.8	0.9	1.0	10.9	2.18
0.3	0.8	0.8	0.8	0.7	0.7	0.8	0.8	0.8	0.7	0.7	0.8	0.8	0.8	10.0	3.00
0.4	0	0	0	0	0	0	0	0	0.5	0.7	0.8	0.8	0.8	3.6	1.44
0.5	0	0	0	0	0	0	0	0	0.5	0.7	0.8	0.9	1.0	3.9	1.95
0.6	0	0	0	0	0	0	0	0	0.5	0.7	0.8	0.8	0.8	3.6	2.16
0.7	1.0	0.9	0.8	0.7	0.6	0	0	0	0.5	0.7	0.8	0.9	1.0	7.9	5.53
0.8	0.8	0.8	0.8	0.7	0.6	0	0	0	0.5	0.7	0.8	0.8	0.8	7.3	5.84
0.9	0.9	0.9	0.8	0.7	0.6	0	0	0	0.5	0.5	0.5	0.5	0.5	6.4	5.76
1.0	1.0	0.9	0.8	0.7	0.6	0	0	0	0	0	0	0	0	4.0	4.00

After selecting the subset, row No. 9, that represents the cost-risk impact, the probability of each element in the cost-risk impact subset was calculated, according to Equation (4.7), as follows:

$P(R_I = 10)=$ $P(R_I = 12.5)=$ $P(R_I = 15) =$ $P(R_I = 35)=$ $P(R_I = 37.5)$ $=P(R_I = 40)$ $\frac{0.8}{7.3}$ = 0.1095,

$P(R_I = 17.5) = P(R_I = 32.5) = \frac{0.7}{7.3} = 0.0958,$

$P(R_I = 22.5) = P(R_I = 25) = P(R_I = 27.5) = \frac{0}{7.3} = 0,$

$P(R_I = 30) = \frac{0.5}{7.3} = 0.0685,$

$P(R_I = 20) = \frac{0.6}{7.3} = 0.082$

The mean and the variance were calculated, according to Equations (4.8) and (4.9), as follows:

$\mu_I = [(10 * 0.1095) + (12.5 * 0.1095) + (15 * 0.1095) + (17.5 * 0.0958) + (20 * 0.082) + (22.5 * 0) + (25 * 0) + (27.5 * 0) + (30 * 0.0685) + (32.5 * 0.0958) + (35 * 0.1095) + (37.5 * 0.1095) + (40 * 0.1095)] * 10^3 = 24910$ $

$\sigma^2{}_I = [(10^2 * 0.1095) + (12.5^2 * 0.1095) + (15^2 * 0.1095) + (17.5^2 * 0.0958) + (20^2 * 0.082) + (22.5^2 * 0) + (25^2 * 0) + (27.5^2 * 0) + (30^2 * 0.0685) + (32.5^2 * 0.0958) + (35^2 * 0.1095) + (37.5^2 * 0.1095) + (40^2 * 0.1095)] * 10^6 - (24910)^2 = 120488150$

Finally, the shape parameters of the risk impact Beta distribution were calculated, based on the minimum, maximum, mean, the variance, according to Equations (4.10) and (4.11), as follows:

$\alpha = \frac{24910-10000}{40000-10000}\left[\frac{(24910-10000)(40000-24910)}{120488150} - 1\right] = 0.43$

$\beta = 0.43\left[\frac{40000-24910}{24910-10000}\right] = 0.43$

The resulting probability density function of the Beta distribution is presented in Figure 4.7.

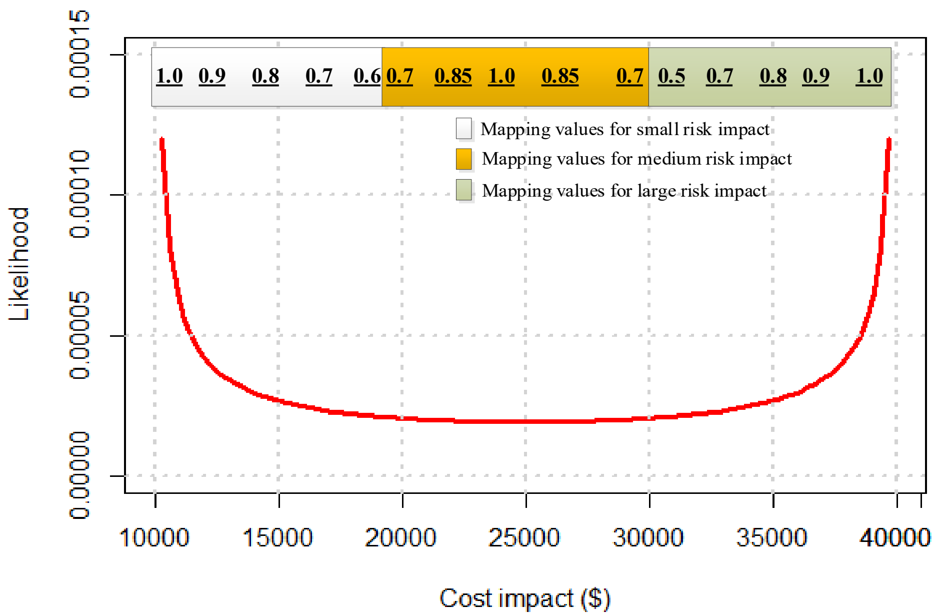


Figure 4.7. Marginal Beta distribution of cost-risk impact.

The marginal distribution of the schedule-risk impact was constructed in a manner similar to the marginal distribution of the cost-risk impact. The same root causes were used together with their evaluation in terms of frequency of occurrence (F) and adverse consequence (C). The mapping values were also the same as the cost-risk impact. Only the lower and upper limits of the distribution were changed. The lower limit was set to 1 day and the upper limit to 10 days. The range was divided into three subranges, namely small (1, 2, 3, 4), medium (4, 5, 6, 7), and large (7, 8, 9, 10), as shown in Figure 4.8, along with their mapping values. The shape parameters $\alpha = 0.412$ and $\beta = 0.523$ and the fitted Beta distribution is presented in Figure 4.8.

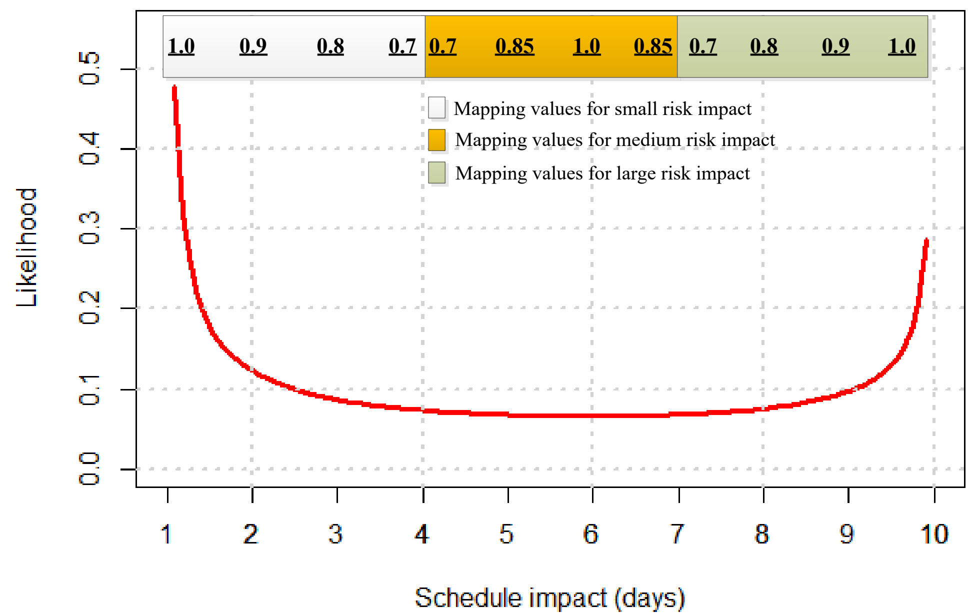


Figure 4.8. Marginal Beta distribution of schedule-risk impact.

4.4.2.2 Validation of the Marginal Distribution

Two approaches, namely sensitivity analysis and expert validation, were used investigate the proposed methodology. In the sensitivity analysis, the influence of input parameters on the fitted distribution was investigated, while the expert validation analysis was performed to evaluate the proposed approach from the perspective of an expert.

- Sensitivity Analysis

Sensitivity analysis is a powerful technique for testing the internal consistency and reliability of models (Lucko and Rojas 2010) by analyzing model behaviour in response to variations in input values or parameters. The purpose of conducting a sensitivity analysis is to assess how the input variables of a model affect the resulting probability distribution, allowing analysts to identify the input variables with the greatest influence on the output of a model or system (Saltelli et al. 2004). Two approaches are commonly used to conduct a sensitivity analysis: local (also known as absolute (Ashraf et al. 2018)) and global. The local approach allows only one variable of a model to be assessed at a time, while fixing all other variables to their original values (Saltelli et al. 2004). Conversely, global sensitivity allows all input factors to vary simultaneously, where the sensitivity is evaluated over the entire range of each input factor (Saltelli et al. 2004).

This study applied a local approach to investigate sensitivity of three input variables: (1) selection of linguistic variables; (2) membership values of the linguistic variables; and (3) membership values for calibrating and mapping the risk impact range. Sensitivity was calculated manually by changing the values of the targeted parameters and examining the effect on the resulting marginal Beta distribution. Parameters resulting in the greatest change were deemed to have the greatest impact on outputs. Thus, experts are encouraged to remain cognizant of such parameters during the application of the proposed method. Sensitivity of these parameters was tested on the parameters of the Beta distribution. The selection of linguistic terms is at the discretion of the analyst (Oliveros and Fayek 2005); however, the range that each linguistic term represents must be investigated. The illustrative case study was investigated again using different membership values for (F) and (C). First, the sensitivity of frequency of occurrence (F) was tested by introducing a new membership function, adopted from (Budayan et al. 2018), where the same linguistic terms are used but the membership values were changed. Results are detailed in Table 4.10.

Table 4.10: New membership function for frequency of occurrence (F).

Element of Linguistic Variable	**Frequency of Occurrence (F)**				
	Very Unlikely	Unlikely	Somewhat Likely	Likely	Very Likely
0	1	0	0	0	0
0.1	1	0	0	0	0
0.2	0.5	0.5	0	0	0
0.3	0	1	0	0	0
0.4	0	0.5	0.5	0	0
0.5	0	0	1	0	0
0.6	0	0	0.5	0.5	0
0.7	0	0	0	1.0	0
0.8	0	0	0	0.5	0.5
0.9	0	0	0	0	1
1.0	0	0	0	0	1

The shape parameters $\alpha = 0.389$ and $ß = 0.392$ and the fitted Beta distribution is shown in Figure 4.9. Differences between the original distribution and the one derived following the change in membership function of the frequency of occurrence (F) were minimal. The results demonstrate that small variations in membership values have little effect on the output distribution.

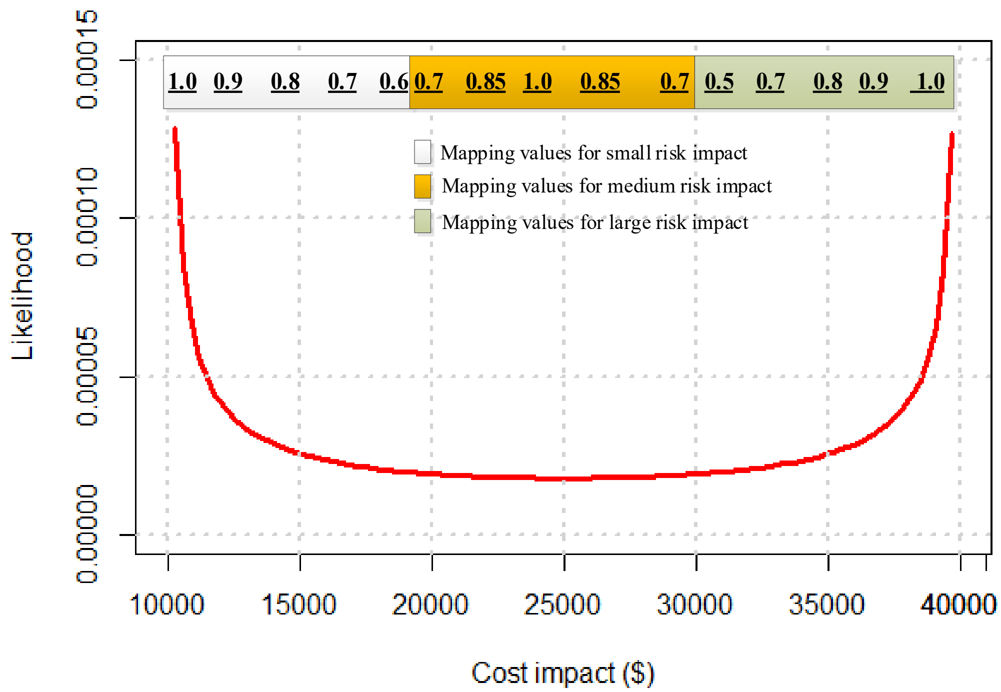


Figure 4.9. Marginal Beta distribution of cost-risk impact after changing the MF of (F).

Next, the influence of changing the membership function of the adverse consequence (C) was investigated by introducing a new trapezoidal membership function, as shown in Table 4.11. The shape parameters α = 0.592 and ß = 0.713 and the fitted Beta distribution is presented in Figure 4.10. Again, the differences between the original distribution and the one derived following the change in the membership function of the adverse consequence (C) were minimal. The results demonstrate that the output distribution is not sensitive to changes in the membership function of the adverse consequence (C).

Table 4.11: New membership function for adverse consequence (C).

Element of Linguistic Variable	Adverse Consequence (C)				
	Very Small	Small	Medium	Large	Very Large
0	1	0	1	0	1
0.05	1	0.05	1	0.05	1
0.1	0.5	0.1	0.5	0.1	0.5
0.15	0	0.15	0	0.15	0
0.2	0	0.2	0	0.2	0
0.25	0	0.25	0	0.25	0
0.3	0	0.3	0	0.3	0
0.35	0	0.35	0	0.35	0
0.4	0	0.4	0	0.4	0
0.45	0	0.45	0	0.45	0
0.5	0	0.5	0	0.5	0
0.55	0	0.55	0	0.55	0
0.6	0	0.6	0	0.6	0
0.65	0	0.65	0	0.65	0
0.7	0	0.7	0	0.7	0
0.75	0	0.75	0	0.75	0
0.8	0	0.8	0	0.8	0
0.85	0	0.85	0	0.85	0
0.9	0	0.9	0	0.9	0
0.95	0	0.95	0	0.95	0
1.0	0	1.0	0	1.0	0

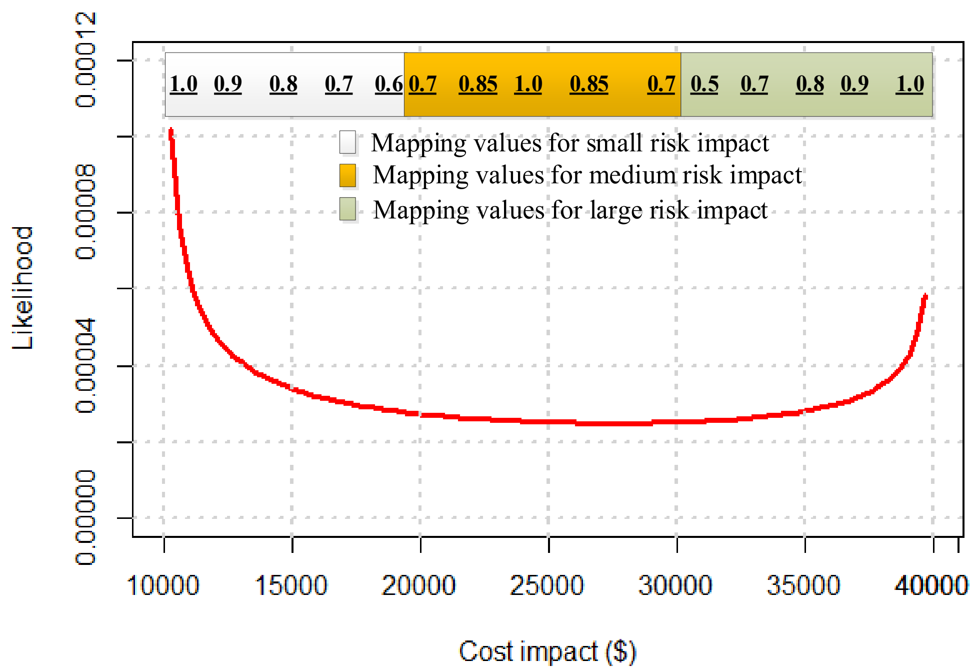


Figure 4.10. Marginal Beta distribution of cost-risk impact after changing the MF of (C).

The final sensitivity experiment investigated the influence of changing the membership values for calibrating the risk impact range. This was conducted by experimenting with different mapping values, while keeping all other values (i.e., membership functions for frequency of occurrence and adverse consequences, boundaries of the risk impact, and root causes and their evaluation) unchanged and set to their original values. The impact mapping values for each impact subset (i.e., “small impact,” “medium impact,” or “large impact,” as in Figure 4.6) were changed for each trial. Specific changes are summarized in Table 4.12. The parameters of the resulting distributions are detailed in Table 4.13, and the resulting probability density functions are shown in Figure 4.11 (a) through (f).

Table 4.12: Summary of sensitivity analysis experimental parameters on mapping values.

Trial	**Impact Mapping Values**[1]			**PDF**[2]	**Distribution**
	Small	**Medium**	**Large**		
(a)	1	0	0	Fig. 11(a)	Skews right, as values for small impact subset are equal to 1.
(b)	0	1	0	Fig. 11(b)	Symmetric, with peak at middle where mapping values equal 1.
(c)	0	0	1	Fig. 11(c)	Skews left, as values for large impact subset are equal to 1.
(d)	↓	peak = 1, other = ↓	↓	Fig. 11(d)	Symmetric as in trial (b), but with greater variance.
(e)	↑ until joint point	↓ until joint point	0	Fig. 11(e)	Skews towards small and medium joint point, where values are greatest.
(f)	0	↑ until joint point	↓ until joint point	Fig. 11(f)	Skews towards medium and large joint point, where values are greatest

[1]As defined in Table 6
[2]Probablity density function
Where ↓ = decreased gradually, and ↑ = increased gradually

Table 4.13: Results of sensitivity analysis of mapping values.

Trial	Statistical Parameters of Beta Distribution			
	Minimum ($)	Maximum ($)	α	ß
(a)	10,000	40,000	1.5	7.5
(b)	10,000	40,000	8.5	8.5
(c)	10,000	40,000	7.5	1.5
(d)	10,000	40,000	1.3	1.3
(e)	10,000	40,000	12.035	32.785
(f)	10,000	40,000	35.175	13.44

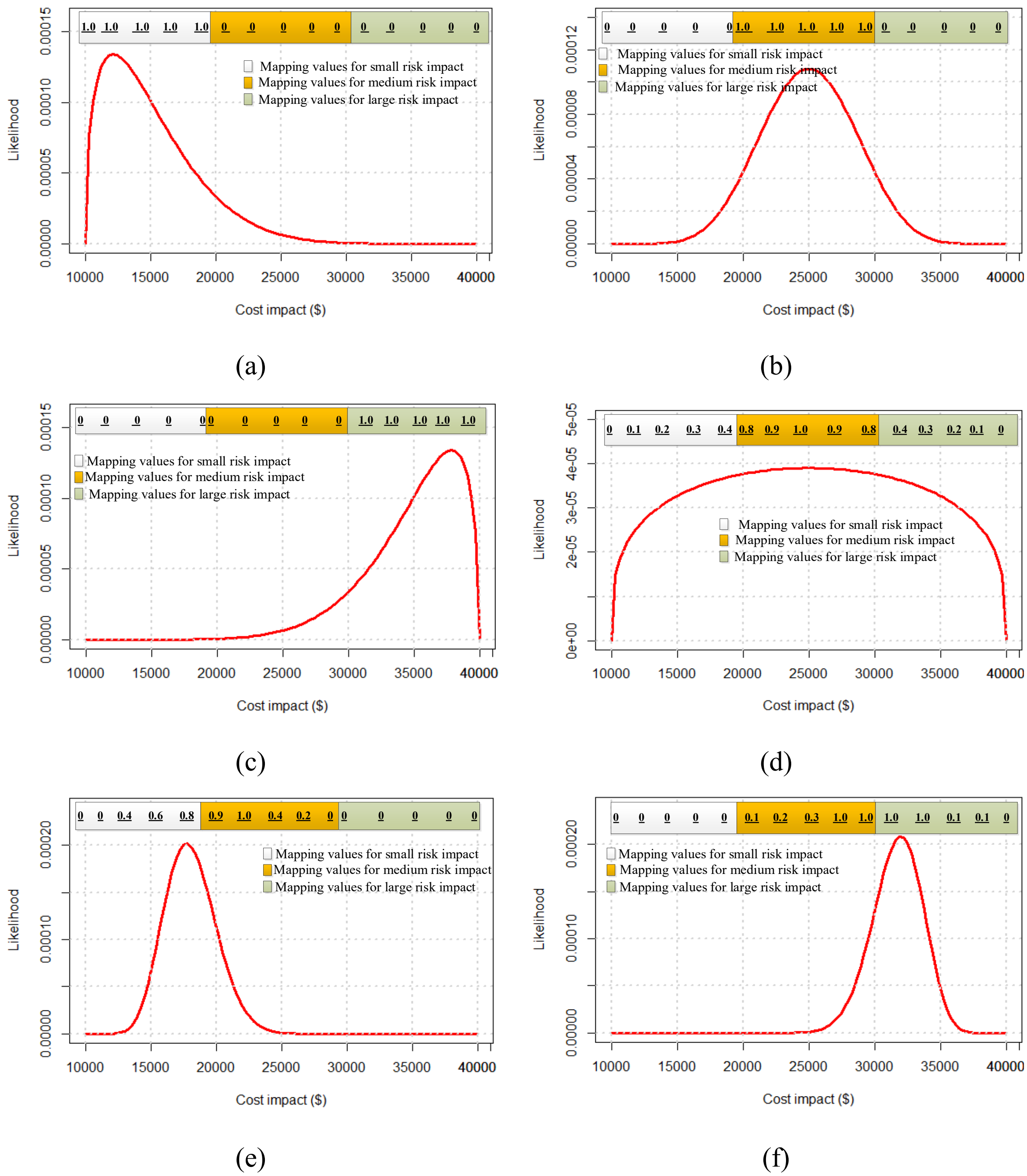


Figure 4.11. Marginal Beta distribution after changing the mapping value of the risk impact range.

Results of the sensitivity analysis demonstrate that the proposed method is not particularly sensitive to changes in the membership function of the frequency of occurrence (F) nor the adverse consequence (C). In contrast, the model was shown to be sensitive to changes in the mapping values of the risk impact range. This finding indicates the importance of capturing an expert's perceived impact values as precisely as possible. As discussed previously, decomposition of (1) a risk factor into its root causes and/or (2) a risk impact range into smaller subsets can be used to reduce biases, thereby enhancing the comprehensiveness and accuracy of model results. This explains the shape of the distribution observed in the illustrative case study (Figure 4.9 and Figure 4.10), where the expert was not confident about the mapping values for the risk impact, resulting in distribution with a uniform-like appearance.

- Expert Validation

Expert face validation is used to assess the practical applicability of a proposed method by having a subject matter expert evaluate the results of a proposed method (Lucko and Rojas 2010). The illustrative case study results and sensitivity analysis were discussed with three experts (i.e., a director, a project manager, and project coordinator) from a large construction company in Alberta, Canada—each with an average of 15 years of practical experience in construction management and risk analysis. Definitions of the terms representative, comprehensive, and ease of use (described as follows) were provided to the experts. Then, experts were asked whether or not they believed that the proposed method was characterized by each definition. Results are detailed as follows.

The experts agreed that the proposed method was representative, defined here as_the ability of a method to representatively express the knowledge of the expert as a probability distribution function. In particular, findings that distribution shape is sensitive to the mapping values of the range impact increased their confidence that the representation was appropriate.

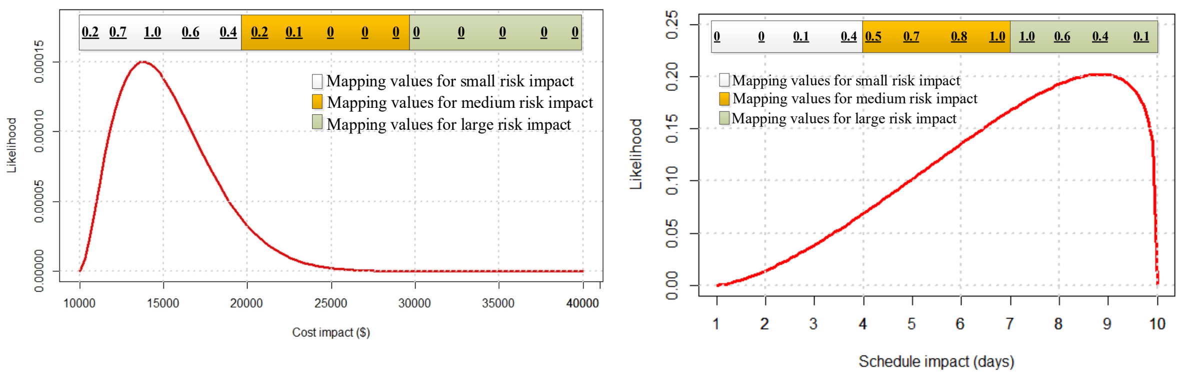
The experts also agreed that the proposed method was comprehensive, defined here as the ability of a method to include available information regarding the risk impact. They were satisfied with the level of information that the method allows them to incorporate while deriving the probability distribution.

In contrast, the experts indicated that the proposed method was, in its current form, not easy to use—particularly by analysts that may not be familiar with fuzzy logic computations. They agreed that full computerization of the approach would considerably facilitate its application in industry. Accordingly, this method was computerized within an in-house developed simulation engine, *SimphonyProject.NET* (Mohamed et al. 2020a), developed for integrated assessment of risks.

4.4.3 Multivariate Representation

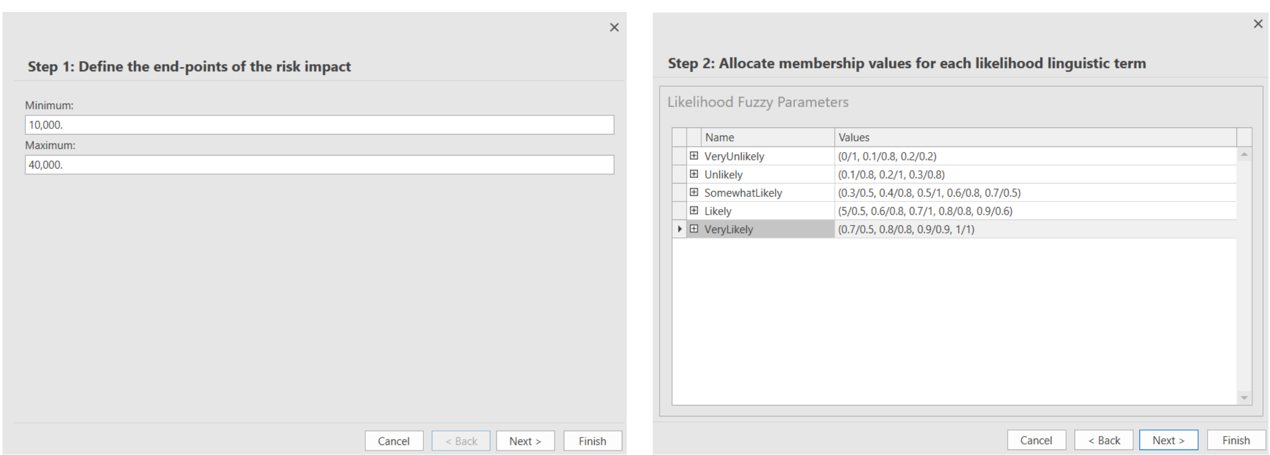
Following expert validation, a marginal distribution of the cost and schedule-risk impact based on expert knowledge was determined, as shown in Figure 4.12. The parameters of the final cost marginal distribution were lower limit = \$10,000, upper limit = \$40,000, shape parameter α = 2.7, and ß = 12.745; and the parameters of the final schedule marginal distribution were lower limit = 1 day, upper limit = 10 days, shape parameter α = 2.26, and ß = 1.13. Membership functions provided in Table 4.2 and Table 4.3 were used to derive the final marginal distributions. The steps of deriving the marginal distribution of the cost-risk impact in

SimphonyProjects.NET are detailed in Figure 4.13 (a to g). To represent the cost and schedule-risk impact of the risk factor using multivariate distribution, an expert was asked to subjectively evaluate the correlation as either weak, moderate, or strong. A strong correlation between cost and schedule impact was evaluated, and the correlation matrix in Equation (4.14) was consequently used in the bivariate distribution.

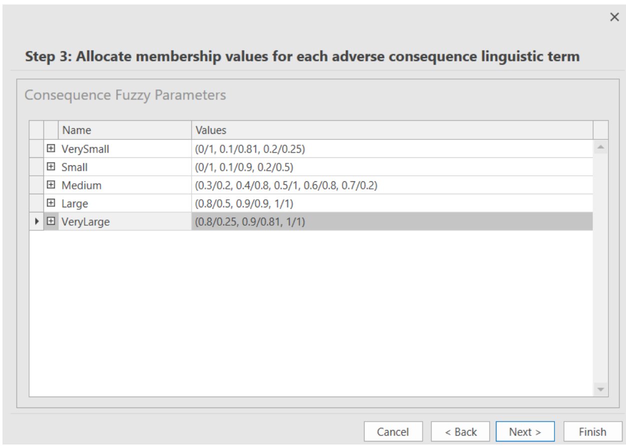


(a) (b)

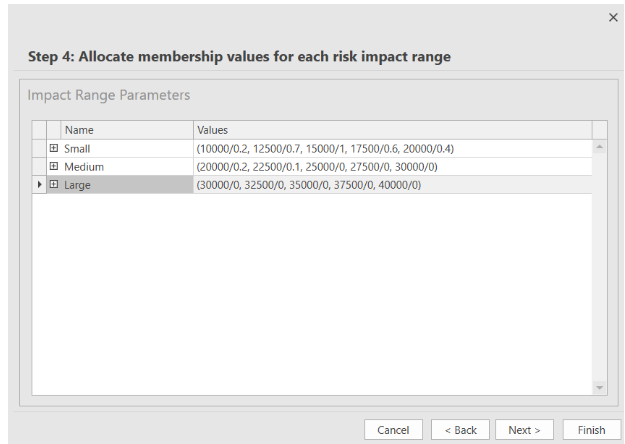
Figure 4.12. Final Marginal distribution of the (a) cost impact and (b) schedule impact.



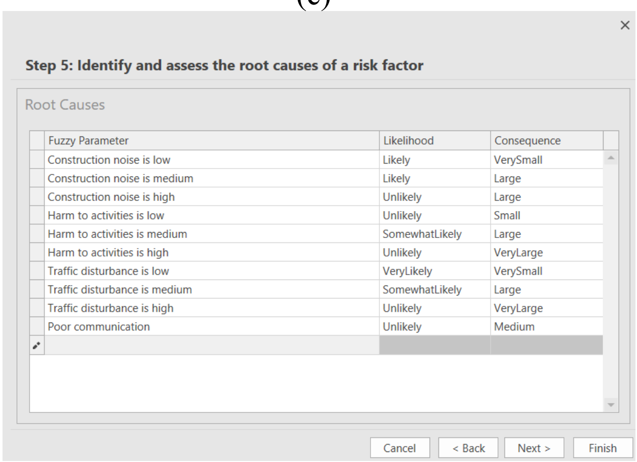
(a) (b)



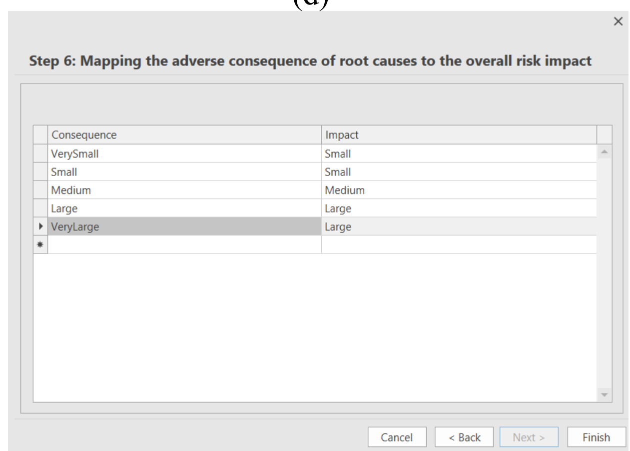
(c)



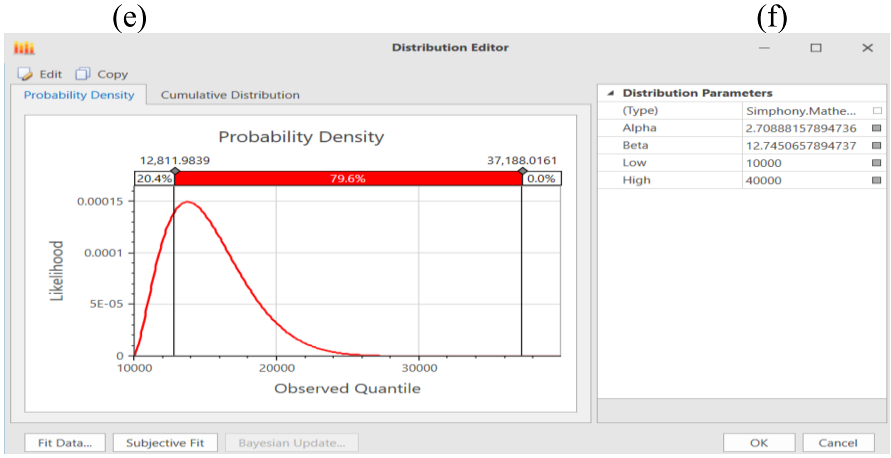
(d)



(e)



(f)



(g)

Figure 4.13. Steps of deriving marginal distribution in *SimphonyProjects.NET*.

Here, a multivariate normal copula (Yan 2007) was chosen because it (1) does not have constraints on the marginal distributions and (2) has been successfully applied in other risk assessment studies with Beta as marginal distributions (Clemen and Reilly 1999). A copula package in *R* (Yan 2007) was used to implement the multivariate modelling of the dependence of the cost- and schedule-risk impacts. The package allows the user to define the dependence structure and the marginal distributions separately. The dependence structure consists of the number of correlated random variables and the correlation coefficient. The marginal distributions were defined using extraDistr package (Wolodzko 2018), which allows for a generalized beta distribution that is not bound between 0 and 1. The dependence structure between the cost and schedule impact, specifically the two marginal distributions and the correlation between them, is presented in Figure 4.14. The output joint probability density function of the bivariate fitted distribution is presented in Figure 4.15 as a contour plot—a representation of the 3-dimentional surface of the joint probability distribution function show in Figure 4.16. The cumulative density function of the bivariate joint distribution is shown in Figure 4.17. It is this fitted distribution that will be used to model the risk factor (i.e. public obstruction) with correlated cost and schedule impact in a MCS experiment.

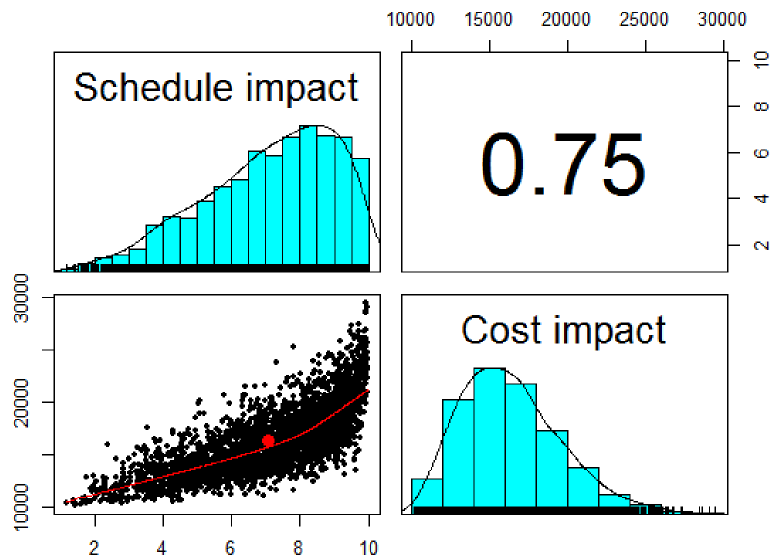


Figure 4.14. Dependence structure between cost and schedule-risk impact.

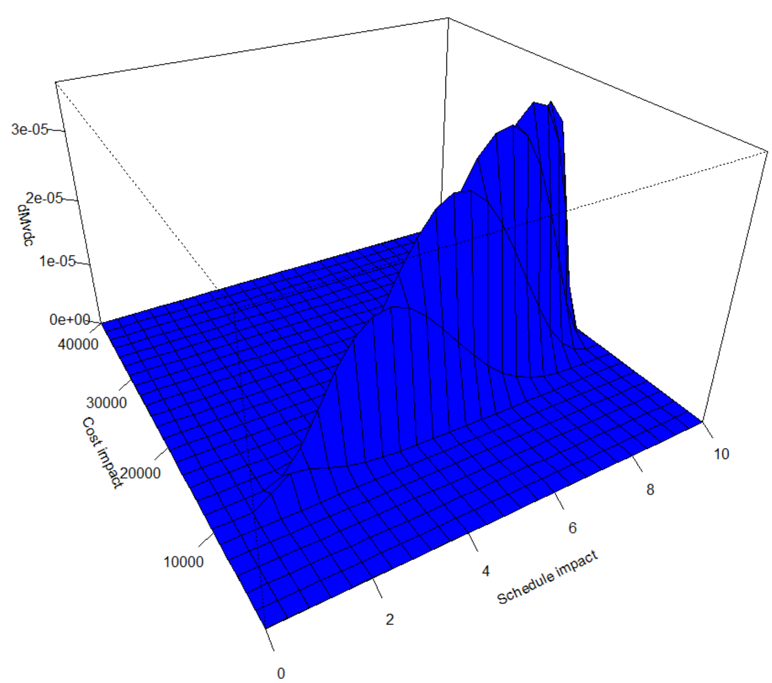


Figure 4.15. Probability density function of the joint distribution.

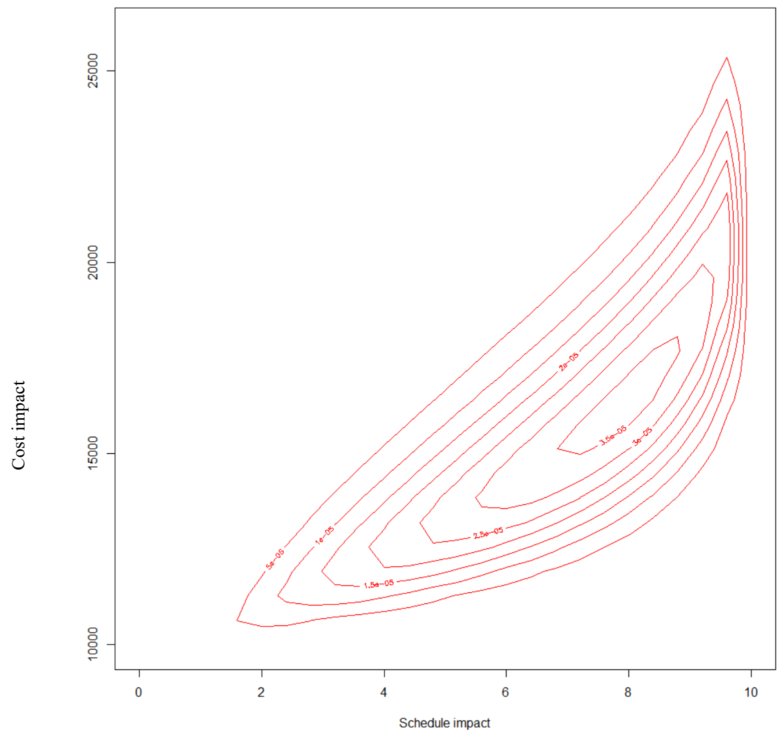


Figure 4.16. Contour plot of the joint probability density function.

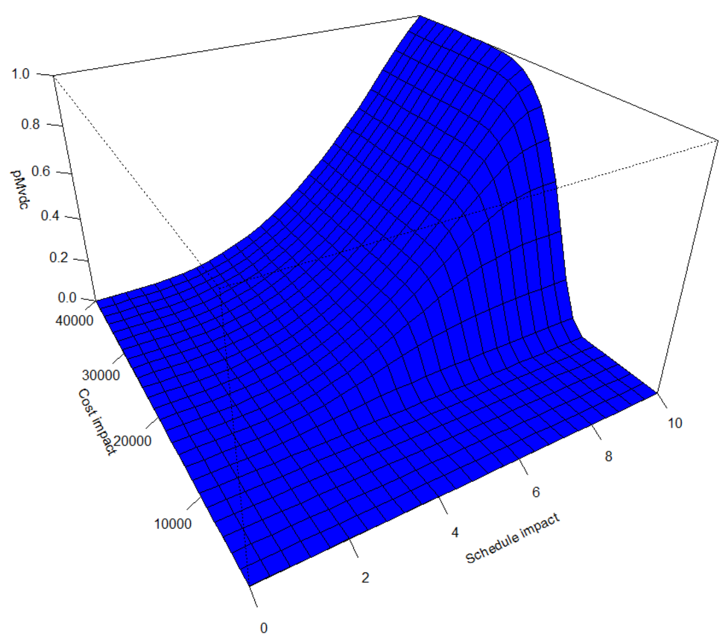


Figure 4.17. Cumulative density function of the joint distribution.

4.5 Application and Practical Benefits

Output of the model is presented in Figure 4.15. The process is repeated until a probability density function of the joint distribution is derived for each risk factor. These distributions can then be input into any existing MCS-based decision-support systems. Notably, for risk factors that have only schedule or risk impacts, marginal distributions will only be calculated for the cost-risk impact or schedule-risk impact [Figure 4.12 (a), (b)]. MCS-based decision-support systems use the distributions to sample a cost-risk impact, schedule-risk impact, or joint cost-schedule risk impact value for each risk factor based on its probability of occurrence. The results of several simulation iterations are then combined to provide a number of project insights, such as (1) the expected project completion date as cumulative distribution, (2) the expected project cost as a cumulative distribution, and (3) time and cost contingencies. Readers are referred to (Hulett et al. 2019), (Mohamed et al. 2020a), and (Moret and Einstein 2016) for more information on the application of MCS-based decision-support systems for risk assessment.

A primary benefit of the proposed method is its ability to incorporate detailed information into risk analysis inputs. Existing methods for deriving probability distributions from expert knowledge (e.g., elicitation of parameters for triangular, Pert, or uniform distributions) can only incorporate minimum, maximum, and most likely risk impact values. Experts are neither able to provide detailed information regarding the consideration of root causes nor perform risk impact decomposition, limiting the specificity and, in turn, accuracy, of model results. In contrast, the proposed method allows experts to consider the root causes of a risk factor while providing impact values within an impact range through value mapping. Indeed, results of the sensitivity analysis, which demonstrated that the model was particularly sensitive to changes in mapping values (Figure 4.11), indicate the importance of accurately capturing subjective information. Methods that allow for the decomposition of input information, such as mapping values to smaller ranges, can allow experts to more precisely express their subjective knowledge, thereby enhancing the comprehensiveness of model results.

A second benefit of the fuzzy logic approach presented here is the transformation of qualitative statements into a quantitative-like format (i.e., probability distribution function), thereby supporting the input of subjective data into quantitative methods, such as MCS. In turn, the proposed approach allows the use of one reliability-based risk assessment method throughout the life-cycle of a project. This alleviates the need for separate qualitative and quantitative methods in different phases of the project, in turn enhancing the consistency of output results.

4.6 Discussion

Difficulty selecting an input distribution that comprehensively represents risk impact (Ospina et al. 2019) has limited the use of probabilistic simulation-based risk assessment in practice—particularly in the planning and construction phase of wind farm projects that are characterized by a lack of historical data. While various methods and recommendations to overcome this challenge have been suggested in literature (Ospina et al. 2019), existing methods are not capable of incorporating a large amount of subjective knowledge in a time-sensitive, practical manner. Indeed, a flexible method that allows the expert to represent their subjective knowledge in a probability distribution has not been described in literature. The proposed approach addresses this limitation by allowing a risk analyst to (1) reliably assess the risk impact based on subjective knowledge and expertise, (2) consider the root causes of a risk factor when calculating its impact, (3) model the dependence between the cost and schedule impacts of a risk factor that has both cost and schedule impact, (4) reduce biases in expert evaluation through the decomposition of a risk factor, and (5) overcome the limitation for using MCS in practice (i.e., the need for historical data) (Salah and Moselhi 2015).

This research study proposed a fuzzy-based multivariate analysis approach to address limitations regarding data availability for construction risk assessment of onshore wind projects. The proposed approach was used to successfully solve an illustrative case study of one risk factor common to wind projects. Benefits of proposed method, which included the ability to incorporate detailed subjective knowledge of an expert through the consideration of additional risk factor details, were demonstrated. Furthermore, mapping values provided by experts within the impact range were found to have a considerable impact on the density function of resulting distribution (Figure 4.11). This was in contrast to minimal impact observed following modifications to the fuzzy membership function of adverse consequence (C) and frequency of occurrence (F) for evaluating root causes (Figure 4.9 and Figure 4.10). Although the proposed approach shares similarities with previously-developed methods (i.e., determination of minimum and maximum impact values), here, the probability density function of the resulting distribution is enhanced by two notable contributions, namely (1) calculating the most probable value from the combination of the root causes and their assessment and (2) mapping values to a risk impact range. Notably, this method can be applied to any type of project characterized by access to limited data and is, therefore, not limited to wind farm construction. However, before replication of the proposed method to other project, a thorough understanding of the input data in addition to the analysis steps should be investigated. Usually, different types of construction projects have different characteristics and assumption which should be investigated before the analysis.

While the proposed method showed an improvement over previously-developed approaches, the findings of this study should be interpreted in consideration of the following limitations. First, the membership function used in this study is a linear triangular and trapezoidal membership function. Other non-linear shapes for membership functions were not investigated and may affect the results. Nevertheless, most membership functions can be accurately represented by either triangular or trapezoidal functions (Fayek and Oduba 2005). Second, the risk impact range was divided into three subsets; the examination of more subsets may help experts to better express their belief and confidence about a risk impact. Third, the multivariate approach proposed here will require additional data pooling efforts to ensure that data for all impact dimensions are collected. Models must be built on information that is available and may need to be adjusted in instances where data are lacking, incomplete, or in an inappropriate format for analysis. In this research, a normal copula was used based on the recommendations of previous studies. Future work will include testing multiple copulas, comparing their performance, and developing a complete MCS model for risk assessment considering the developed probability distributions by the proposed method.

4.7 Conclusion

Input modelling is the first step in MCS-based risk assessment of construction projects.

Typically derived using historical project data, the use of MCS-based risk assessment in newer projects has been limited. Because of this, the subjective knowledge of risk analysts at a detailed level has not been properly considered when developing probability distributions for Monte Carlo risk assessment in construction. Therefore, this research tried to address the limitation of input modelling for risk assessment when historical data is lacking with only detailed subjective knowledge available. In particular, this research tried to devise a method that can make used of the experts' subjective knowledge with minimized biases when deriving a probability distribution for a risk factor impact. This research has developed a method capable of capturing and modelling expert subjective knowledge by deriving a flexible generalized Beta distribution through fuzzy logic. Distribution for risk factor impacts with either one type of impact (i.e., cost or time) or both (i.e., cost and time) can be developed with the proposed method. Risk factors that have both cost and schedule impact can be modeled using Bivariate distribution by considering the correlation between cost and schedule impact of a risk factor, with the fitted generalized Beta distribution representing the marginal distributions for schedule and cost-risk impact. The method was applied to assess one of the risk factors common to wind farm construction. Sensitivity analysis was performed, and the model was found to be sensitive to changes in the mapping values of a risk factor impact range. In contrast, changing the shape of the membership function did not affect the resulting distribution. We found that the decomposition of a risk factor into its root causes and decomposition of the risk impact into smaller ranges allows the experts to better depict their subjective knowledge using probability distribution accurately and comprehensively with lower biases. An implication of these findings is that both expert subjective knowledge and risk impact decomposition should be taken into account when deriving input distributions for MCS risk assessment. This will enable the application of quantitative methods in early stages of the project, thereby improving decision making processes. The proposed approach enables the effective, representative, and comprehensive elicitation of the probability distribution for input modelling in MCS-based risk assessment when only a detailed level of subjective knowledge exists.

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Chapter 5 : Domain-specific risk assessment using integrated simulation: A case study of an onshore wind project

5.1 Introduction

Wind power, as a renewable source of energy (Saidur *et al.* 2010), has gained popularity due to its relative cleanliness, sustainability, and cost-competitiveness. Anticipated to lead the transformation of the electricity sector, wind energy is expected to produce about 35% of global electricity demands by 2050. To meet this need, significant investments in the construction of wind energy farms are being made. In 2018 alone, an estimated 67 billion USD were invested in onshore wind power worldwide, with investments expected to double or triple by 2050 (IRENA 2019).

Similar to any large-scale project, wind farm construction has schedule and cost objectives, wherein the project must be completed within a specific timeframe and budgeted cost. As a relatively new type of endeavor, onshore wind farm construction is associated with a high level of uncertainty and risk (Gatzert and Kosub 2016; Rabe *et al.* 2019). Accurately assessing and managing this risk is essential for ensuring project success, and choosing a suitable risk assessment method is a key step in this process.

Risk assessment methods can be divided into two categories, namely qualitative and quantitative (Kendrick 2015; Salah and Moselhi 2016). In recent years, there has been a large development of quantitative risk models due to their increased accuracy over qualitative approaches (Taroun 2014). In spite of these advancements, however, quantitative models are rarely applied in construction practice (Laryea 2008). In 2014, Abdulmaten Taroun conducted a comprehensive literature review of risk modelling and assessment approaches used in construction since 1980 (Taroun 2014). This study concluded that, although numerous theories and techniques for improving risk assessment in construction have been proposed, theoretical advancements are not being translated into advances in construction practice (Taroun 2014). These findings align with those of a recent study by Jung and Han (2017), which reported that because of a lack of knowledge and real-world applicability, practitioners continue to rely on experienced-based, qualitative risk management approaches. Several studies have investigated barriers for the practical applications of quantitative models, with assessment and analysis identified as the most challenging issues (Baloi and Price 2003).

Quantitative methods described in literature are often presented using simple illustrative examples or generic project information. Although useful for demonstrating method generalizability, construction practitioners often have difficulty adapting and applying these generic methods to a specific project. This is particularly apparent in the wind farm construction sector, where real case studies and domain-specific models and tools are in short supply. Indeed, application of the gold standard quantitative risk assessment approach—the integrated Monte Carlo simulation and critical path method (MCS-CPM)—to a real wind farm project has yet to be reported in literature.

This case study details the first reported application of the state-of-the-art MCS-CPM approach to develop a domain-specific risk assessment model in wind farm construction. The domain-specific model is used to assess the impact of multiple risk factors on the cost and schedule of a real wind farm project. Notably, this case study also demonstrates the first application of a newly proposed input modelling method to consider the influence of correlations between cost and schedule impacts of risk factors in MCS. Time and cost contingencies, project durations, and overall project costs are then estimated. Demonstration of domain-specific models and approaches, such as the one presented here, are expected to help guide and promote the application of more accurate risk assessment methods in industry—in turn contributing to improved project planning, outcomes, and success.

Specific contributions of this study are two-fold. First, the case study demonstrates how to academically apply the MCS-CPM method to evaluate the impact of risks on a construction project. Domain-specific tools such as this are expected to facilitate the adoption and application of MCS-CPM by industry practitioners to more effectively assess construction risk in onshore wind projects. Second, this case study applies bivariate distributions to consider correlations between cost and schedule-related risk factors. The findings of this study not only support the use of a bivariate approach for risk assessment in construction, but also serve as an important demonstration of the types of decision-support that can be gleaned when correlations between cost and schedule-related risk factors are considered.

5.2 Literature Review

5.2.1 Risk Assessment in Wind Farm Construction

As a new construction type, both related literature and historical data for risk assessment in onshore wind farm construction remain scarce (Somi *et al.* 2020). While several studies have explored risk management in onshore wind farm projects, the majority of these studies are limited to the identification of risk factors in different phases of onshore wind projects across different countries (Gatzert and Kosub 2016; Xinyao *et al.* 2017; Gang 2015; Somi *et al.* 2020; Fera *et al.* 2014; Enevoldsen 2016; Montes and Martin 2007; Rolik 2017; Angelopoulos *et al.* 2016; Zhou and Yang 2020). Focusing primarily on identification, these approaches are unable to evaluate the potential impact of risk factors through quantification, greatly limiting their effectiveness in construction practice.

Certain studies have expanded upon identification by focusing on ranking safety hazards (Gul *et al.* 2018; Mustafa and Al-Mahadin 2018). Where quantification of risk factors in onshore wind farm construction has been attempted, methods have been developed for a specific subset of risk factors. Many available quantitative models for onshore wind projects have focused on analyzing specific risk factors affecting construction activities, such as adverse weather (Atef *et al.* 2010; Guo *et al.* 2017), while overlooking other types of risk. Few researchers have proposed methods by which risk factors can be quantified. Kucukali developed a methodology for assessing the overall risk severity in wind projects based on a linguistic subjective scale (Kucukali 2016), and Rolik proposed a Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis approach to assess the risk level in wind energy projects (Rolik 2017b). Despite this growing body of work, however, the use of a quantitative approach for assessing risk in onshore wind farm construction that is capable of analyzing the correlated impact of different subsets of risk factors on project cost and schedule has yet to be reported in literature.

5.2.2 Application of Quantitative Risk Models in Industry

Numerous studies have explored the barriers limiting the application of quantitative risk assessment techniques in practice. A lack of required expertise in or familiarity with techniques was consistently identified as a primary factor limiting the application of quantitative risk assessment methods in practice in many studies (Forbes *et al.* 2008; Akintoye and MacLeod 1997; Dey and Ogunlana 2004; Tang *et al.* 2007; Hlaing *et al.* 2008; Zhao *et al.* 2014; Lyons and Skitmore 2004; Chileshe and Kikwasi 2014). Specifically, Laryea and Hughes (2008) observed that many models in literature were not derived from the type of data or information that are commonly used in practice. Rather, many models were “desk-based” or analytically-derived (Laryea and Hughes 2008). Several researchers have promoted the development of risk assessment methodologies that reflect actual practice in construction (Laryea and Hughes 2008; Taroun 2014). This is a sentiment that is shared by Tang and colleagues, who have highlighted the potential for improving risk assessment in practice by systematically increasing risk management knowledge and skills—especially with regards to quantitative techniques (Tang *et al.* 2007).

One such approach is the application of quantitative techniques to real construction projects together with the development of domain-specific models and tools. In addition to facilitating model development and experimentation, domain-specific models allow for a better understanding of the simulation model by practitioners. An effective, domain-specific model should satisfy certain requirements as follows (Valentin and Verbraeck 2005):

(1) Support developers of domain-specific models by reducing the inherent difficulty associated with this process.

(2) Provide insight into complexity of the system to practitioners and future model developers.

(3) Detail required data, information, and system knowledge.

(4) Describe system deliverables.

5.2.3 Risk Management and Assessment Methods

Risk is an uncertain event that can negatively or positively affect the outcome of a project (Al-Bahar and Crandall 1990). Risk management processes begin by identifying potential risks that may occur during project execution (Abdelgawad 2011; Mills 2001; AbouRizk 2009; Chapman 2001). Then, a risk assessment, which converts the impact of risk into numerical terms (Mills 2001; Meyer 2015), is performed. Risk assessments are typically carried out using risk management support tools (Dikmen *et al.* 2004), which help to systematise the process, overcome analytical difficulties, and incorporate experience from previous projects into the decision-making process. Quantitative risk assessment methods can be classified into two categories (Bakhshi and Touran 2014):

(1) *Deterministic methods* can apply either a simple or complex mathematical approach. Simple mathematical approaches (e.g., pre-determined percentages) are considered the least sophisticated methods for risk analysis and are often performed when time is limited, projects are small, or owner budgets are insufficient. Simple deterministic methods depend on the subjective experience of the estimator, occasionally resulting in over- or underestimations (Salah and Moselhi 2015). Complex mathematical approaches develop theoretical mathematical models, often in the form of linear and non-linear equations such as regression and fuzzy logic (Meyer 2015). If historical data are unavailable, experts can provide qualitative or subjective assessment of risks, and fuzzy-set theory can then be applied to convert qualitative statements into numerical

values (Bakhshi and Touran 2014).

(2) *Probabilistic methods* typically incorporate the random uncertainty associated with construction projects by using probability theory to assess risk. Due to their accuracy, probabilistic methods are often considered the 'gold standard' of risk assessment approaches, especially when critical decision-making is required (Bakhshi and Touran 2014).

Previous risk assessment model research is summarized in Table 5.1. Models capable of assessing risk impact and estimating contingency are categorized into three types according to the focus of the analysis: cost-oriented, schedule-oriented, or integrated cost and time. Cost-oriented models focus on cost contingency and how risk factors affect project cost. Schedule-oriented models focus on time contingency and the impact of risk factors on project duration. Finally, integrated models address the impact of risk factors on project cost and time simultaneously. The advantages of integrating risks for schedule and cost, as described by Hulett and colleagues (2011), include (1) calculating schedule contingency, (2) calculating cost contingency, (3) presenting a joint probability distribution of project cost and schedule, and (4) prioritizing project risks, which, in turn, assist with the development of risk mitigation strategies for both time and cost. It is important to note, however, that these integrated models do not consider correlations between cost and schedule impact, which can lead to over- or underestimations of project contingencies.

Table 5.1: Summary of risk assessment models in construction

References	Model Category	Modelling Approach
Salah and Moselhi 2015 Idrus et al. 2011 Fateminia et al. 2020b Elbarkouky et al. 2016 Fateminia et al. 2020a	Cost	Fuzzy Logic
Barraza and Bueno 2007 Hammad et al. 2016 Molenaar 2005	Cost	Monte Carlo Simulation
Sonmez et al. 2007 Thal et al. 2010	Cost	Regression
Siraj and Fayek 2020	Cost	Fuzzy System Dynamics
Barraza 2011 Ökmen and Öztaş 2008 Schatteman et al. 2008 Khedr 2006 Koulinas et al. 2020	Time	Monte Carlo Simulation
Nasir et al. 2003	Time	Belief Network
Pawan and Lorterapong 2016	Time	Fuzzy Logic
Moret and Einstein 2016 Eldosouky et al. 2014 Hulett et al. 2019 Choudhry et al. 2014	Integrated	Monte Carlo Simulation

A commonly-applied probabilistic technique for risk assessment is Monte Carlo Simulation (MCS) (Molenaar *et al.* 2013; Bakhshi and Touran 2014; Liu *et al.* 2017). MCS has been widely applied for the quantitative assessment of risks in construction (Table 5.1) due to its ability to simulate the potential impact of risks on individual activities while also determining the amalgamated impact at a project-level (Hulett et al. 2011). Furthermore, MCS remains the only modelling approach capable of simultaneously addressing the integrated impact of risks on cost and schedule. While fuzzy logic has been successfully applied to model and evaluate cost and time contingencies separately (Table 5.1), current fuzzy logic-based models are limited in their ability to consider the integrated impacts of risk factors. While type-2 fuzzy numbers are required to consider the impact of both time and cost, the implementation of mathematical operations on type-2 fuzzy numbers is computationally complex and may result in the overestimation of uncertainty through the consecutive implementation of fuzzy arithmetic operations (Gerami Seresht and Fayek 2019).

The ability of MCS to integrate these impacts offers several advantages, including alleviating the need for analysts to calculate correlations between activities affected by the same risk factor (Eldosouky *et al.* 2014) and improving the prioritization of project risks during the development of risk mitigation strategies (Hulett *et al.* 2011).Well-known for its ability to generate accurate and realistic results (Zhao *et al.* 2014), MCS is considered the state-of-the-art technique for risk assessment (Raz and Michael 2001; Hulett *et al.* 2019).

Monte Carlo simulation is often coupled to a CPM network to create an integrated MCS-CPM risk assessment model. In comparison to other risk assessment techniques (e.g., PERT), combining the CPM with MCS improves the accuracy of stochastic project schedules by:

(1) Considering all possible values for the duration of each stochastic activity when determining project duration (as compared to mean durations) (Karabulut 2017).

(2) Considering the uncertainty associated with all project activities for determining project duration (as compared to only critical activities).

(3) Allowing practitioners to calculate the criticality index of each activity by running the

simulation model for a number of iterations and determining the frequency of occurrence of each activity in the critical path.

As a result of these advantages, MCS-CPM has become a recommended practice for risk assessment by the American Association of Cost Engineering (Hulett *et al.* 2019). Although considered a superior approach, previous MCS-CPM-based models consider cost and schedule impacts of a risk factor as independent variables (Table 5.2). While a method for considering the dependency between cost and schedule impacts through bivariate distributions has been recently proposed (Mohamed *et al.* 2020b), the method has not been applied to a real case study. As such, its functionality and practical utility for the evaluation of real case data remains unknown.

Table 5.2: Types of distributions used to represent the impact of risk on cost and schedule

Reference	**Cost Impact Distribution**	**Schedule Impact Distribution**	**Impact Value**
Eldosouky et al. 2014 Hulett et al. 2011	Triangular	Triangular	% of Baseline Activities
Hulett 2011	Triangular or Beta Pert[1]	Triangular or Beta Pert[1]	% of Baseline Activities
Smith et al. 2009 Moret and Einstein 2016	Triangular	Triangular	Absolute or %
Choudhry et al. 2014	Triangular	Triangular	Absolute
Mohamed et al. 2020	Generalized Beta	Generalized Beta	Absolute

[1]Where triangular and Beta Pert distributions have been verified as a proxies for each other (Johnson 1997).

5.3 Methodology

Monte Carlo simulation-critical path method was applied to develop a domain-specific risk assessment model. This model was then used to assess construction risks of a real wind farm project. The MCS-CPM methodology consists of four stages, namely input data preparation, modelling and quantification, decision-support, and sensitivity analysis. An overview of the methodology is provided in Figure 5.1. Model development, as well as a discussion of the results and practical implications of the method, are detailed as follows. The simulation logic of the MCS-CPM method is detailed in Figure 5.2

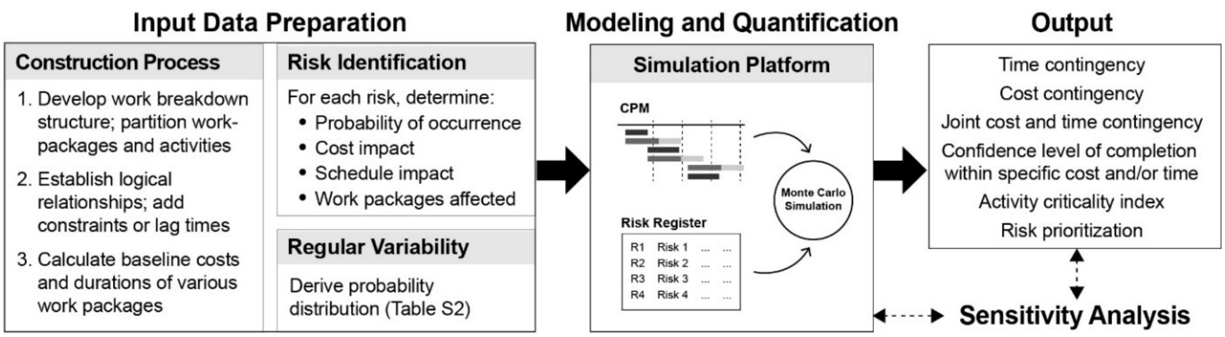


Figure 5.1. MCS-CPM Methodology.

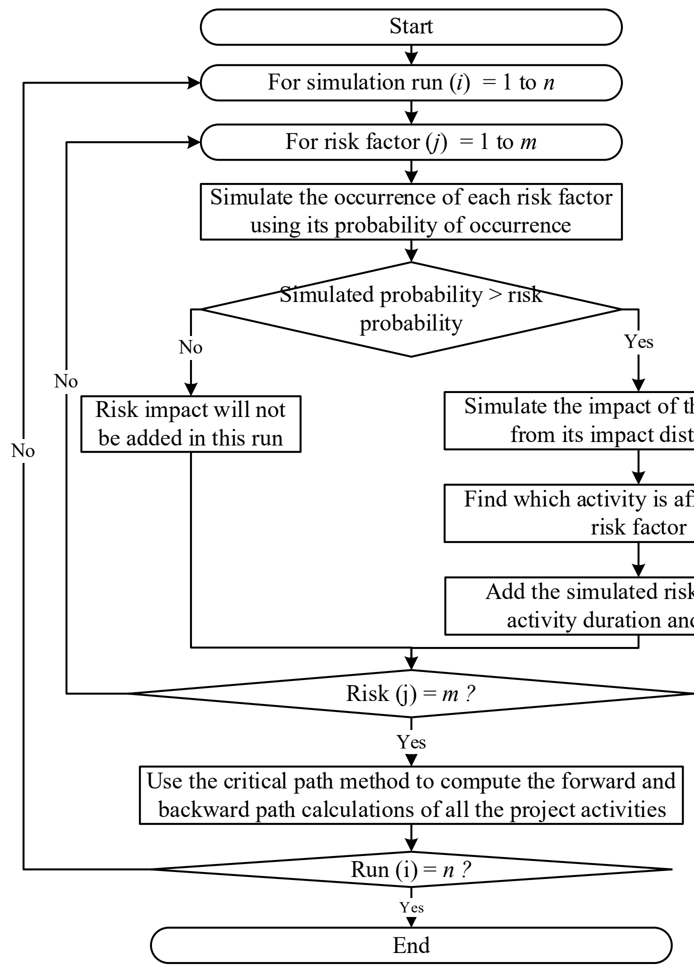


Figure 5.2. Simulation logic of MCS-CPM method.

5.3.1 Input Data Preparation

Construction Process Configuration

In this step, construction data are used to develop the cost-loaded schedule of the project and, using the CPM, to estimate baseline duration and cost. These data include work-package and activity information and are commonly prepared as follows:

(1) Work breakdown structure of the project is developed, and the project is partitioned into work-packages and activities at the required level.

(2) Logical relationships (e.g., finish to start) between work-packages and activities are established, and applicable constraints or required lag times are added.

(3) Construction durations and baseline costs of different work-packages and/or activities are calculated.

Risk Identification

Risk data are used to develop the risk assessment portion of the model as follows:

(1) Risks are identified using an established technique or a combination thereof; readers are referred to Siraj and Fayek (2019) for a review of commonly used techniques.

(2) Work-package(s) affected by each risk are determined.

(3) The probability of occurrence for each risk factor is determined using probability scales, such as those detailed in AbouRizk (2009), PMI (2008), and Abdelgawad and Fayek (2010).

(4) Risk impact distributions for cost and schedule are determined.

A challenge limiting the practicality of MCS is the requirement that impact parameters be input as probability distributions (Step 4). Distributions can be derived using a variety of methods depending on the types and amount of data available (Biller and Gunes 2010). As a relatively new type of construction, wind farm projects typically lack the volume of historical data required to derive probability distributions using statistical means. Types of distributions used in previous studies are summarized in Table 5.2. Due to a lack of historical data, a fuzzy-based multivariate method for determining risk impact distributions recently proposed by Mohamed *et al.* (2020b) was adopted in this study. The method is capable of integrating the detailed subjective knowledge of experts through fuzzy logic to derive the distributions for cost and schedule risk impact. The method is characterized by several advantages, including:

(1) It can be applied when the distribution type is unknown.

(2) It reduces bias through risk decomposition and inclusion of root causes.

(3) Unlike other methods, it considers the dependence between the risk and cost impact of a variable through copula-based bivariate distributions.

Readers are referred to Mohamed *et al.* (2020b) for more information.

Regular Variability

In addition to the uncertainty associated with risk impact and occurrence, uncertainty associated with regular variability in the duration and cost of construction activities must also be considered. Variability in cost and duration of project activities under regular conditions (Moret and Einstein 2016) can arise due to a number of factors including, but not limited to, estimation errors or biases (Eldosouky *et al.* 2014; Hulett *et al.* 2019). Although regular variability has an occurrence likelihood of 100%, the resulting impact on project cost and schedule is uncertain. This is in contrast to the variability associated with specific risks, where both likelihood and impact are uncertain. This study makes a clear distinction between uncertainty stemming from risk or from regular variability; here, regular variability is modeled stochastically by probability distributions (Moret and Einstein 2016; Hulett *et al.* 2019), and risks are modeled using likelihood and impact.

Previous research studies have proposed different types of probability distributions to model regular variability, as shown in Table 5.3.Triangular or beta pert distributions are most commonly used in the absence of historical data due to the ease in deriving the parameters of these distributions under such conditions. Lognormal distributions have also been used to represent the variability of activity costs (Moret and Einstein 2016); notably, cost variability was shown to be best fitted to this distribution when historical data were available (Touran and Wiser 1992).

Table 5.3: Types of distributions used to represent regular variability

Reference	**Activity's Cost Distribution**	**Activity's Duration Distribution**	**Project Type**
Moret and Einstein 2016	Lognormal	Triangular	Railway
Eldosouky et al. 2014	Triangular	Triangular	Water plant
Naderpour et al. 2019	Beta Pert	Beta Pert	Bridges
Khadem et al. 2018	Triangular	Triangular	Oil and gas
Hulett 2010 Hulett 2009	Triangular or Beta Pert	Triangular or Beta Pert	Generic

5.3.2 Modelling and Quantification

Once the input data are prepared, modelling and simulation can begin. Data are input into the MCS-CPM model and various parameters, including the early start/finish times, late start/finish times, activity float, and the critical path are calculated. Project activities or work-packages that are characterized by uncertainty are modeled stochastically using probability distributions (as previously described). Baseline costs of activities are evaluated and input into the model, and project risks are defined and assigned to specific activities/work-packages. Then, multiple iterations of MCS are performed. In each iteration, whether or not a risk occurred is determined by its probability of occurrence. If a risk is simulated to occur, a random value is sampled from the cost and schedule distributions, and the simulated impact is added to the cost and/or schedule of the affected activities/work-packages. The process is repeated until the specified number of iterations are reached. An illustrative example of the process is provided in Figure 5.3.

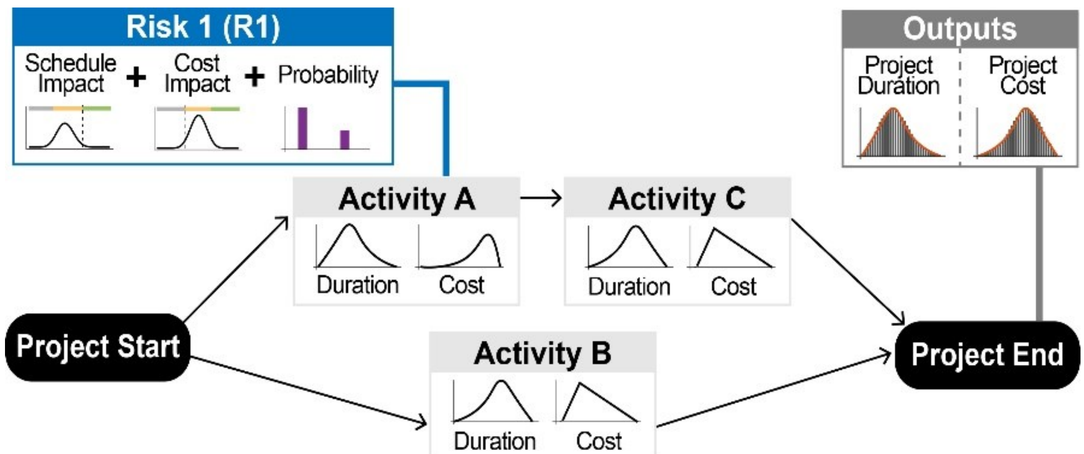


Figure 5.3. Illustrative example of the MCS-CPM method for a project consisting of three activities (A, B, and C) and one risk factor (R1) that affects Activity A.

5.3.3 Outputs and Decision Support

If a sufficient number of simulation iterations are performed, estimated project duration and cost can be represented as a probability distribution. Because the output of each simulation iteration (i.e., project time and cost) represents a possible project outcome, a joint cost-time contingency, which provides greater insight as compared to individual cost or time contingency values, can also be obtained. The MCS-CPM-based approach also allows for the investigation of the criticality of project activities. Risk factors that affect the duration of project activities can result in changes to the critical path of the project, which, in turn, can change the criticality of other project activities. A tornado diagram, which allows analysts to visualize the risks with the greatest impact on project cost and time (De Marco et al. 2012), can also be created. Finally, functionality of the simulation model is verified by testing the sensitivity of simulation outputs to changes in inputs (Kleijnen 2010).

5.4 Case Study

A real wind farm project was used to demonstrate the applicability of the MCS-CPM method. The onshore project consists of eight 5.0 MW wind turbine generators for a total project output of 40 MW. The project includes eight major work-packages as shown in Figure 5.4: pre-construction work, foundation, turbine delivery, turbine assembly, collection system, mechanical completion, commissioning, and site rehabilitation.

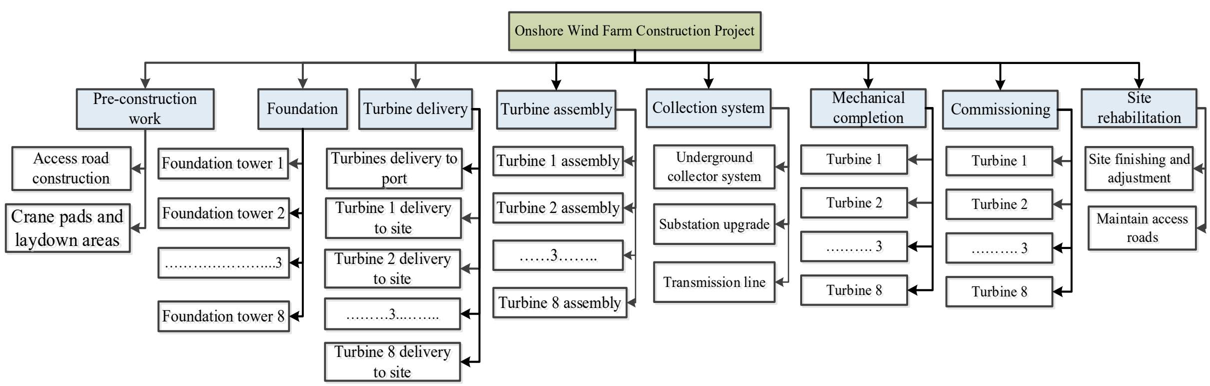


Figure 5.4. Work breakdown structure of case study.

5.4.1 Input Data Preparation

Construction Process Configuration and Regular Variability

Each of the work-packages was further partitioned into more detailed work-packages, as shown in Figure 5.4. Logical relationships between the work-packages and their durations were extracted from project plan documents, as shown in Table 5.4. The stochastic duration (i.e., regular variability) of work-packages was represented using either triangular or uniform distributions based on recommendations from previous studies (Table 5.3) and project experts.

Table 5.4: Work package details of the project

ID	Work Package Name	Duration (Days)	Predecessor/ Relationship (Lag)
W1	Access road construction	Triangular (40, 55, 47)	–
W2	Crane pad and laydown areas	Triangular (40, 55, 47)	1/F.S
W3	Foundation construction of tower[1]	Triangular (5, 10, 7)	2/F.S
W4	Delivery of turbines to port	Uniform (90, 110)	1/S.S
W5	To site delivery of turbine[2]	Triangular (7, 12, 10)	2/F.S; 4/F.S
W6	Erection and install of turbine[2]	Triangular (5, 10, 7)	5/F.S; 3/F.S Lag (15)
W7	Underground collection circuit	Triangular (100, 110, 105)	2/F.S
W8	Substation upgrade	Triangular (210, 215, 220)	1/S.S
W9	Transmission line	Triangular (105,115,110)	2/S.S
W10	Mechanical completion of turbine[2]	Triangular (3, 7, 5)	6/F.S
W11	Commissioning of turbine[2]	Triangular (5, 9, 7)	7/F.S; 8/F.S; 10/F.S
W12	Maintaining access road	Triangular (90, 100, 95)	5/S.S
W13	Project completion and final site verification	Triangular (7, 12, 9)	11/F.S

[1]Towers 1 or (2, 3, 4, 5, 6, 7, 8), [2]Turbines 1 or (2, 3, 4, 5, 6, 7, 8)

Risk Identification

Risk factors were identified and evaluated following a review of project documents and a brainstorming session with a group of three experts who were directly involved in the project. The list, which was collected and supplied by the industrial collaborator, is shown in Table 5.5; detailed descriptions of each risk factor are available in Table 5.6. It is important to note that risk factors were identified based on the characteristics of the studied project, and these risk factors may not be applicable to all onshore wind projects.

Table 5.5: Risk factor pre-evaluation

ID	Risk name	Probability of Occurrence	Cost Impact	Schedule Impact	Affected Work Package(s)
R1	Landmines	Unlikely	✓	✓	Entire Project
R2	Unexpected poor site geology	Very Unlikely	✓	✓	3
R3	Project completion delay	Somewhat Likely	✓	✓	Entire Project
R4	COVID-19-related delays	Likely	–	✓	Entire Project
R5	Limited experience	Likely	–	✓	11
R6	Blade erection failure	Very Unlikely	✓	✓	6
R7	Installation errors	Very Unlikely	✓	✓	6
R8	Concrete foundation issues	Very Unlikely	✓	✓	3, 11

Table 5.6: Risk factors description

ID	Risk	Description
R1	Landmines	The project is located in a previous warzone. The contractor/sub-contractors used a random technique to spot check for landmines in the project site area.
R2	Unexpected poor site geology	The contractor is relying on the owner's geotechnical data, which may not accurately represent ground conditions at the site. Additional geotechnical investigations may be required.
R3	Project completion delay	The owner/operator may not be able to satisfy requirements to provide commissioning and acceptance procedures by the specified dates; therefore, a liquidated damage must be paid.
R4	COVID-19-related delays	COVID-19 may result in delays in turbine component delivery and/or may limit the number of technicians onsite.
R5	Limited experience	With any new turbine model on the market, new technologies and upgrades bring forth a higher number of teething issues that require additional up-tower repairs, part replacements, and/or retrofits during construction, which can delay project completion.
R6	Blade erection failure	The blades installed on the project turbines are a relatively new technology on the market. As such, new installation procedures are required, which increases the risk of failure during blade erection/installation.
R7	Installation errors	There is a greater likelihood that installation errors will occur during erection/installation stages (e.g., tower section misalignment).
R8	Concrete foundation issues	Poor concrete placement/consolidation and congested reinforcement may cause foundation concrete voids, which will require additional engineering studies

The probability of occurrence of each risk factor was evaluated linguistically using the scale in Table 5.7; average values of the numerical ranges, summarized in Table 5.7 under the heading 'input value', were used as inputs to the model. Then, the ability of each risk factor to impact cost and schedule and the work-packages affected by each risk factor were determined, as shown in Table 5.5.

Table 5.7: Probability of occurrence scale. Adapted from (Abdelgawad and Fayek 2010).

Linguistic Term	Value Range (%)	Input Value (%)	Description
Very Unlikely	≤ 1	1	A risk factor is highly unlikely to occur
Unlikely	2 – 10	6	A risk factor is unlikely to occur
Somewhat Likely	11 – 33	22	A risk factor may occur
Likely	34 – 67	50	A risk factor is expected to occur
Very Likely	> 67	90	A risk factor will certainly occur

The probability distributions for cost and schedule risk impact were determined using the method introduced by Mohamed et al. (2020b) for input modelling of MCS in wind farm construction. First, the root causes/scenarios of the risk factors were determined and evaluated. A complete list of the root causes of the risk factors and their evaluations are detailed in Table 5.8.

Table 5.8: Root causes of risk factors and their evaluation.

ID	Root Causes/Scenarios	Frequency of Occurrence	Adverse Consequence
R2	Data provided by the owner is low accuracy	Likely	Very Large
	Data provided by the owner is medium accuracy	Somewhat Likely	Medium
	Site investigation by contractor is poor	Likely	Large
	Site investigation by contractor is medium	Unlikely	Small
	Low experience with characteristics of project area	Somewhat Likely	Very Large
R3	Shortage of laborers	Unlikely	Very Large
	Unqualified laborers	Unlikely	Large
	Poor project planning	Somewhat Likely	Large
	Poor site supervision	Unlikely	Very Large
	Late payments of contractors	Somewhat Likely	Medium
R4	Laborers do not follow health guidelines	Unlikely	Very Large
	Higher infection rate in the surrounding area	Somewhat Likely	Large
	Poor site supervision and enforcement	Unlikely	Medium
	Restricted number of laborers onsite	Somewhat Likely	Large
R5	Familiarity with technology is low	Unlikely	Very Large
	Familiarity with technology is medium	Somewhat Likely	Small
	Less qualified laborers	Unlikely	Very Large
	Unavailability of training	Unlikely	Large
R6	Familiarity with installation of new blades is low	Unlikely	Very Large
	Familiarity with installation of new blades is medium	Likely	Small
	Site supervision is poor	Unlikely	Very Large
R7	Tight project schedule	Unlikely	Very Large
	Poor communication and coordination	Somewhat Likely	Small
	Poor site supervision	Unlikely	Large
R8	Poor concrete placement	Unlikely	Large
	Congested reinforcements	Somewhat Likely	Medium
	Compacting and curing is poor	Unlikely	Very Large
	Compacting and curing is medium	Likely	Small
	Concrete mix design quality is poor	Unlikely	Large
	Concrete mix design quality is medium	Somewhat Likely	Medium

Second, the frequency of occurrence and adverse consequence of root causes/scenarios were evaluated subjectively using a fuzzy membership function, as shown in Figure 5.5.

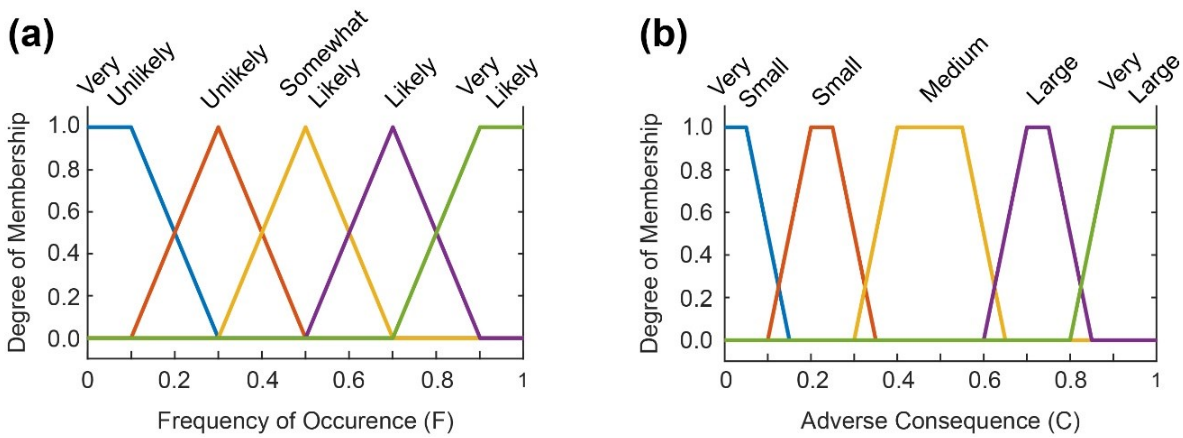


Figure 5.5. Fuzzy membership function for (a) frequency of occurrence and (b) adverse consequence. Adapted from Mohamed *et al.* (2020).

Then, the lower and upper boundaries of each risk factor were determined. Third, the impact range was divided into three subsets (small, medium, and large), and a mapping degree for each value was determined based on expert belief. Example mapping for R2 is illustrated in Figure 5.6; mapping for all other risk factors are shown in Figures 6 through 11. Finally, the correlation between the cost and schedule risk impact was evaluated subjectively as either weak (ρ=0.15), moderate (ρ=0.45), or strong (ρ=0.8), allowing the risk impact to be represented using a normal copula. Resulting marginal distributions for cost and schedule impacts of the risk factors are summarized in Table 5.9.

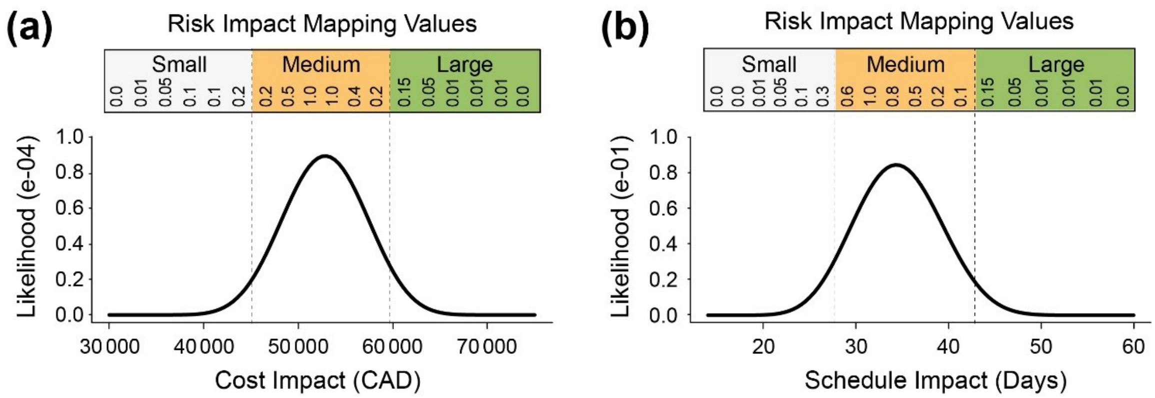


Figure 5.6. Probability distribution for (a) cost and (b) schedule impact of R2.

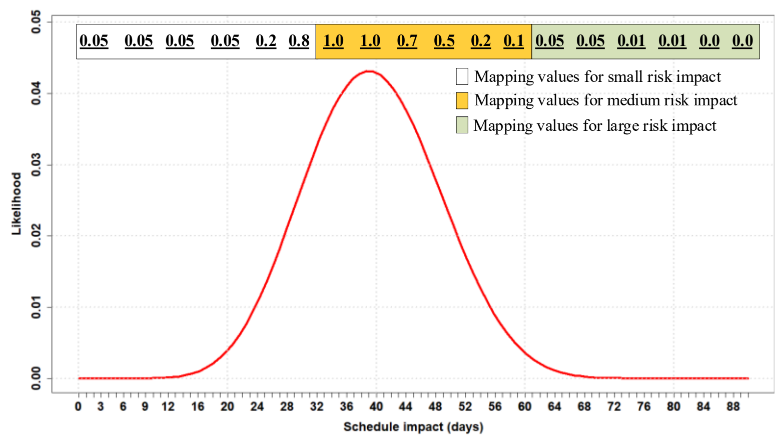


Figure 5.7. Probability distribution for impact of R3 on schedule

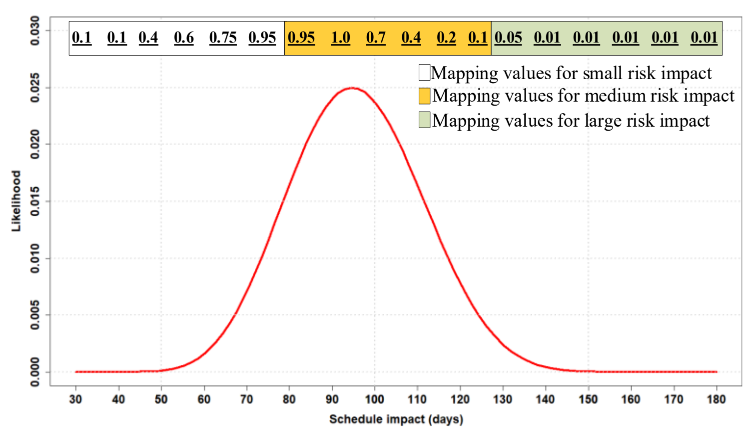


Figure 5.8. Probability distribution for impact of R4 on schedule

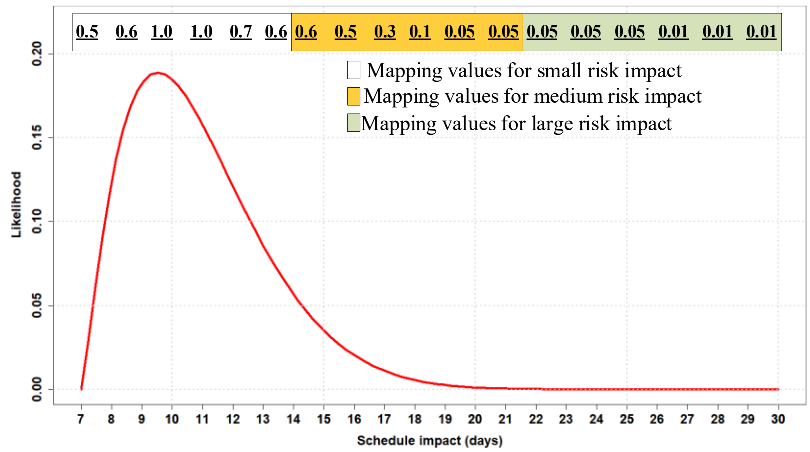
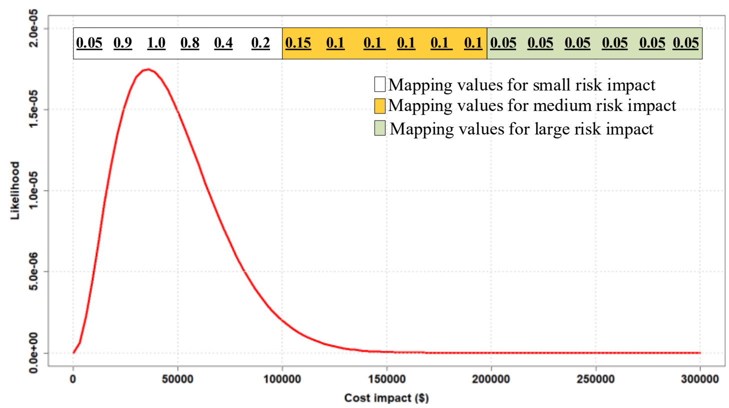
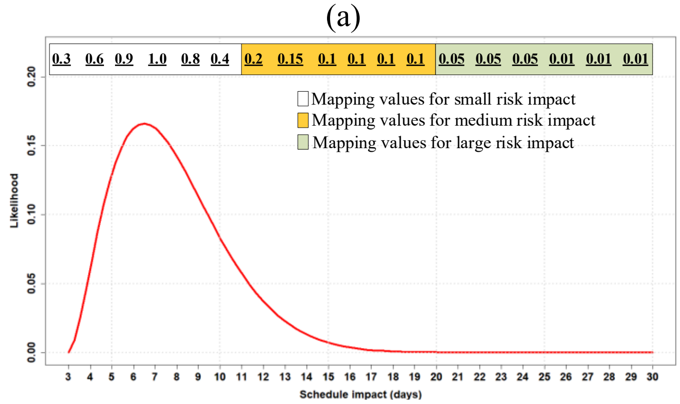


Figure 5.9. Probability distribution for impact of R5 on schedule

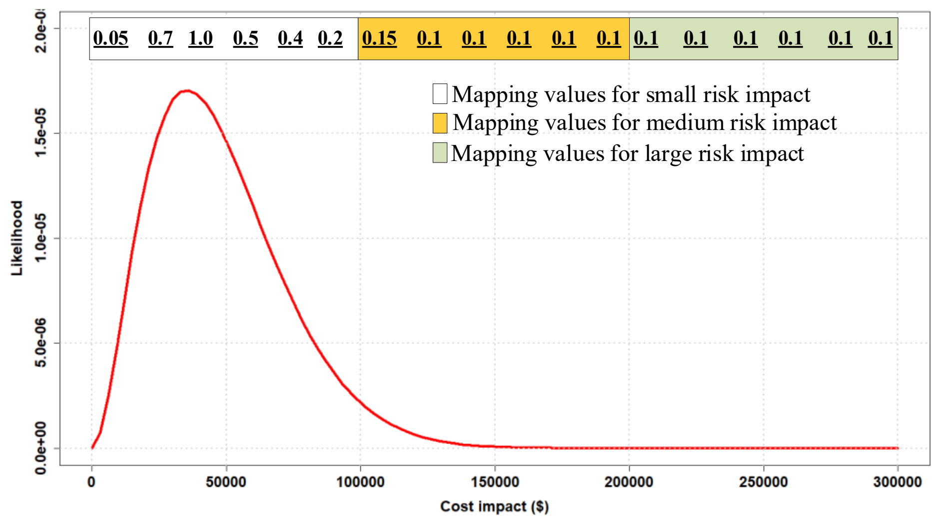


(a)

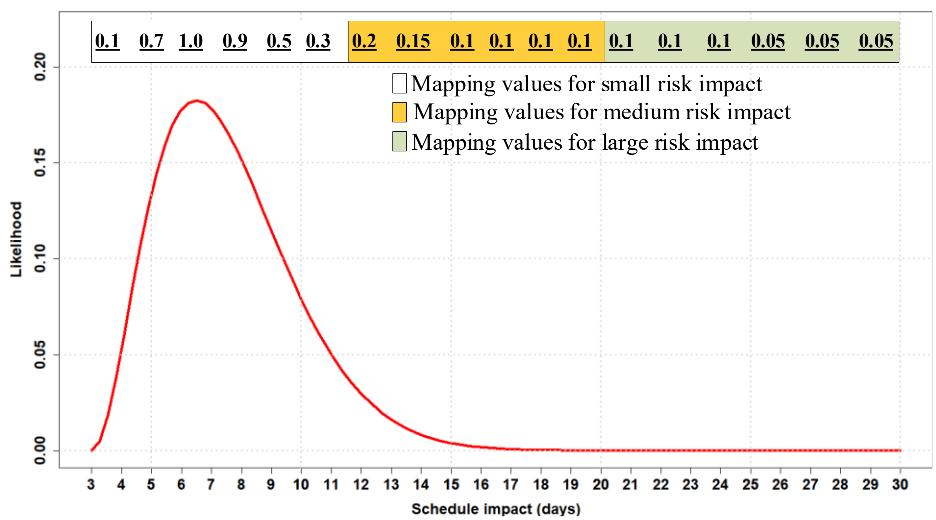


(b)

Figure 5.10. Probability distribution for impact of R6 on (a) cost and (b) schedule

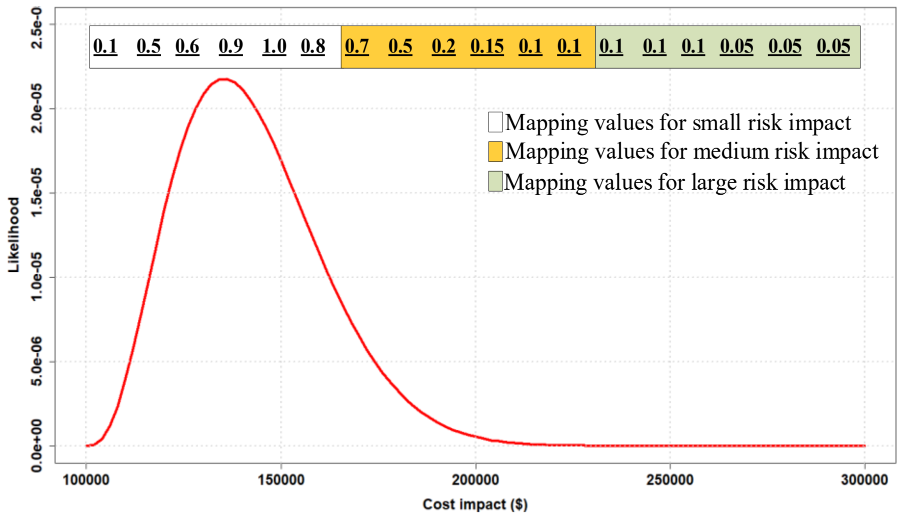


(a)

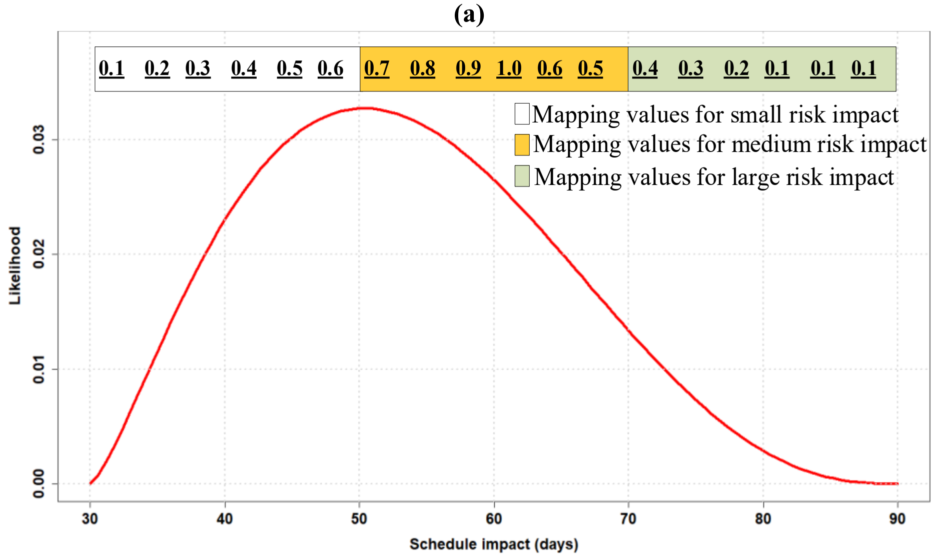


(b)

Figure 5.11. Probability distribution for impact of R7 on (a) cost and (b) schedule



(a)



(b)

Figure 5.12. Probability distribution for impact of R8 on (a) cost and (b) schedule

It is important note that because the root causes of risk factor R1 were difficult to determine, the cost impact was defined as triangular (50 000, 250 000, 100 000) and the schedule impact was determined as pert (30, 365, 90) with a strong correlation of 0.8. For R3, a fixed value of 50 000 CAD per turbine/day was assigned to represent the liquidated damage specified in the contractual documents. Because the cost impact of R3 depends on the length of the schedule delay, a probability distribution with the same α and β values as the schedule impact distribution was derived. Then, the lower and upper bound values were multiplied by the fixed liquidated damage, resulting in values of 0 CAD and 4 500 000 CAD, respectively (i.e., 50 000 CAD/day * 90 days = 4 500 000 CAD).

Table 5.9: Parameters of distributions for cost and schedule risk impact.

ID	**Cost Impact**				**Schedule Impact**				ρ[1]
R1	Triangular (50 000, 250 000, 100 000)				Pert (30, 365, 90)				0.8
	Lower	**Upper**	**α**	**β**	**Lower**	**Upper**	**A**	**β**	
R2	30 000	75 000	13.195	12.826	14	60	10.535	13.016	0.8
R3	0	4 500 000	10.428	13.334	0	90	10.428	13.334	0.8
R4	-	-	-	-	30	180	9.676	12.453	-
R5	-	-	-	-	7	30	2.222	10.930	-
R6	0	300 000	3.066	16.439	3	30	2.747	12.802	0.8
R7	0	300 000	2.959	15.644	3	30	3.146	15.412	0.8
R8	100 000	300 000	3.889	14.461	30	90	2.359	3.650	-

[1]Where ρ = assigned correlation value

Risk factors with correlated schedule and cost impacts were represented by a bivariate distribution using a normal copula (Mohamed *et al.*, 2020b). A copula package in *R* (Yan 2007) was used to implement the multivariate modelling of the cost- and schedule-risk impact dependence. Bivariate distributions for R2, R6, and R7 are shown in Figure 5.13, Figure 5.14 and Figure 5.15.

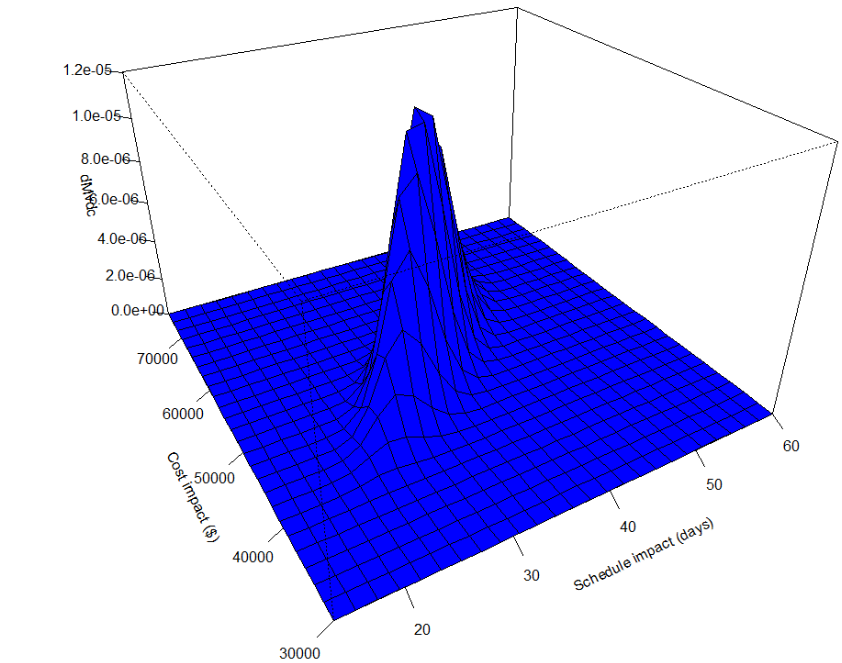


Figure 5.13. Bivariate impact probability distribution of R2.

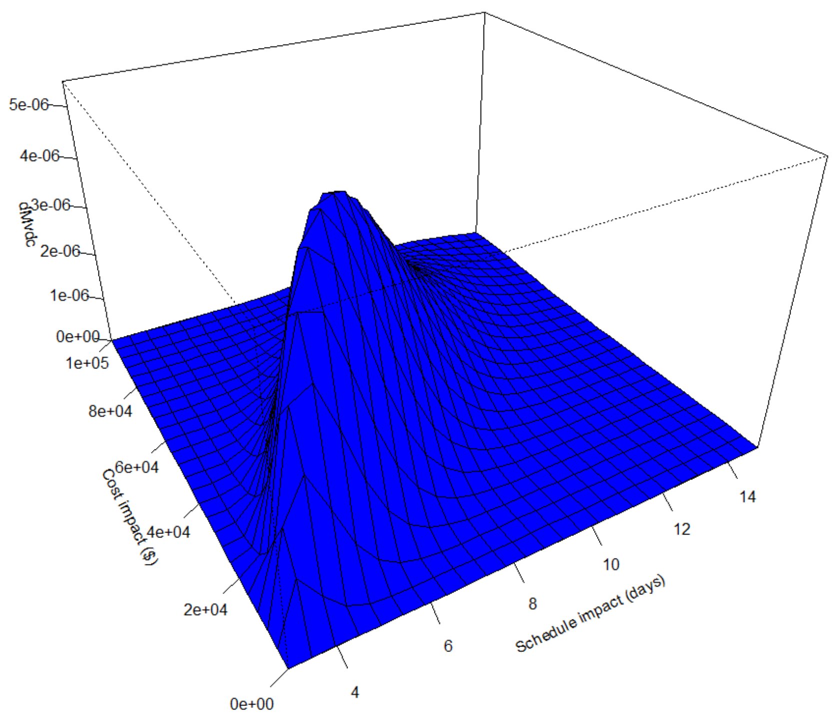


Figure 5.14. Bivariate impact probability distribution of R6

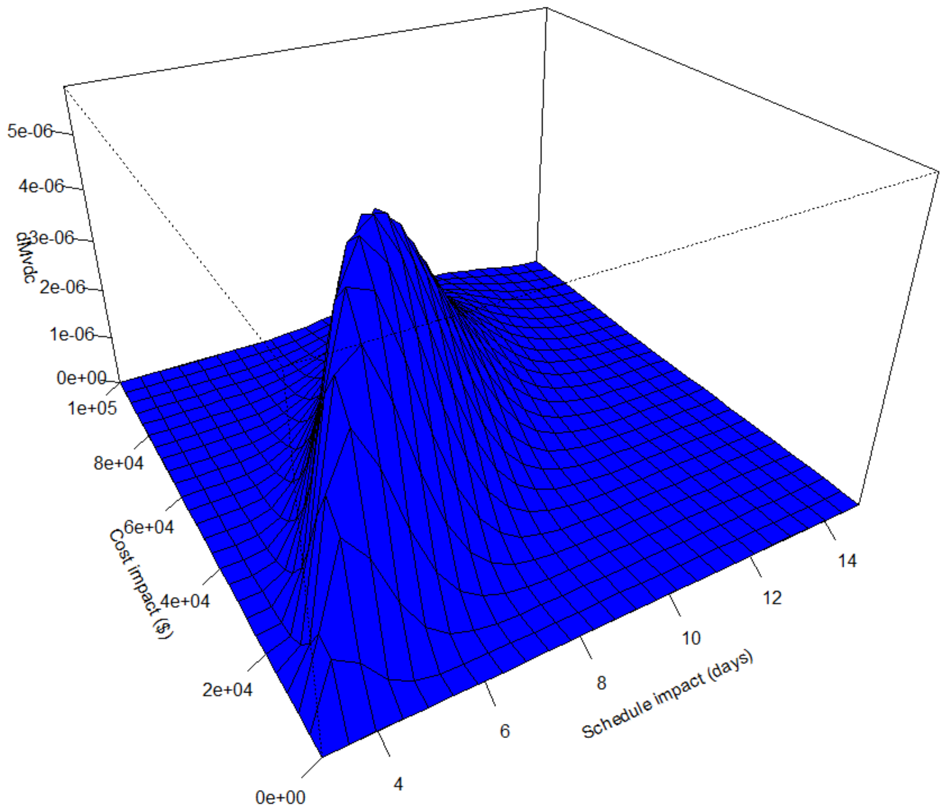


Figure 5.15. Bivariate impact probability distribution of R7

5.4.2 Modelling and Quantification

SimphonyProject.NET is an in-house developed simulation platform designed to facilitate the application of an integrated simulation-based assessment of project risks. Notably, the use of *SimphonyProject.NET* addresses common practical limitations associated with MCS-CPM, including difficulty interpreting results (Senesi *et al.* 2015) and modelling of simulation inputs. By making use of popular scheduling techniques, such as the CPM and MCS (Karabulut 2017; Mohamed *et al.* 2020a), *SimphonyProject.NET* is able to simulate project cost and duration in consideration of project risks.

The user interfaces for entering schedule and cost data as well as risk data in *SimphonyProject.NET* are shown in Figure 5.16 and Figure 5.17, respectively. Once input data were entered, the simulation was initiated and was run for 1 000 iterations, as recommended by Dawood (1998), to achieve the desired level of confidence; notably, this is well in excess of the 120 iterations recommended for a simulation to reach appropriate maturity (Lee and Arditi 2006).

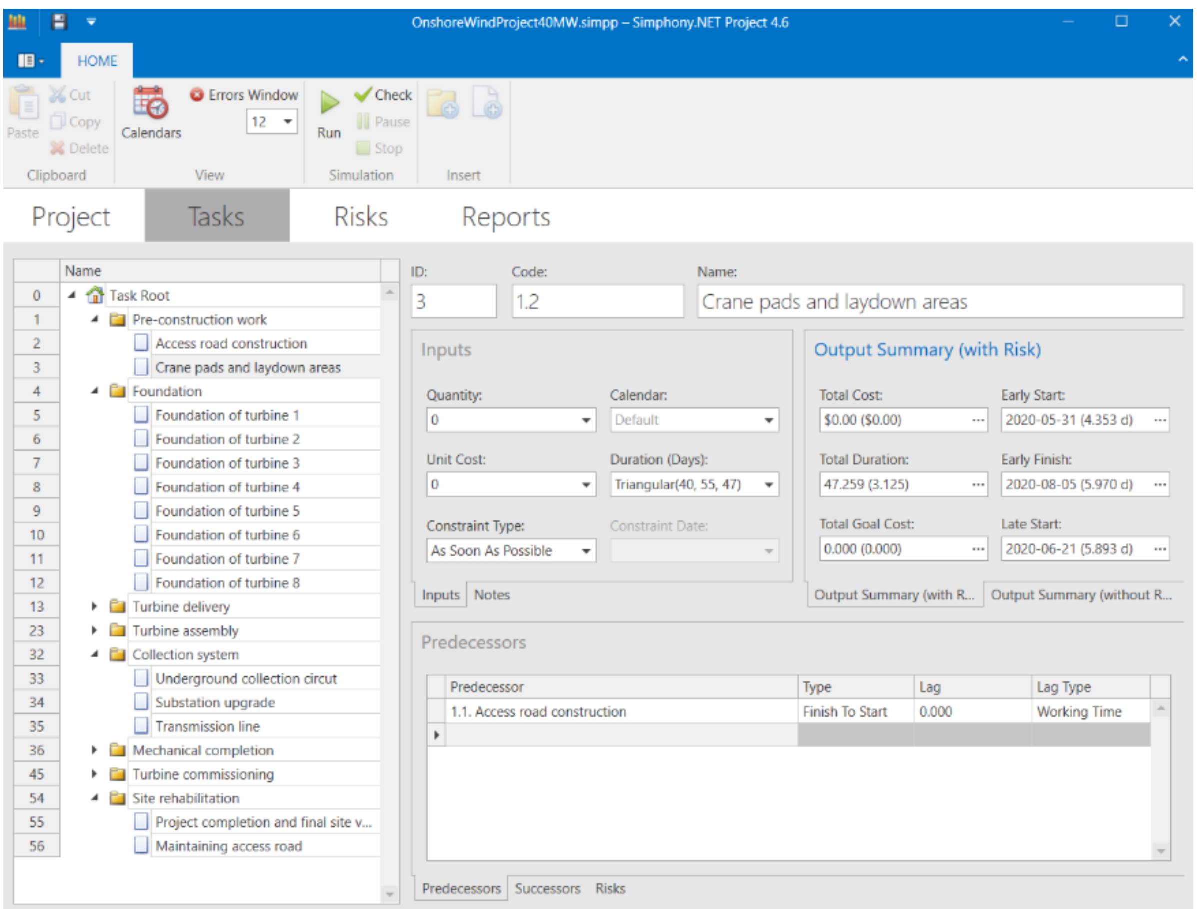


Figure 5.16. User interface for input of schedule and cost project data in *SimphonyProject.NET*

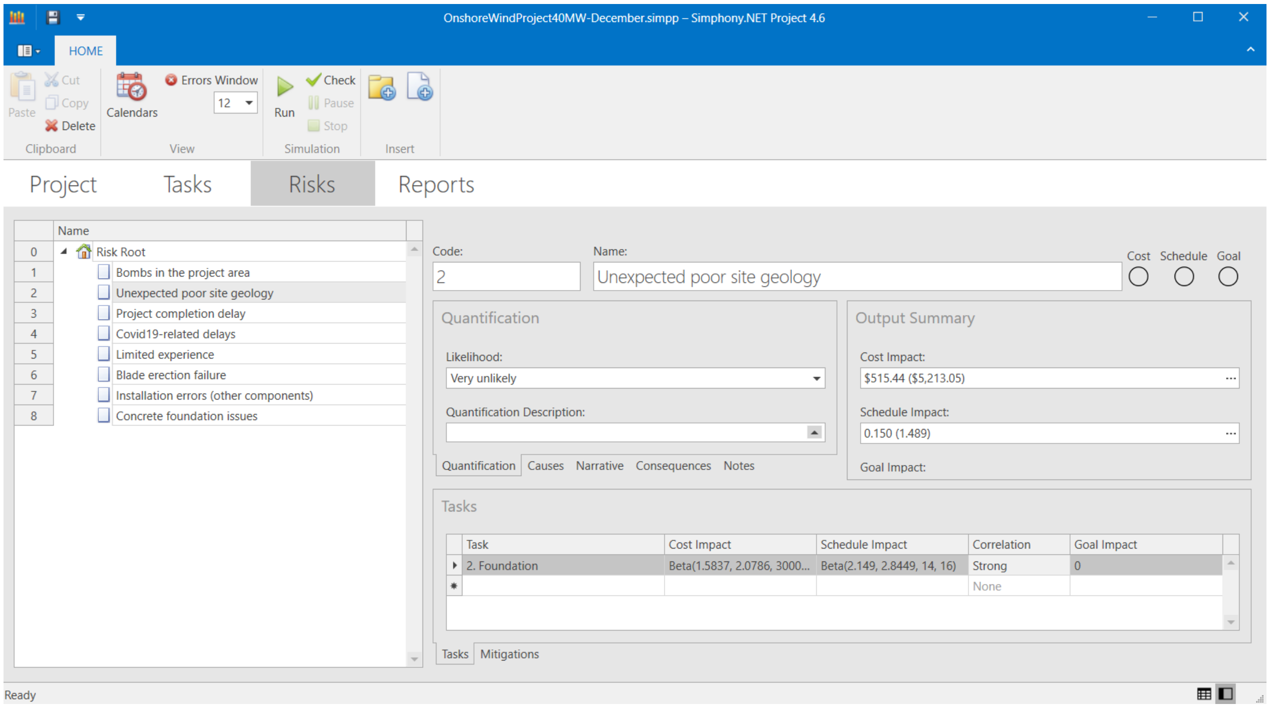


Figure 5.17. User interface for input of risk data in *SimphonyProject.NET*

5.4.3 Outputs and Decision Support

Various results and reports were extracted from *SimphonyProject.NET*. A baseline project schedule (i.e., without risk but with regular variability) is shown in Figure 5.18 a. Average duration of the baseline project (P_{50}) was determined to be 281 days (σ = 3 days), with a 90% likelihood (P_{90}) that the duration of the baseline project would not exceed 285 days (Figure 5.18). This resulted in a project completion date of April 22, 2021, and April 28, 2021, for P_{50} and P_{90}, respectively (Figure 5.19).

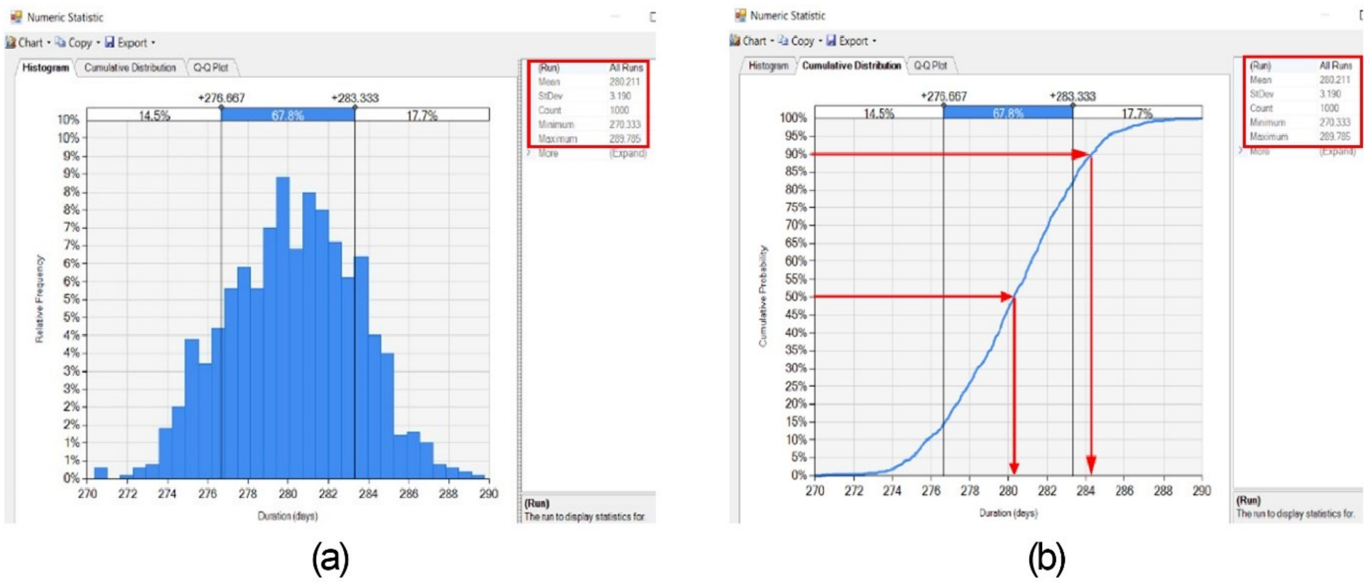


Figure 5.18. Baseline project (i.e., no risk) duration as a (a) probability density function and (b) cumulative distribution function.

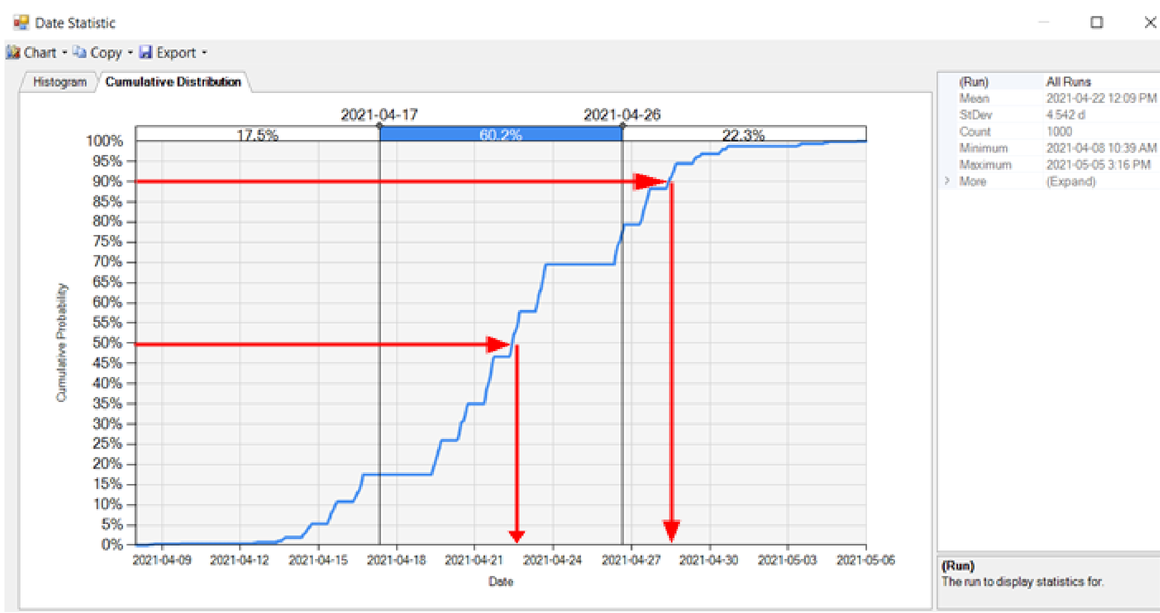


Figure 5.19. Baseline project (i.e., no risk) completion date as a cumulative distribution

Initially planned using a deterministic approach, the project was expected to be completed in 270 days. As is observed in Figure 5.18, there is a very low probability (~1%) that the project will be completed within this time. These results highlight the limitations of deterministic approaches, which often result in underestimation due to their inability to consider the randomness and variability inherent to construction.

Risk factors were then added to evaluate the resulting impact on project time and cost. When risk was considered, the average project duration was extended to 348 days (σ = 64 days) (Figure 5.20). There was a 50% likelihood (P_{50}) that the project would be completed in 355 days, and a 90% likelihood (P_{90}) that the project would be completed in 415 days (Figure 5.20).

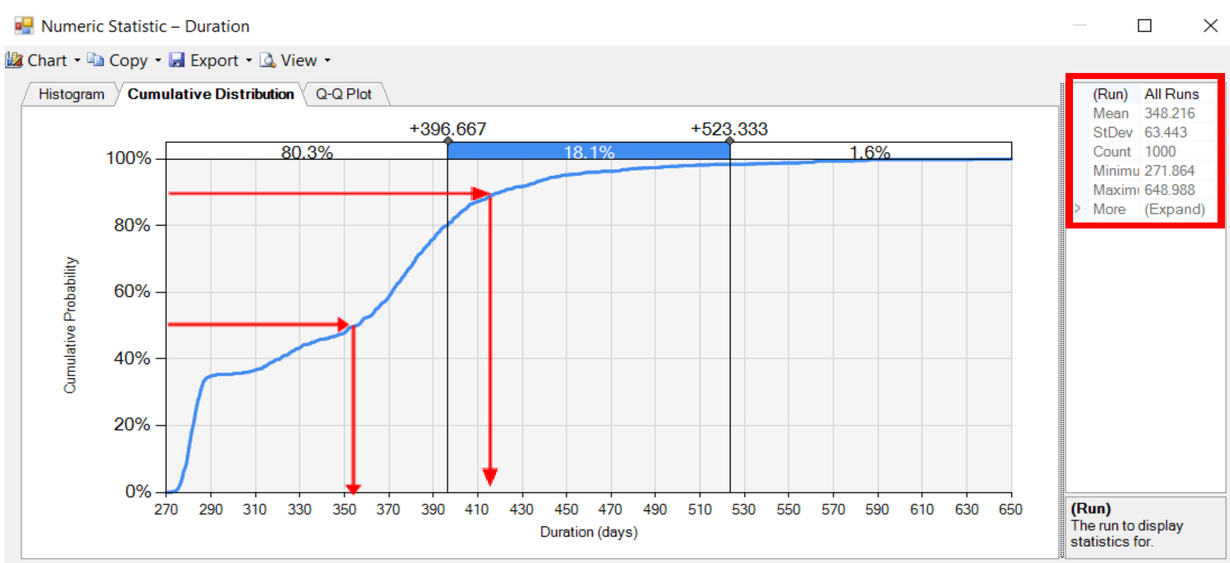


Figure 5.20. Project duration considering risk impact as a cumulative distribution function.

Notably, the average duration and the 50% likelihood values differ, as the distribution is not symmetric. Project completion dates for P_{50} and P_{90} were August 10, 2021, and November 1, 2021, respectively (Figure 5.21). Compared to the baseline project, risks were estimated to delay the project by 68 days (or 13 weeks), resulting in a substantial effect on project completion time.

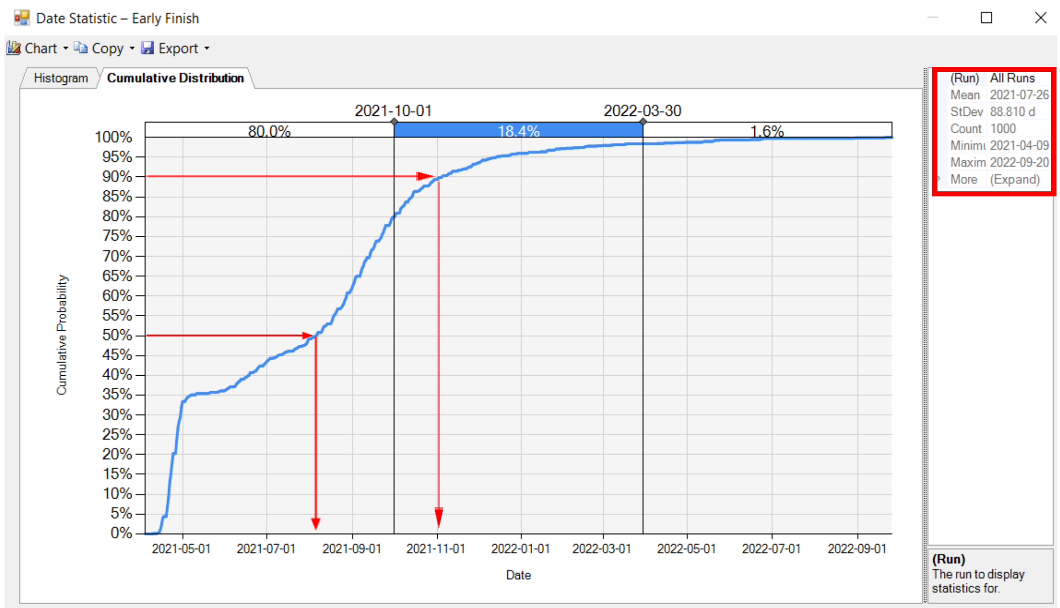


Figure 5.21. Project completion date considering risk as a cumulative distribution

Time contingency, or the average impact of all risks on schedule at the project level, in consideration of project risk, was extracted separately. The time contingency was determined to be 73 days (σ = 64 days) (Figure 5.22). An 18% likelihood that the impact on project duration would be zero, and a 90% likelihood (P_{90}) that the project time contingency would not exceed 140 days was observed (Figure 5.22). The time contingency varied between 0 and 375 days due to the long-tailed beta distributions for schedule impacts of risk factors.

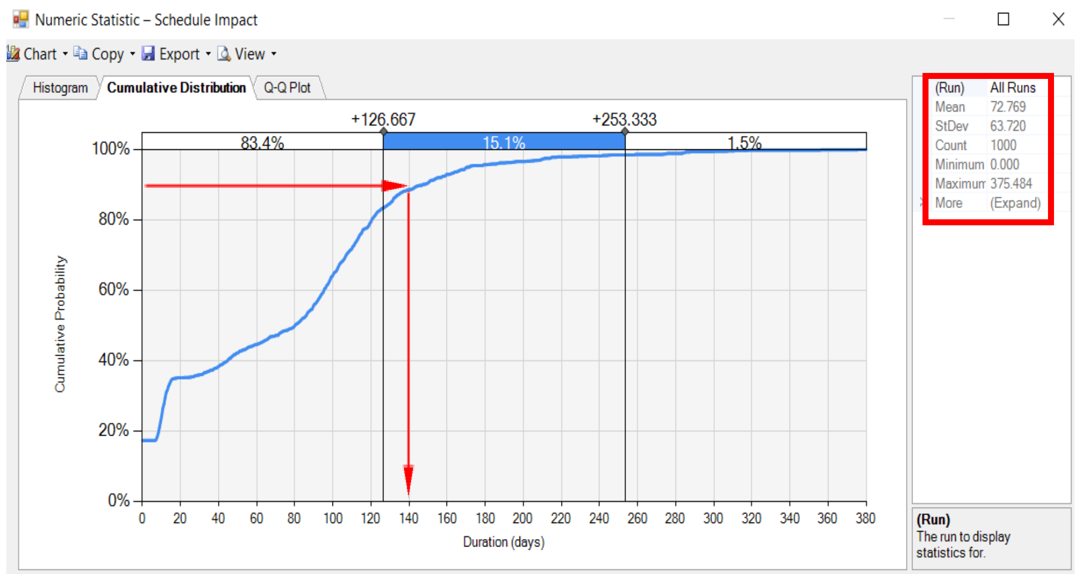


Figure 5.22. Time contingency as a cumulative distribution function.

Because baseline cost information was not available for analysis, total project costs could not be quantified. However, cost information for each risk was available, allowing the cost contingency to be evaluated (Figure 5.23). The average cost contingency for the project was 444 691 CAD (σ = 840 337) CAD (Figure 5.23), with a 90% likelihood (P_{90}) that the cost contingency would not exceed 2 000 000 CAD (Figure 5.23). Due to a low probability of risk factors' occurrence, a 70% likelihood (P_{70}) that the cost contingency would be zero was observed.

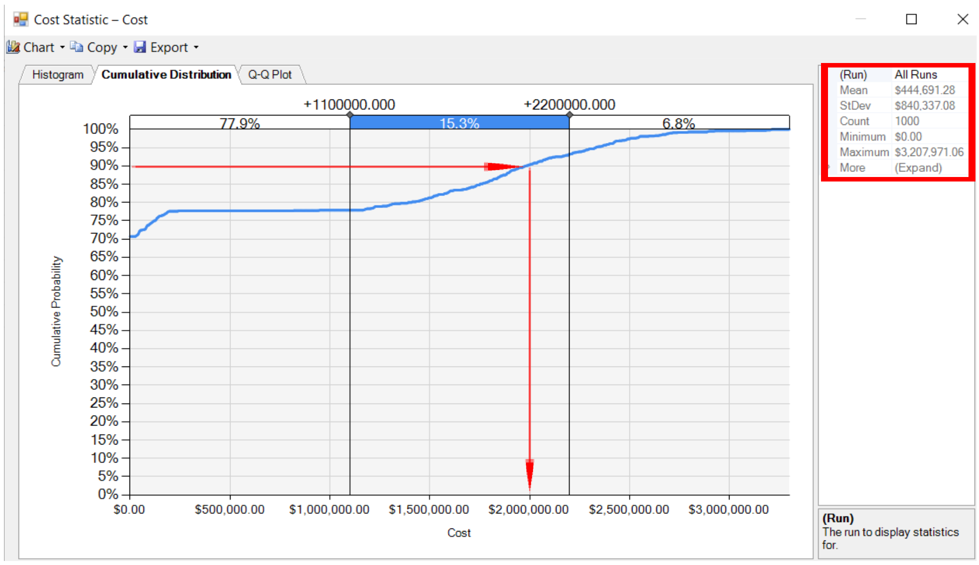


Figure 5.23. Cost contingency as a cumulative distribution function.

A tornado diagram, which visualizes risk factor rankings based on their mean simulated risk impact of all runs, was extracted from *SimphonyProject.NET* (Figure 5.24). Results suggest that project completion delays have the largest potential cost impact, while COVID-19-related delays have the largest potential schedule impact.

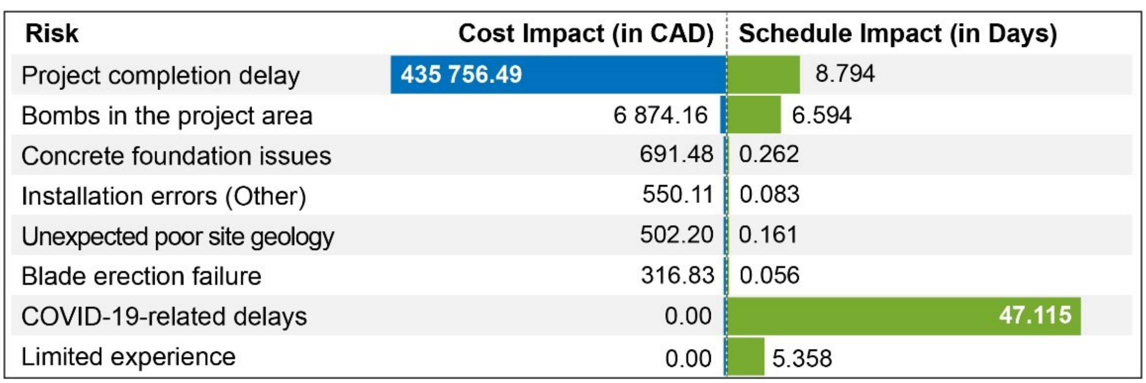


Figure 5.24. Tornado risk diagram.

A joint time-cost contingency scattergram was generated from the data of each simulation iteration (Figure 5.25). Each iteration was plotted as estimated project completion (x-axis) versus cost contingency (y-axis). The green lines (Figure 5.25) represent baseline (i.e., no risk) values of project duration and cost. The gathering of points at the horizontal green line (Figure 5.25) can be explained by the finding that there is a 70% likelihood that the cost contingency will be zero (Figure 5.23). The scattergram also reveals that the completion date of the project is moderately correlated with cost contingency (Figure 5.25).

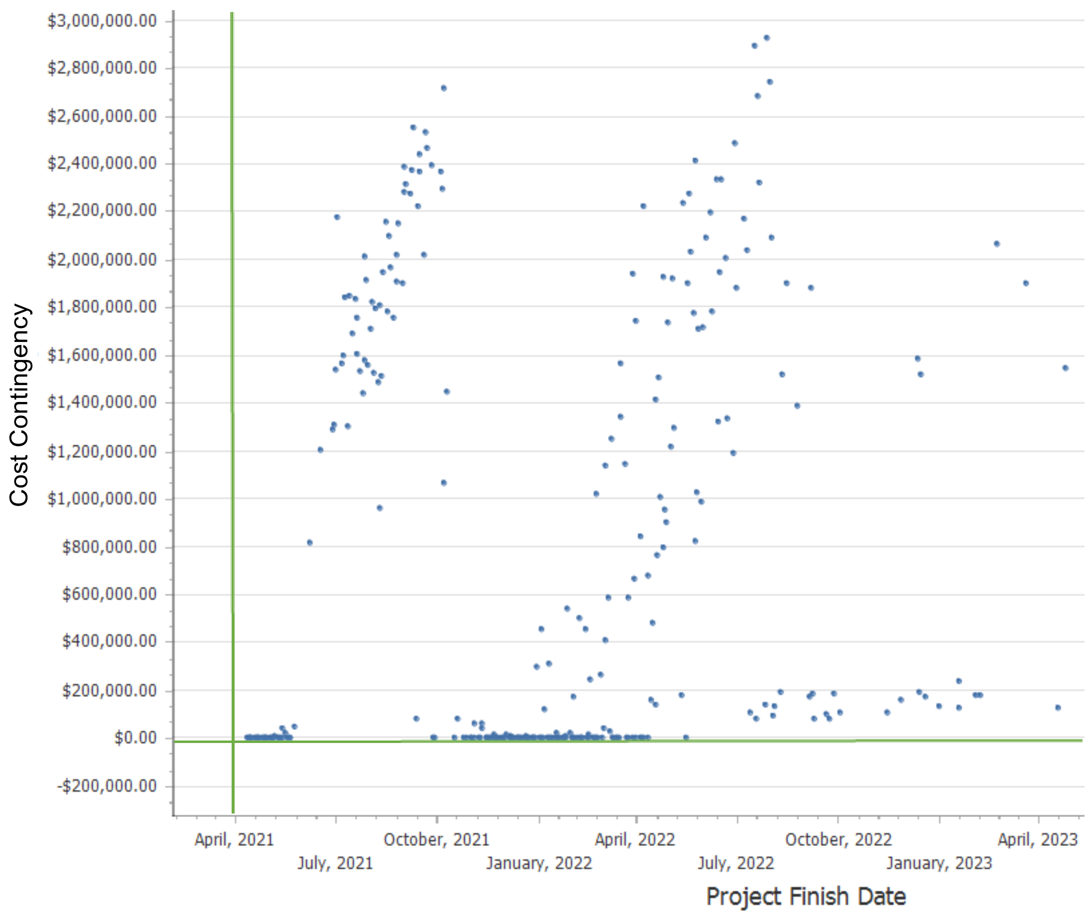


Figure 5.25. Joint cost-time contingency.

The impact of risk on the critical path of the project and criticality of the activities was examined. Table 5.10 summarizes the impact of risk on critical activities and work-packages, criticality indexes, and total float. While the critical path of the project was unchanged following the addition of risk, criticality of the activities was reduced, as certain risk factors (i.e., 1, 3, and 4) delayed the entire project, resulting in the addition of float to all activities.

Table 5.10: Critical path and activity criticality.

Critical Activity	**Before Risk Impact**		**After Risk Impact**	
	Criticality Index	**Total Float (Days)**	**Criticality Index**	**Mean Total Float (Days)**
Access road construction	1	0	0.227	68
Substation upgrade	1	0	0.227	68
Commissioning of turbine	1	0	0.227	68
Project completion and final site verification	1	0	0.227	68

5.5 Sensitivity Analysis

Because the present case study is the first reported application of the MCS-CPM to a wind farm construction project in literature, the size impact of select parameters on model outcomes was assessed using a sensitivity analysis. Two parameters were examined: probability of occurrence and correlations between cost and schedule impact.

5.5.1 Sensitivity to Probability of Occurrence

Sensitivity of the model to probability of occurrence values was examined (Figure 5.26 a and b) based on ten scenarios (Table 5.11).

Table 5.11: Scenarios for sensitivity of probability of occurrence.

Linguistic Probability	Probability of Occurrence by Scenario									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Unlikely	2	4	6	8	10	10	10	10	10	10
Somewhat Likely	11	14	17	23	26	29	33	33	33	33
Likely	34	37	40	43	46	49	52	56	63	67

In the original model, the average value of the range associated with the linguistic term (Table 5.7) was used as the input into the model. Increasing the probability of occurrence value increased cost and time contingencies. Conversely, decreasing this value reduced contingencies for both cost and time. Although logical and expected, these findings highlight the importance of carefully evaluating and assigning probability of occurrence values when using simulation as a risk assessment method. Accordingly, it is recommended that the scale used in Table 5.7 be expanded to seven linguistic terms to allow for a more precise selection of average input values. If possible, researchers and practitioners may also consider the use of more sophisticated techniques to calculate probability of occurrence values.

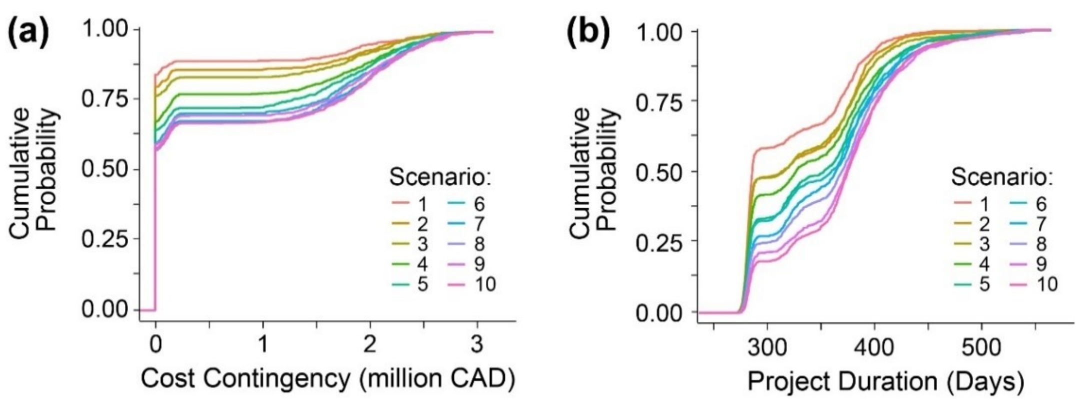


Figure 5.26. Sensitivity of (a) cost contingency and (b) project duration, as a cumulative distribution function, with respect to probability of occurrence.

5.5.2 Sensitivity to Cost and Schedule Impact Correlation

As discussed previously, the impact of risk factors on both cost and schedule were represented by bivariate distributions (i.e., dependent). The simulation was then re-run using separate input distributions for cost and schedule risks, thereby considering the impacts as independent. Cumulative distribution functions of cost contingency and expected project duration for both cases are illustrated in Figure 5.27 a and b, respectively. While overall differences were small, higher contingency values for time and cost were observed when the impact of correlation was evaluated for individual risk factors (Figure 5.28). Here, cost and schedule values were consistently elevated when impacts were correlated (Figure 5.28). Therefore, considering the impacts of cost and schedule as dependent is recommended to ensure that contingencies are not underestimated—especially in large risk models.

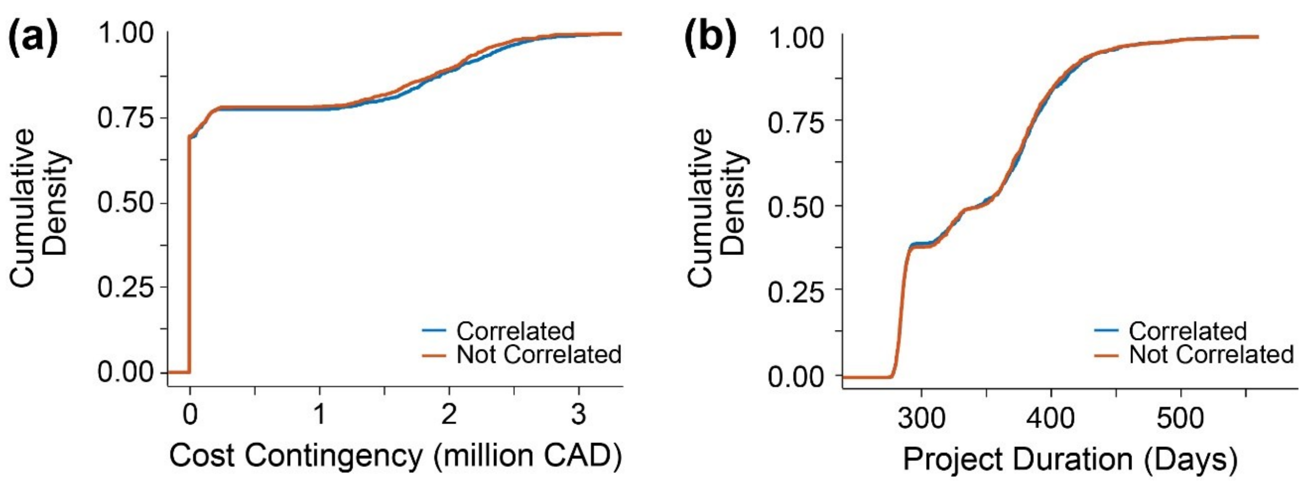


Figure 5.27. Sensitivity of (a) cost contingency and (b) project duration, as a cumulative distribution function, with respect to cost-schedule impact correlation.

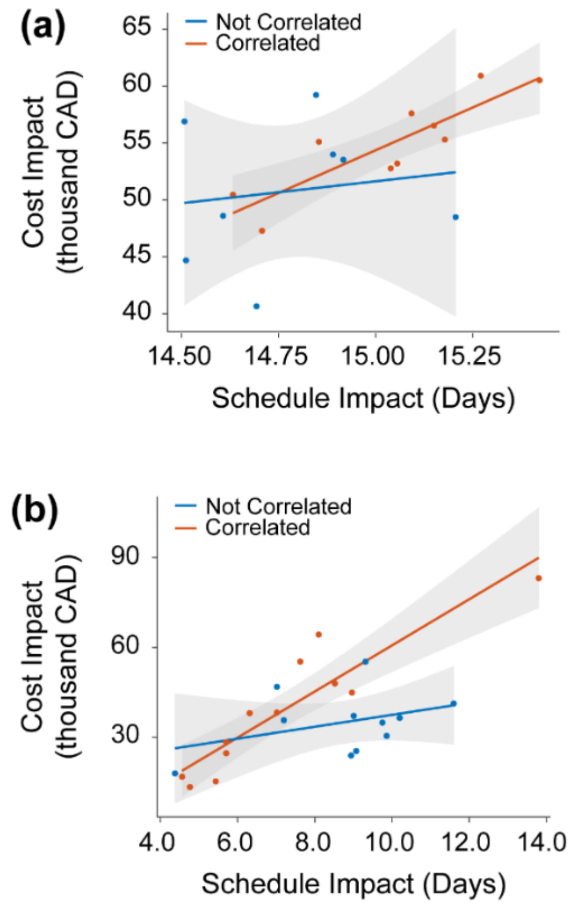


Figure 5.28. Simulated risk impact of (a) R2 and (b) R6.

5.6 Discussion And Managerial Implications

Construction practitioners continue to rely on simple and subjective tools for risk management and assessment. Several barriers limiting the application of quantitative risk assessment tools in construction practice have been reported in literature, including a lack of experience with quantitative techniques, lack of time for analysis, and difficulty appreciating the benefits and advantages of such tools.

As a new type of construction, onshore wind farms are associated with a relatively large amount of risk and uncertainty (Gatzert and Kosub 2016; Somi *et al.* 2020; Mohamed *et al.*, 2020b). Accurately estimating the impact of risk to ensure adequate cost and time contingencies is particularly important in wind farm construction due to electricity production requirements mandated in power purchase agreements, with contracts imposing liquidated damages of up to 50 000 CAD per turbine/day for any delays in the operation date. However, application of state-of-the-art risk assessment methods, such as MCS-CPM-based approaches, to real wind farm projects have yet to be demonstrated in literature.

This study aimed to facilitate the application of domain-specific techniques for risk assessment in onshore wind projects by providing the first reported application of the MCS-CPM to wind farm construction. The present case study demonstrated the practicality and benefits of the MCS-CPM-based approach, particularly when applied using the risk management support tool *SimphonyProject.NET*. Specifically, the MCS-CPM was capable of generating a variety of reports that can be used to support decision-making in practice by:

(1) Obtaining the probabilistic completion time and cost of the project under regular variability without risk consideration.

(2) Obtaining the probabilistic completion time and cost of the project in consideration of regular variability and project risk.

(3) Providing confidence levels for completing the project within a specific time.

(4) Providing confidence levels for completing the project within a specific risk contingency.

(5) Identifying the most critical risks affecting project time and cost.

This study focused on providing an analytical generalization rather than statistical generalization to demonstrate how an onshore wind project can be analyzed using the MCS-CPM approach. The analytical generalization allows one to establish logic that may be applicable to similar situations (Goh *et al.* 2013). The following are recommended considerations for practitioners of onshore wind construction projects when applying MCS-CPM for risk assessment.

(1) To achieve successful completion of the project, uncertainty and risks of the project must to be quantified as thoroughly and accurately as possible. Risks should be integrated with project schedule, and cost and should not be managed separately.

(2) Deterministic approaches fail to provide a complete overview of the different scenarios of project cost and duration under the effect of risk and uncertainty. In contrast, simulation-based approaches are capable of simultaneously considering all identified project risks, dependency between cost and schedule impacts, and the inherent uncertainty of construction projects. Simulation-based approaches, therefore, provide a more realistic projection of expected project costs and durations and allow practitioners to better understand the probability of achieving schedule and cost targets.

(3) MCS-CPM allows practitioners to prioritize and rank risks according to their severity, in turn allowing practitioners to develop risk mitigation strategies that focus on the most critical risks.

(4) To avoid underestimation of contingencies, correlation and dependencies between schedule and cost impact of risk factors should be modeled.

5.7 Conclusion

In this paper, a domain-specific, MCS-CPM-based method was applied to simultaneously quantify and assess the impact of risk factors on project cost and time. The method was adopted because of its advantages as an integrated tool for risk assessment and its ability to consider two types of uncertainty due to regular uncertainty and occurrence of risk factors. The MCS-CPM method was applied to a real 40 MW onshore wind project and was found capable of generating more comprehensive and representative results than the deterministic approach initially used by industrial practitioners.

A newly developed method for input modelling (i.e., distribution elicitation for risk impact) was adopted to overcome limitations with the lack of historical data that is common to many wind farm projects. A risk assessment management support tool, *SimphonyProject.NET*, was found to substantially reduce the complexity associated with MCS-CPM, simplifying its use in practice. By facilitating the incorporation of risk and regular variability in project planning, the applied methodology is expected to reduce under- or overestimation of project contingencies, thereby developing more realistic project plans and enhancing the likelihood of project success.

This case study contributes to wind farm construction practice by providing a domain-specific model and application example for wind farm construction. Also, the case study contributes to other sectors of construction practice by demonstrating the ability of the *SimphonyPoject.NET* tool to overcome the practical limitations associated with integrated simulation-based approaches. Future work includes developing models to evaluate the probability of risk occurrence more accurately and developing strategies that allow MCS-CPM risk simulation models to be updated in real-time.

Acknowledgments

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Chapter 6 : Simulation-based Approach for Lookahead Scheduling of On-shore Wind Projects Subject to Weather Risk

6.1 Introduction

Many countries are transitioning their energy production towards renewable sources to reduce greenhouse gas emissions and meet sustainability targets. Since 2009, global onshore wind capacity has increased fourfold, producing more than 594 GW in 2019 alone (Jaganmohan 2019). To meet the growing demand, installation of additional wind farms and supporting infrastructure is necessary. However, onshore wind projects are constructed in outdoor environments characterized by high wind speeds (Guo et al. 2017b) and other adverse weather events that can result in significant construction delays (Atef et al. 2010; Guo et al. 2017b; Prpich et al. 2014b). Indeed, the schedule delay of an average wind farm project has been estimated to be approximately 10% of the planned project duration (Kostka and Anzinger 2016). Delays in wind farm construction are particularly problematic, as most contracts between the owner and the engineering, procurement, and construction (EPC) contractor(s) include a provision for liquidated damages if a project exceeds the contractually-specified end date (Hinze and Couey 1989). Completing wind farm construction tasks on time is essential for ensuring profitability.

Variability is an inherent characteristic of construction projects, with as-built progress regularly deviating from planned schedules. To mitigate delays, practitioners often schedule projects from two perspectives, generating (1) a *master schedule* that provides a holistic view of the entire project and (2) a *lookahead schedule* that provides a short-term, detailed work plan for upcoming tasks (Song and Eldin 2012). Together, master scheduling and short-term or lookahead scheduling are key elements of successful project delivery (Azimi et al. 2011). Master scheduling provides a global view of a project that can be used for long-term coordination, rough budgeting, and bid preparation (Azimi et al. 2011; Ballard 1997; Song et al. 2009), while lookahead scheduling is used for ongoing performance analysis, increasing reliability of detailed work plans, and for identifying and implementing effective corrective actions during execution (Azimi et al. 2011; Chen et al. 2020; Song et al. 2009).

Evaluation of the impact of weather on construction project scheduling has been addressed and successfully applied by numerous research studies (Apipattanavis et al. 2010; El-Rayes and Moselhi 2001; Guo 2000; Guo et al. 2017b; Pan 2005; Shahin et al. 2011). These approaches use historical weather data (either extreme conditions or averages) to predict weather-related delays when generating master project schedules. Although useful for high-level pre-construction scheduling and bid preparation, the suitability of these approaches for short-term lookahead scheduling is primarily limited by two factors. First, as a consequence of being designed for long-term master scheduling, existing approaches are not able to incorporate as-built data, limiting the reliability of lookahead schedules. Second, previous methods use average or extreme weather data that do not capture fluctuations in weather conditions that occur during project execution (Nguyen et al. 2010). These limitations have resulted in the development of unrealistic lookahead schedules, preventing practitioners from identifying and implementing corrective actions in the time-frame required to mitigate weather-related delays. Indeed, a model capable of integrating as-built information while simultaneously considering short-term weather forecasts to improve lookahead scheduling has yet to be described in the literature.

To address the aforementioned gaps, this research is proposing a simulation-based approach that integrates as-built information with short-term weather forecast data to improve lookahead scheduling in onshore wind farm construction. The proposed framework includes a newly-developed and generic hybrid simulation model (i.e., discrete-event and continuous) of both weather-sensitive and non-sensitive activities in onshore wind farm construction. Short-term weather precipitation, wind speed, and temperature data are used to derive a productivity factor for weather-sensitive activities. These data—together with as-built information—are input into the model, which generates a 14-day lookahead schedule. Functionality and validity were demonstrated following the application of the proposed framework to a case study of a real onshore wind farm construction project. As the first reported framework to integrate as-built construction information and short-term weather forecast data for lookahead scheduling, practical application of this approach is expected to improve the evaluation, understanding, and monitoring of weather uncertainties on project execution for improved project management and control of wind farm construction.

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6.2 Literature Review

6.2.1 Adverse Weather in Construction Projects

Adverse weather was ranked as the second leading cause of construction-related claims in Canada (Semple et al. 1994) and as the third most critical risk factor for construction schedule overruns in Jordan (Sweis 2013). Negative consequences of adverse weather on construction projects includes reduced productivity, work stoppage, and ruined materials, often resulting in schedule delays, cost overruns (Ibbs and Kang 2018; Shahin et al. 2014), and disputes between project stakeholders (Ballesteros-Pérez et al. 2017; Nguyen et al. 2010). Weather-related parameters that have been extensively studied in construction include precipitation, air temperature, and wind speed.

Precipitation alone has a significant effect on materials and construction productivity (Apipattanavis et al. 2010; Larsson and Rudberg 2019), both during and after periods of rain. The length of the resulting delays are typically proportional to the amount of precipitation and the duration of the event (Larsson and Rudberg 2019), with work stoppages resulting if precipitation rates become too high. Estimates of reduction in productivity resulting from precipitation events range between 40% for light precipitation (Moselhi and Khan 2010) to upwards of 60% (Thomas and Ellis 2009). Productivity is also affected by both low and high air temperatures (Larsson and Rudberg 2019). High temperatures may lead to heat stress or dehydration of workers (Larsson and Rudberg 2019), and work stoppages are recommended when temperatures decrease below –25 °C to ensure worker safety (Moselhi and Khan 2010)—particularly when low temperatures are combined with high wind speeds (measured as wind chill) (Apipattanavis et al. 2010). Wind alone can result in work stoppages, decreased productivity, and negative impacts on materials. High wind conditions may cause the surface of fresh concrete to dehydrate and crack and can increase the risk of accidents when performing high-altitude work (Larsson and Rudberg 2019). Lifting activities are also affected by wind, with the impact depending on a combination of factors, such as wind speed, height of the lifting operation, and the type of object to be lifted (Larsson and Rudberg 2019).

Wind farm projects require locations with relatively high and consistent wind speeds to maximize electricity generation during the operation phase of the project. From a contractor's perspective, however, high wind speeds represent a significant risk in terms of safety, time, and cost (Atef et al. 2010; Guo et al. 2017b). Installation of the turbine and tower sections of a structure is completed using heavy cranes. In addition to effects on worker and equipment productivity, safety regulations mandated by many regulatory bodies require lifting activities to be halted at certain wind speed thresholds to avoid crane overturning (Atef et al. 2010). Reductions in productivity of turbine installation due to wind speed have been detailed by Guo, Chen, and Chiu (Guo et al. 2017b) .

The impact of weather on construction projects is highly variable, depending on numerous factors, including the type of construction, location, and season (Al-alawi et al. 2017), and affecting the individual tasks of a construction project differently. Low temperature, rain, and other weather conditions may hamper productivity of certain workers and machinery, while others may be unaffected. Regulations mandating threshold values for weather conditions at which work must stop varies between countries and even from city to city (Jung et al. 2016). Given the uncertainty in weather and the variability associated with its impact, appropriately considering weather as a risk factor requires the use of sophisticated risk analysis and decision-support tools before and during construction execution (Pan 2005). To achieve the planned schedule, advanced planning is required to prepare mitigation strategies that can effectively reduce the negative impact of weather on project cost and time (Alvanchi and JavadiAghdam 2019; Jung et al. 2016; Larsson and Rudberg 2019).

6.2.2 Weather-Related Project Delays in Construction

"Clear and specific" weather-related clauses are a common component of wind farm construction contracts (Ballesteros-Pérez et al. 2017). Designed to allocate responsibilities and reduce claims, these clauses clarify compensation for weather delays caused by productivity loss or work stoppages (Jung et al. 2016). Construction contracts generally differentiate between weather delays that can be anticipated and those that cannot (Ibbs and Kang 2018). Delays resulting from severe weather that is anticipated is usually considered non-excusable, where only delays caused by abnormal and unforeseeable weather events are granted a time extension (Jung et al. 2016; Nguyen et al. 2010). Many wind farm construction projects are awarded by the owner on a calendar-day basis (Guo et al. 2017b). To determine the expected project duration for bidding, contractors typically use approximation or quantitative methods to calculate the number of days expected to be impacted by severe weather for bidding (and other pre-construction) purposes. Often, the expected number of non-working days due to weather are specifically defined in the contract (Apipattanavis et al. 2010), with severe penalties imposed on the contractor for projects that are not completed by the contract-specified end date.

Typically, approximation methods are used to determine the number of severe weather associated days for bidding and pre-construction planning. Approximation methods involve the review of historical weather data to calculate the average number of days associated with severe weather conditions each month and using the remaining working days to develop the project schedule (Jung et al. 2016). In addition to approximation methods, numerous quantitative methods have been developed. Quantitative methods use historical weather data to evaluate the impact of weather on project schedules, either directly or through a weather generator, as shown in Table 6.1. Weather generators are numerical models that reproduce synthetic weather data as a daily time-series of weather variables with the same statistical properties as historical weather data (Jung et al. 2016). Both parametric and non-parametric approaches have been applied. While most models use simulation, others have adopted a mathematical approach or a combination of fuzzy logic with the critical path method (CPM). Three weather parameters have received the most attention: temperature, precipitation, and wind speed. Previous studies have either modeled the effect of one weather parameter or a combination thereof.

Table 6.1: Summary of quantitative weather models

Reference	Modelling Theory[1]	Project Type	Weather Modelling	Weather Parameters[2]		
				Temp.	Wind	Prec.
(Guo 2000)	Fuzzy + CPM	Highway	Historical	-	-	✔
(Pan 2005)	Fuzzy + CPM	Highway	Historical	-	-	✔
(Guo et al. 2017b)	Fuzzy + CPM	Onshore Wind	Historical	-	✔	-
(Zhou et al. 2021)	Mathematical	Onshore Wind	Historical	-	✔	✔
(El-Rayes and Moselhi 2001)	Mathematical	Highway	Historical	-	-	✔
(Apipattanavis et al. 2010)	Mathematical	Highway	Generator	-	-	✔
(Ballesteros-Pérez et al. 2017)	Mathematical	Buildings	Historical	✔	✔	✔
(Ballesteros-Pérez et al. 2018)	Mathematical	Buildings	Historical	✔	✔	✔
(Ballesteros-Pérez et al. 2015)	Mathematical	Bridge	Historical	✔	✔	✔
(Atef et al. 2010)	DES	Onshore Wind	Generator	-	✔	-
(Shahin et al. 2014)	DES	Tunneling	Generator	✔	✔	✔
(Zhang et al. 2018)	DES	Dams	Generator	-	-	✔
(Jung et al. 2016)	DES	Tall Buildings	Generator	✔	✔	✔
(Larsson and Rudberg 2019)	DES	In Situ Wall	Historical	✔	✔	✔
(Shahin et al. 2011)	DES + Continuous	Pipeline	Generator	✔	✔	✔
(Marzoughi et al. 2018)	M.-Crit. + Reg.	Residential	Historical	✔	✔	✔

[1]Fuzzy + CPM: Fuzzy Logic and Critical Path Method, DES: Discrete-Event Simulation, M. Crit. + Reg.: Multi-Criteria and Regression; [2]Temp.: Temperature, Prec.: Precipitation

6.2.3 Assessing the Impact of Weather on Wind Farm Construction

Of the quantitative weather models previously-developed, only two have been designed for onshore wind farm construction: Guo et al. (Guo et al. 2017b) proposed a fuzzy-based approach for assessing the impact of wind speed uncertainty on wind turbine installation, and

Atef et al. (Atef et al. 2010) introduced a discrete-event simulation approach of wind turbine assembly activities coupled with a weather generator. Notably, only the effect of wind speed on turbine assembly was considered by these two studies, and both studies were designed to generate a holistic, master scheduling of the project. Although useful for early scheduling during the pre-construction phase, these approaches are not suitable for developing short-term lookahead schedules used during the execution phase.

Currently, lookahead scheduling in wind farm construction relies on conventional scheduling techniques, such as bar charts and the CPM. However, these techniques are not able to precisely capture the impact of weather uncertainties or to model productivity-influencing factors when developing short-term project schedules (Guo et al. 2017b). In practice, the impact of wind uncertainty is usually estimated by a rule of thumb approach and subjective judgements based on practitioners' past experiences (Guo et al. 2017b). This approach can result in inappropriate adjustments, which may lead to deviations from the planned schedule (Guo et al. 2017b). Tools capable of reliably quantifying—in a detailed manner—the schedule delays associated with adverse weather are expected to result in improved management of weather risks, more realistic scheduling, enhanced utilization of construction resources, and safer work environments (Atef et al. 2010). Reliable quantitative tools for short-term lookahead scheduling in wind farm construction, however, have yet to be reported in construction engineering and management literature.

6.2.4 Research Gaps

Barriers limiting the application of existing quantitative methods to assess the impact of weather in onshore wind farm construction for short-term lookahead scheduling include:

1. Methods for assessing the impact of weather in onshore wind farm construction (Atef et al. 2010; Guo et al. 2017b) have only addressed the impact of wind speed on turbine installation and do not consider the influence of other weather parameters, such as precipitation and air temperature, on project schedules.

2. Existing methods (Atef et al. 2010; Guo et al. 2017b) have been limited to turbine installation, and cannot consider the impact of weather on other construction activities. To examine the impact of weather on the project schedule, all project activities and their criticality should be modeled and considered. This is particularly important when considering that certain non-critical activities may become critical as a result of weather delays. Conversely, certain weather-sensitive activities may not fall on the critical path, with weather-related delays in these instances not affecting project duration.

3. Short-term weather forecasts are typically more accurate and reliable than historical weather data (Mailier 2010). Existing methods presented in Table 6.1 use historical weather data as input—either directly or through a weather generator—which often results in daily weather predictions that are not matched to actual weather conditions during the short-term lookahead period.

4. Existing methods presented in Table 6.1 are unable to incorporate as-built data into the quantitative scheduling system as the project progresses, thereby limiting the accuracy and representativeness of the output schedules during the construction phase.

6.2.5 Simulation as a Proposed Approach

Construction simulation allows the development of and experimentation with computer-based representations of construction projects at a detailed level to understand their underlying behaviour and investigate the effects of external factors (AbouRizk 2010). The ability of discrete-event simulation (DES) to incorporate the variability associated with external factors, such as weather, to determine the impact of uncertainty on system outcomes has been well-established. As presented in Table 6.1, several studies have successfully applied DES to investigate the effects of adverse weather on construction activities (Atef et al. 2010; Jung et al. 2016; Larsson and Rudberg 2019; Shahin et al. 2011, 2014; Zhang et al. 2018), and DES has been shown to be a reasonable tool for scheduling construction activities of onshore wind projects (Zankoul and Khoury 2016). However, a simulation model capable of considering the impact of weather on the activities on onshore wind farm construction has not been developed.

6.3 Proposed Framework

This research is proposing a hybrid DES-continuous simulation-based framework to integrate as-built information with short-term precipitation, air temperature, and wind speed forecast data to improve lookahead scheduling at the project-level in onshore wind farm construction. The proposed framework centers around a newly-developed and generic hybrid simulation model (i.e., discrete-event and continuous) of both weather-sensitive and non-sensitive activities in onshore wind farm construction. Advances to the existing state-of-the-art include the ability of the model to simultaneously (1) consider the influence of additional weather parameters, such as precipitation and air temperature, on project schedules, (2) model all critical and non-critical activities construction activities, (3) incorporate short-term weather forecast information, and (4) integrate as-built data to enhance short-term lookahead scheduling in onshore wind farm construction.

The proposed framework consists of three components, (1) data collection and preparation, (2) simulation, and (3) framework outputs, as shown in Figure 6.1. First, the method examines short-term weather forecast data and determines upcoming weather conditions over the lookahead period (e.g., 14 days). The productivity of any uncompleted activities during the lookahead periods are multiplied by a pre-established productivity factor to determine a new activity duration given the expected weather.

Using the new durations for the activities within the specified lookahead period together with (1) the actual durations of completed activities and (2) the planned durations of activities in the post-lookahead period, the method generates an updated project schedule each time new as-built information is entered (Figure 6.2).

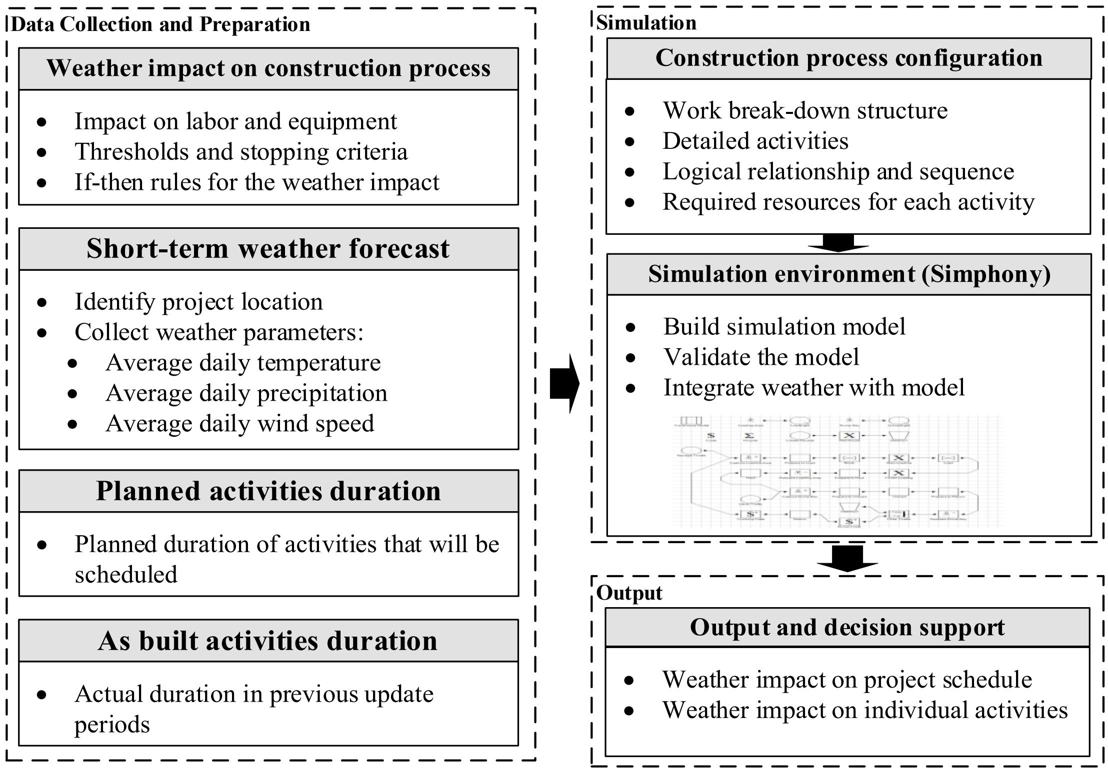

Figure 6.1. Proposed framework.

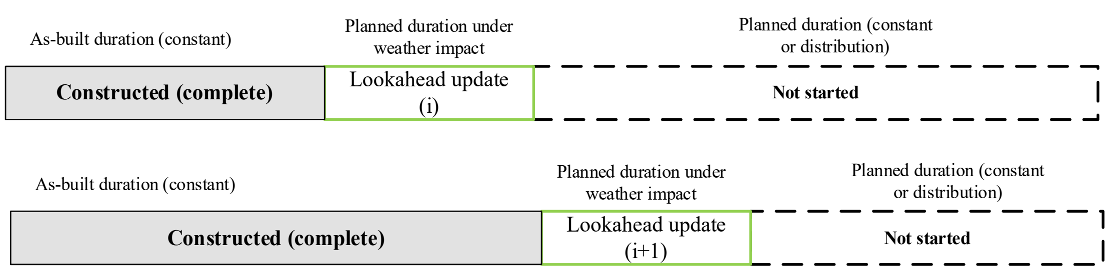

Figure 6.2. As-built versus planned durations for two lookahead update periods.

6.3.1 Data Collection and Preparation

Inputs required to apply the proposed approach include (1) weather impact on productivity of construction activities, (2) short-term weather forecast for the lookahead period, (3) planned duration of activities not yet completed, and (4) as-built (i.e., actual) duration of completed activities.

6.3.1.1 Weather Impact on Productivity

This input associates weather parameter values to construction productivity using if-then rules encompassing three considerations (Shahin et al. 2011): (1) weather parameters that influence the activity, (2) weather conditions that would cause each activity to stop (i.e., stopping conditions), and (3) the relationship between activity productivity and weather conditions.

First, activities are listed, and whether or not each activity is sensitive to weather is determined. Then, the specific weather parameters that are capable of affecting productivity are identified for each weather-sensitive activity. For example, turbine assembly is sensitive to wind speed because of the crane lifts associated with this activity, whereas labor-dependent activities are generally influenced by both temperature and wind speed.

Then, thresholds for each weather parameter for each activity are determined. Thresholds are divided into *work stoppage thresholds*, which define the weather values beyond which the construction activities cannot proceed, and *productivity loss thresholds*, which define the weather values at which construction work can continue but at a lower productivity. Threshold values can be obtained from a variety of sources, including work safety regulations, organization-specific practices, historical data, subject matter experts, and/or construction literature.

Finally, for activities with productivity loss thresholds, a mathematical relationship between weather parameter values and productivity is established for each set of weather parameter values. Two methods for deriving a mathematical relationship have been reported in literature. The first method calculates the impact on activity duration directly (i.e., percentage of duration is added to the original duration (Atef et al. 2010)), while the second method calculates the impact of weather on activity productivity through a productivity factor (Shahin et al. 2011). Productivity factor values can be calculated by inputting historical project data and/or subjective information into the productivity factor equation proposed by (Shahin et al. 2011). Notably, in the absence of applicable historical information, productivity factor values can also be obtained from construction literature. In adverse conditions, productivity factors are less than a value of 1; while in favorable conditions, productivity factors are higher than a value of 1.

6.3.1.2 Short-Term Weather Forecasts

Short-term weather forecasts are available from a variety of publicly-available and commercial providers, which typically provide daily weather forecasts for the upcoming 7, 10, and/or 14 days.

6.3.1.3 Activity Durations: Planned and As-Built

Planned durations for activities that have not yet been completed are determined using historical project data or subject matter expert opinion. At the initial stage of construction, all activities will be input with planned durations. Methods for determining activity durations have been extensively discussed in construction literature. Readers are referred to (Ahuja et al. 1994) for a detailed review of activity duration planning. Planned durations can be input as constant values or as probability distributions. As activities are completed, planned durations will be replaced with as-built (i.e., actual) durations within the simulation model. This applies to both weather-sensitive and non-sensitive activities. As-built durations can only be input as constant values, given that as-built durations are known.

6.3.2 Simulation

Once required data are collected, they are input into the proposed simulation model for onshore wind farm construction. Here, DES is used to model non-sensitive weather activities, and—due to dynamic changes in weather conditions—continuous simulation is used to model weather-sensitive activities. The model is capable of considering both regular variability (through the input of planned durations as probability distributions) and the impact of weather on productivity (through the application of the productivity if-then rules) to predict durations of both the individual activities and of the overall project. Model development and application are detailed as follows.

6.3.2.1 Model Development

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A simulation model can be developed once the underlying system behaviour is defined and understood. The construction process of onshore wind projects and simulation logic are detailed as follows.

- Construction Process Configuration;

To develop the model, common components of onshore wind farm construction were identified and abstracted. Previous studies were reviewed (Hao et al. 2019; Mohamed et al. 2020a; Zankoul and Khoury 2016), and a typical onshore wind farm project was found to be comprised of six major work packages: site preparation, foundation, turbine assembly, collection system, mechanical completion, and commissioning. Each of these work packages was further partitioned into more detailed work-packages, as shown in Figure 6.3. Because the proposed method requires weather impacts on activity duration to be determined, the work packages were further partitioned at the activity level following a detailed review of (1) previous onshore wind farm construction projects available in literature (Atef et al. 2010; Guo et al. 2017b; Mohamed et al. 2020a; Zankoul and Khoury 2016) and (2) 10 real onshore wind farm projects as detailed in Table 6.2.

Table 6.2: Characteristics of historical onshore wind farm projects.

No.	Project Size (MW)	Number of Turbines	Project Location
1	74	30	Ontario, Canada
2	74	30	Ontario, Canada
3	19	6	Ontario, Canada
4	10	5	Ontario, Canada
5	270	140	Ontario, Canada
6	10	5	Ontario, Canada
7	40	16	Alberta, Canada
8	20	8	Alberta, Canada
9	110	46	Alberta, Canada
10	66	22	Alberta, Canada

The detailed activities within each work package and the logical relationships between them are illustrated in Figure 6.4. The generic activity-level WBS (Figure 6.3 and Figure 6.4) was reviewed by subject matters experts, who confirmed that the WBS was accurate and representative of a typical onshore wind farm construction project.

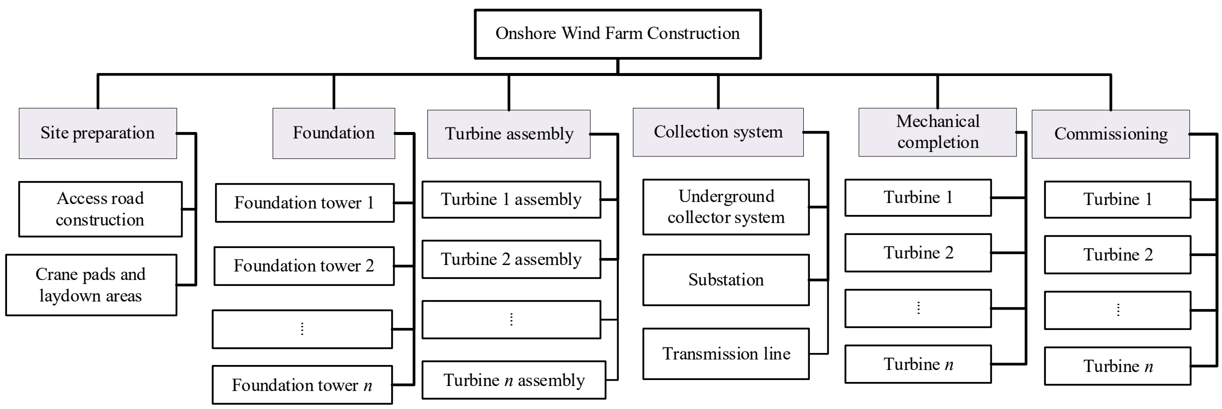


Figure 6.3.Work breakdown structure of an onshore wind project.

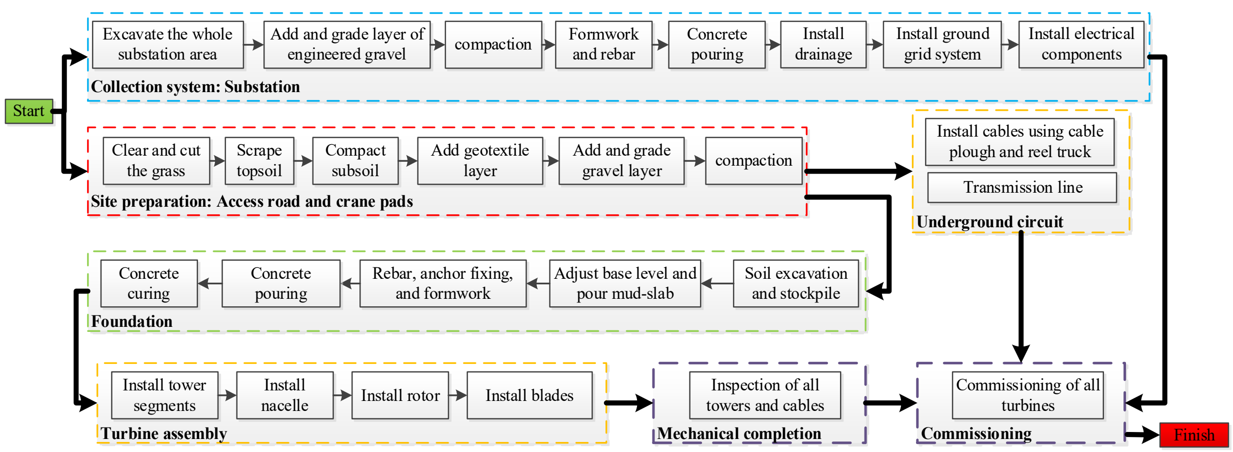


Figure 6.4. Detailed activities and sequence of work for an onshore wind project.

- Simulation Logic;

Once the generic construction process was established, a combined discrete-event and continuous simulation modelling approach was used to develop a generic simulation model. The simulation logic underlying the hybrid simulation model is detailed in Figure 6.5. In DES, entities are objects that have attributes, experience events, consume resources, and enter queues over time. An entity can be dynamic by moving through the system or remain static to serve other entities (Banks 2000). As an entity moves through the model, events are scheduled, thereby representing progress of the system.

In the current study, one entity is created at the beginning of the simulation. Depending on the activity sequence, further entities are created as needed. Following the creation of an entity, the simulation model retrieves the forecasted weather parameter values for each day of the update period (i.e., 14 days). When an entity arrives at a weather-sensitive activity, one of three statuses is selected based on the “Time Now” value:

(1) If the “Time Now” value is greater than the lower boundary of the update period, but less than the upper boundary of update period, the weather-sensitive activity is included in the lookahead period. Continuous simulation, as is recommended in literature (Shahin et al. 2011), is then applied to model productivity in consideration of weather impact.

(2) If the “Time Now” value is greater than the upper boundary of update period, the weather-sensitive activity does not fall within the lookahead period, so the planned activity duration is used.

(3) If the “Time Now” value is less than the lower boundary of update period, the weather-sensitive activity has been completed in the previous lookahead period, so the actual duration is used.

A non-sensitive weather activity has only two statuses: completed or to be executed. For completed activities, actual durations are used. Planned durations are used for incomplete or to be executed activities.

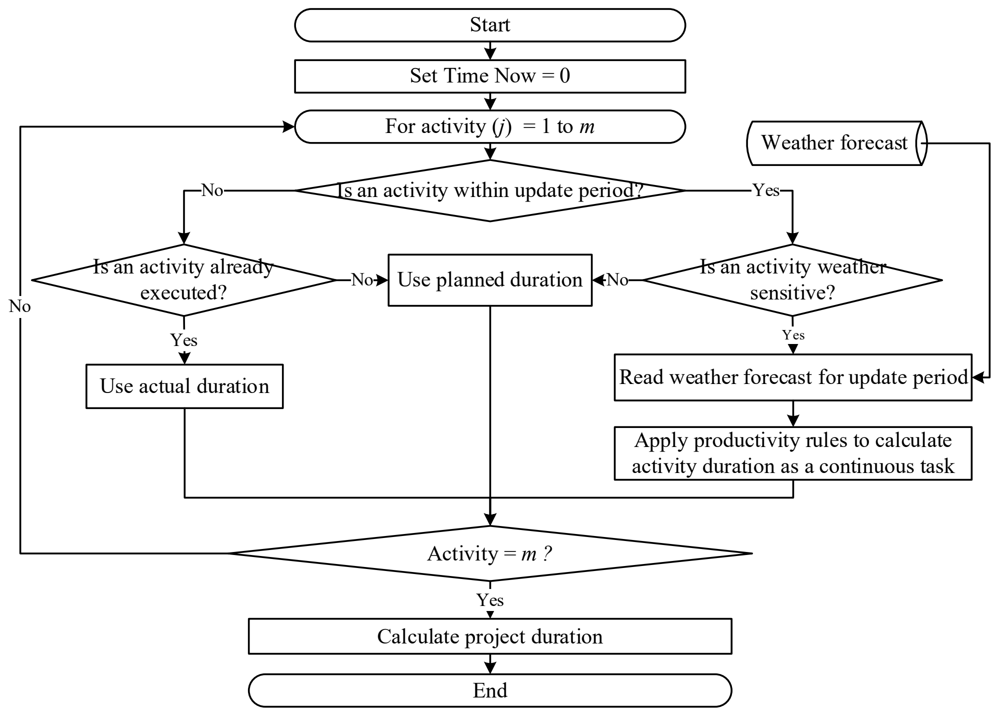


Figure 6.5. Simulation logic for activities and project duration calculation for an update period.

The simulation model provides successive progress updates at one-day intervals. Partial completion of a weather sensitive activity is permitted at the end of an update cycle. Activities with a duration greater than the lookahead period (i.e., 14 days) are divided into segments with durations equal to or less than the lookahead period. The progress for discrete activities is assessed based on the number of discrete units completed and the time required for their execution. This process continues until the project has been fully simulated. Based on the simulation results, a total project duration is calculated. The simulation model is run for a pre-determined number of iterations, and the results of each iteration are combined to provide final results.

6.3.3 Framework Outputs

The first output of the model is the expected duration of the individual weather-sensitive activities in consideration of the short-term weather forecast. This is presented as a plot that visualizes the progress of activities and total accumulated duration. The second output of the model is the expected duration of the entire project. This is visualized as a histogram illustrating the range and distribution of project durations obtained from each run of the simulation model. Various statistics can also be obtained from the simulation results, including minimum, average, and maximum durations as well as the standard deviation. Lastly, the model allows tracking and extraction of finish times for individual activities, which can be visualized as a histogram.

These outputs can provide effective, proactive decision-support to practitioners, helping activities (particularly those on the critical path) remain on schedule and reducing the likelihood of project delays. For example, if a simulated activity duration is delayed by 4 days due to unfavorable weather, the project team may choose to proactively extend working days to include weekends during the lookahead period. Or, if the weather is forecasted to cause work stoppages during the second week of the lookahead period, practitioners may choose to proactively double the number of shifts during the first week when weather conditions are expected to be favorable. Targeted actions such as these not only keep the project on schedule but may also prevent irreversible delays that can lead to disputes.

6.4 Case Study

A real wind farm project was used to demonstrate the functionality and applicability of the proposed framework. The onshore project consisted of eight 5.0-MW wind turbine generators for a total project output of 40 MW. The focus of the case study was on construction activities that were of interest to our industrial partner. Other activities, such as electrical tasks, were not included in this study. Data from two points (i.e., update periods) during construction execution were collected and used to evaluate the ability of the framework to incorporate as-built data.

6.4.1 Data Collection and Preparation

6.4.1.1 Weather Impact on Productivity

First, rules that describe the impact of weather parameters on productivity were developed. Influencing weather parameters and threshold conditions for each activity were collected from construction literature or were provided by the contractor. Input data were reviewed by experts in the field, who confirmed that the thresholds were appropriate for the jobsite. The input data, together with their sources, are summarized in Table 6.3 and Table 6.4 Qualifications of the subject matter experts are listed in Table 6.5. Importantly, the experts indicated that work must also be suspended for approximately 5 working days following a heavy snowfall to ensure that all materials, including blades and other components, are cleared of snow.

Table 6.3: Weather-sensitive activities and influencing weather parameters.

Activity	**Weather Parameters**		
	Temperature	**Wind**	**Precipitation**
Excavation	✔		✔
Compaction	✔		✔
Formwork and Rebar	✔	✔	✔
Concrete pouring	✔	✔	✔
Install tower segments	✔	✔	
Install nacelle	✔	✔	
Install rotor	✔	✔	
Mechanical completion	✔	✔	
Commissioning	✔	✔	

Table 6.4: Stopping thresholds for weather-sensitive activities.

Activity	**Weather Parameters**			**Reference**
	Temperature (°C)	**Wind (m/s[1])**	**Precipitation (mm/h)**	
Excavation	< –25	-	> 5	(Apipattanavis et al. 2010)
Compaction	< –25	-	> 5	(Apipattanavis et al. 2010)
Formwork and rebar	< –25	> 15	> 5	(Apipattanavis et al. 2010), (Larsson and Rudberg 2019)
Concrete pouring	< 0	> 11.5	2.5*	(Apipattanavis et al. 2010), (Larsson and Rudberg 2019)
Install tower segments	< –25	> 14	-	(Guo et al. 2017b), (Atef et al. 2010)
Install nacelle	< –25	> 14	-	(Guo et al. 2017b), (Atef et al. 2010)
Install rotor	< –25	> 14	-	(Guo et al. 2017b), (Atef et al. 2010)
Mechanical completion	< –25	> 11	-	Expert
Commissioning	< –25	> 11	-	Expert

[1] 1 m/s = 3.6 km/h

*During precipitation event

Table 6.5: Expert qualifications.

No.	Years of Experience in Industry	Education Level
1	8	Doctorate
2	15	Master
3	7	Bachelor

As historical project data were not available, relationships between productivity and weather parameters were obtained from those proposed in construction literature. Reported impacts of air temperature (Figure 6.6) (Moselhi and Khan 2010), precipitation (Figure 6.7) (Larsson and Rudberg 2019), and wind speed (Figure 6.8) (Guo et al. 2017b) on productivity from literature were examined, previous projects were reviewed, and a list of rules was prepared based on these findings. A total of 150 rules were defined for this case study. As mentioned previously, the list of rules can differ between organizations and from project-to-project. As such, the list of rules should be reviewed and modified, if required, for each new project. A sample of the developed rules is summarized in Table 6.6. The complete list of rules was validated by the subject matter experts.

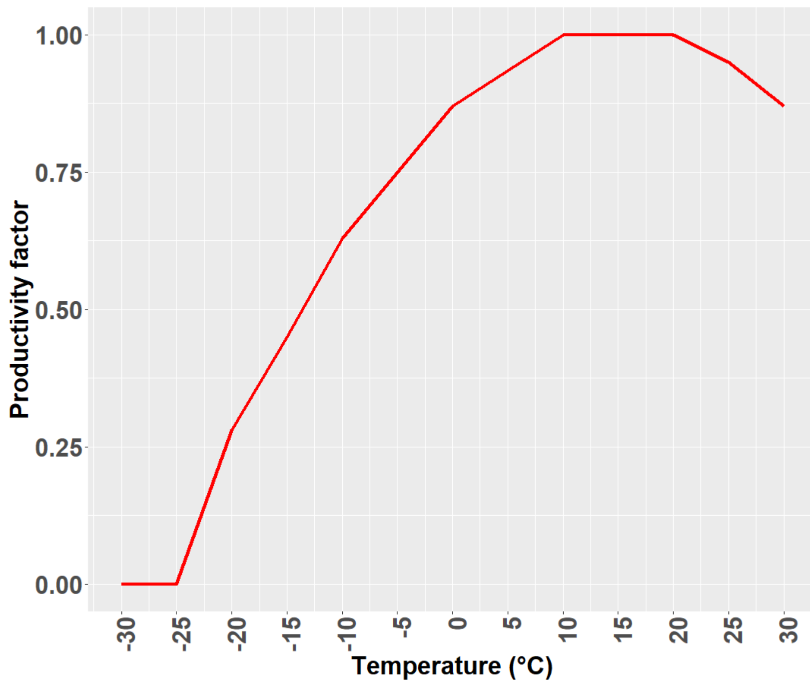


Figure 6.6. Effect of temperature on construction productivity based on results from (Moselhi and Khan 2010).

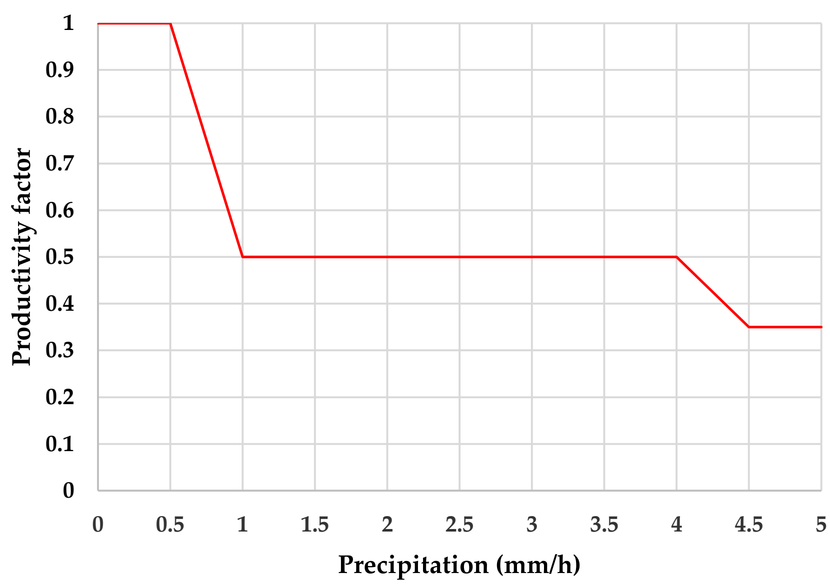


Figure 6.7. Effect of precipitation on construction productivity based on results from (Larsson and Rudberg 2019).

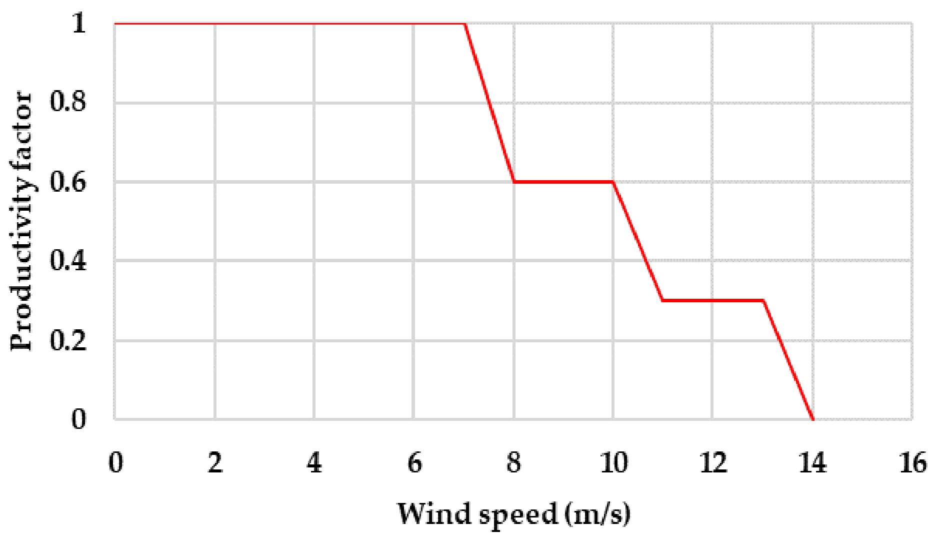


Figure 6.8. Effect of wind speed on construction productivity of crane based on results from (Guo et al. 2017b).

Table 6.6: Sample of developed rules.

Weather Parameters			**Productivity Factor**
Temperature (°C)	**Wind (m/s)**	**Precipitation (mm/h)**	
T < –25	P = 0	W = 0	0
–24.9 < T < –15	P = 0	W = 0	0.25
–24.9 < T < –15	0 < P < 0.5	W < 7	0.4
–24.9 < T < –15	0.5 < P < 1	W > 7	0
–24.9 < T < –15	1 < P <4	W >7	0
–14.9 < T < –5	P = 0	W = 0	0.75
–14.9 < T < –5	0 < P < 0.5	0 < W < 7	0.65
–14.9 < T < –5	0.5 < P < 1	7 < W < 10	0.6
–14.9 < T < –5	1 < P < 4	7 < W < 10	0.5

6.4.1.2 Short-Term Weather Forecasts

In this study, a 14-day weather forecast was selected, as it matched the lookahead update period used by the contractor, which was two weeks. Due to its easy-to-use interface, Dark Sky API (Dark sky API - weather forecast n.d.) was used to collect weather data, including temperature, wind, and precipitation levels. Because weather forecast data were provided hourly, hourly values during the period of construction operations (8:00 AM to 5:00 PM) were averaged to obtain daily forecast values. Data for two updates periods (i.e., 28 days) was collected, as detailed in Table 6.7.The project was located in Alberta, Canada, therefore weather information of the project specific location was extracted.

6.4.1.3 Activity Durations

The third input is the planned durations and logical relationships of the activities under each work package, as shown in Table 6.8. Activity durations specific to this case study were provided by the contractor. Widely-used and commonly-recommended (Hulett 2009; Khadem et al. 2018; Mohamed et al. 2020a; Moret and Einstein 2016), triangular distributions were used to stochastically represent regular (i.e., non-weather) variability in construction activity durations. Notably, activities related to site preparation, foundation, turbine assembly, mechanical completion, and commissioning are repeated for each of eight turbines.

Table 6.7: Weather parameters values for update periods 1 and 2.

Update Period	Days Since Start	Average Temperature (°C)	Average Precipitation (mm/h)	Average Wind Speed (m/s)
Period 1	1	22.2	5.8	4.08
	2	23.4	0.4	3.44
	3	21.2	0	5.25
	4	18.1	0	2.83
	5	20.3	0.1	2.94
	6	20.9	0	4.33
	7	17.2	0	8.75
	8	17.2	0	7.30
	9	14.3	0	3.05
	10	19	0	5.08
	11	17.7	0.2	3.27
	12	15.2	0	4.83
	13	15.5	0	5.00
	14	17.1	0	3.72
Period 2	15	20.2	0	3.52
	16	20.9	0	3.22
	17	24.6	0	4.66
	18	23.4	0	5.38
	19	21.9	0	3.75
	20	20.2	0	5.13
	21	20.5	0	3.47
	22	20	0	6.16
	23	17.2	0	3.30
	24	18.1	0	3.16
	25	18	0	2.88
	26	17.3	0	2.91
	27	14.9	0	5.05
	28	18.1	0	3.83

Table 6.8: Project activity details.

Work Package[1]	Activity	ID	Duration (Days)[2]	Pred. ID/ Rel. (Lag)[3]	Required Resources[4]
Site Preparation	Scrape topsoil	A1	Tri (5, 7, 6)	-	Bulldozer
	Compact subsoil	A2	Tri (5, 7, 6)	A1/F.S	Compactor
	Add geotextile layer	A3	Tri (2, 4, 3)	A2/F.S	Geotextile Crew
	Add and grade gravel layer	A4	Tri (5, 7, 6)	A3/F.S	Grader
	Compaction	A5	Tri (5, 7, 6)	A4/F.S	Compactor
Collection System: Substation	Excavate substation area	A6	Tri (7, 12, 10)	A0/F.S	Excavator
	Add and grade gravel layer	A7	Tri (3, 5, 4)	A6/F.S	Grader
	Compaction	A8	Tri (2, 4, 3)	A7/F.S	Compactor
	Formwork and rebar	A9	Tri (7, 12, 10)	A8/F.S	Crew
	Concrete pouring	A10	Tri (1, 3, 2)	A9/F.S	Pouring Crew
	Install drainage	A11	Tri (5, 12, 7)	A10/F.S	Crew, Excavator
Foundation Construct.	Soil excavation	A12	Tri (2, 3, 2.5)	A5/F.S	Excavator
	Adjust base level, pour slab	A13	Tri (1, 2, 1.5)	A12/F.S	Pouring Crew
	Rebar, anchor, formwork	A14	Tri (2, 4, 3)	A13/F.S	Crew
	Concrete pouring	A15	Tri (1, 2, 1.5)	A14/F.S	Pouring Crew
	Concrete curing	A16	21	A15/F.S	-
Circuit	Install cables	A17	Tri (100, 110, 105)	A5/F.S	Cable Plough, Crew
Turbine	Install tower segments	A18	Tri (2, 3, 2.5)	A16/F.S	Crane, Assy. Crew
	Install nacelle	A19	Tri (0.5, 1, 1)	A18/F.S	Crane, Assy. Crew
	Install rotor and blades	A20	Tri (2, 3, 2.5)	A19/F.S	Crane, Assy. Crew
Mechanical	Inspection of one tower	A21	Tri (3, 7, 5)	A22/F.S	Crane, Insp. Crew
Commis.	Commissioning 1 turbine	A22	Tri (5, 9, 7)	A11/F.S; A17/F.S; A21/F.S	Crew

[1]Commis.: Commissioning; [2]Tri: Triangular Distribution; [3]Pred.: Predecessor Activity, Rel.: Relationship; [4]Assy.: Assembly, Insp.: Inspection

6.4.2 Simulation

In this study, an in-house developed simulation engine, *Simphony.NET* 4.6 (Hajjar and AbouRizk 1999, 2002), was used as the simulation environment to model the onshore wind project activities and associated weather impact. The model was built using the approach detailed in Section 6.3.2.1. The unit of time was set to days, which included an 8-hour workday and no night shifts. The developed rules were coded as if-then rules and stored using global variables in *Simphony.NET*, such that they are readable by all activities in the simulation model. Whether or not a weather-sensitive activity occurred during the update period was determined using a conditional branch in *Simphony.NET*, as shown in Figure 6.9. A snapshot of the entire model is provided in Figure 6.10.

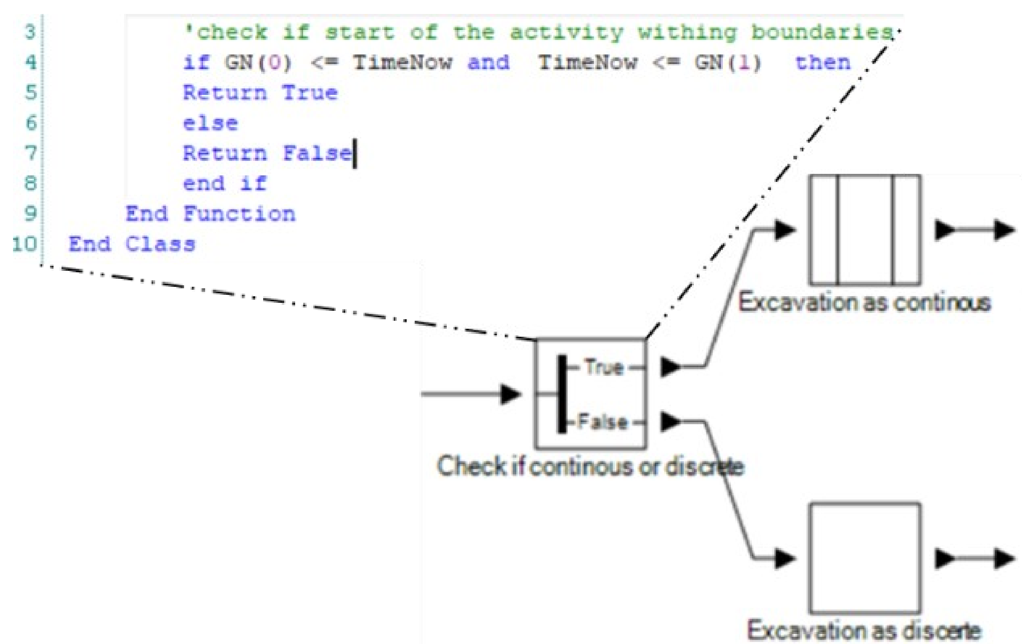


Figure 6.9. Modelling of weather-sensitive activity.

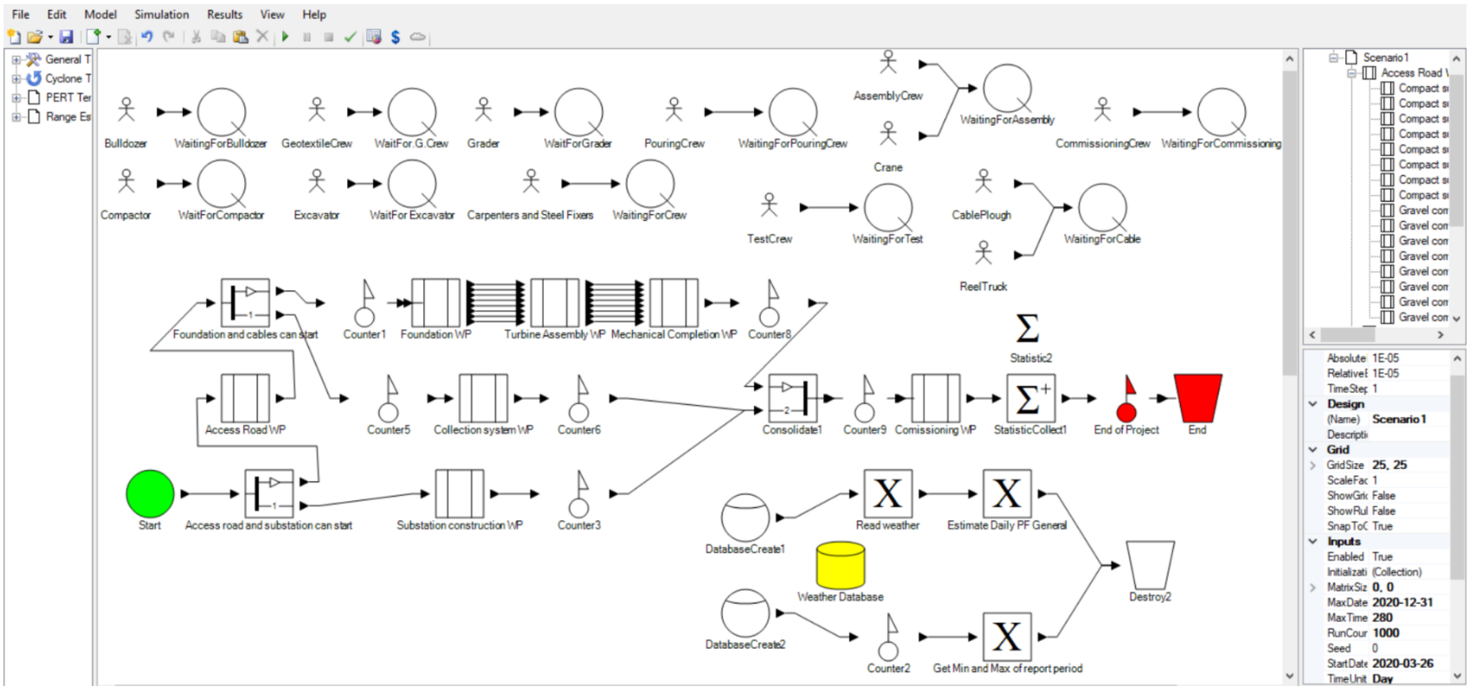


Figure 6.10. Snapshot of simulation model in *Simphony.NET*.

If a weather-sensitive activity did not occur during the update period (i.e., already completed or scheduled to begin in subsequent periods), the actual or planned duration was used, as described in Section 6.3.2.1. Weather data were input to a database that was read by the model every simulated day. For weather-sensitive activities occurring during the update period, the appropriate rule was identified, and the simulated activity duration was multiplied by the corresponding productivity factor.

The simulation was then run for 1 000 iterations, as recommended in (Dawood 1998), to achieve the desired level of confidence. Notably, this is well in excess of the 120 iterations recommended for a simulation to reach maturity (Lee and Arditi 2006).

6.4.2.1 Simulation Model Validation

The generic hybrid simulation model was validated using trace validation, event validity, and face validation approaches (Sargent 2013). First, trace validation, which records the behaviour of various entities in a trace window, was used to evaluate the logic of the simulation model. The sequence of the activities through which the entities flowed was the same as the planned activity sequence, indicating that the logic of the simulation model was consistent with the logic observed in practice.

Second, using event validity, the simulated project duration was compared with the planned duration calculated by the contractor using commercial scheduling software ("Microsoft Project | Project Management Software | MS Project" n.d.). The simulated project duration (without considering weather impact) was an average of 246 days ($\sigma = 4$), which was similar to the original deterministic project duration of 240 days, demonstrating that the model is capable of generating results that are representative of real events.

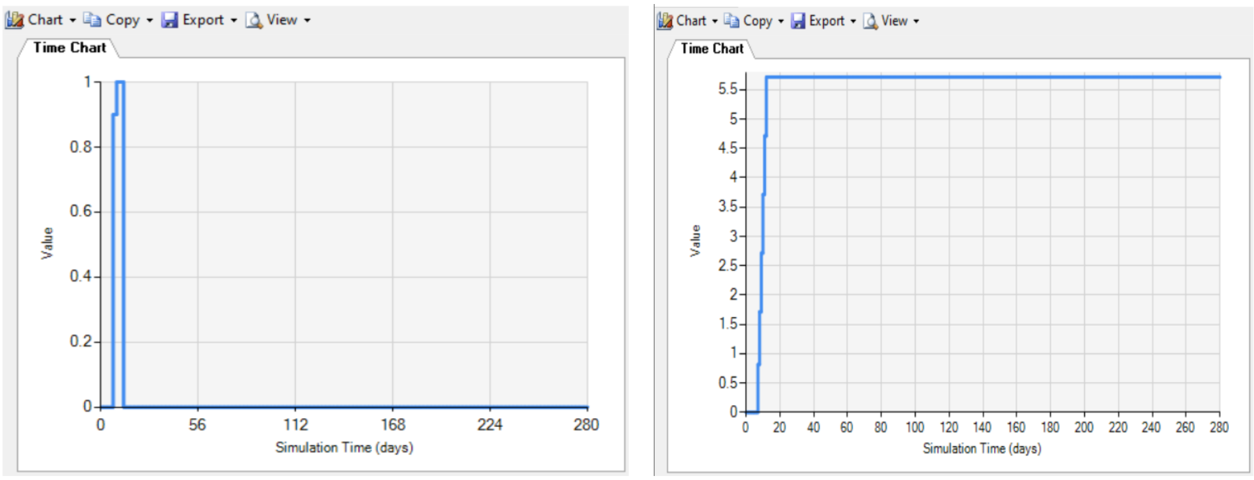
Third, face validation of the model's logic was conducted. Three subject matter experts, whose qualifications are listed in Table 6.5; reviewed the simulation logic of the model. All three experts confirmed that the logic was sound. Based on the findings of the trace validation, event validity, and face validation tests, the model was applied to the case study.

6.4.3 Framework Outputs and Results

The framework was applied to each of the two lookahead update periods. During the first lookahead update period, activities of two work-packages—site preparation and collection system—were initiated in this lookahead period. Of the two work packages, only two weather-sensitive activities (i.e., compaction of subsoil in site preparation and excavation of substation in collection system) were initiated during the first lookahead period. The planned duration of compaction was Triangular (5, 7, 6) (Table 6.8) and excavation was Triangular (7, 12, 10) (Table 6.8). Planned durations were used for the remainder of the activities scheduled to be executed during the first update period.

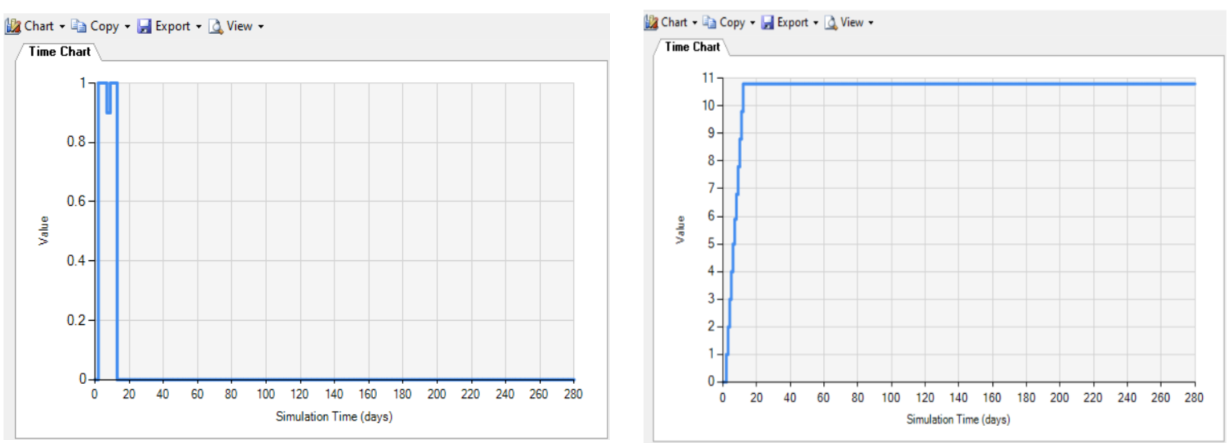
Weather conditions during the first update period were favorable (Table 6.7), with air temperatures ranging between 14.3°C to 23.4°C, wind speeds remaining below 8.75 m/s, and precipitation rates below 0.5 mm/h for 13 out of the 14 days.

As expected, the impact of weather on the productivity of the weather-sensitive activities were minimal, ranging between 0.9 and 1.0 for both compaction (Figure 6.11 a) and excavation (Figure 6.12 a). The average simulated duration for compaction was 5.5 days, while the average simulated duration of excavation was 10.5 days. The accumulated duration for one simulation run of both activities are illustrated in Figure 6.11 b and Figure 6.12 b. The impact of weather resulted in a simulated finish time (considering the impact of weather on productivity) for compaction of 11.5 days ($\sigma = 1$; Figure 6.13b) and excavation of 11 days ($\sigma = 1$; Figure 6.14b), which is similar to the finish time obtained when weather impact was not considered (Figure 6.13a and Figure 6.14a). The average simulated total project duration was determined to be 246 days ($\sigma = 4$; Figure 6.15) compared to the planned project duration of 240 days. Since weather had a negligible impact on project duration, practitioners determined that no corrective actions were needed for this lookahead period.



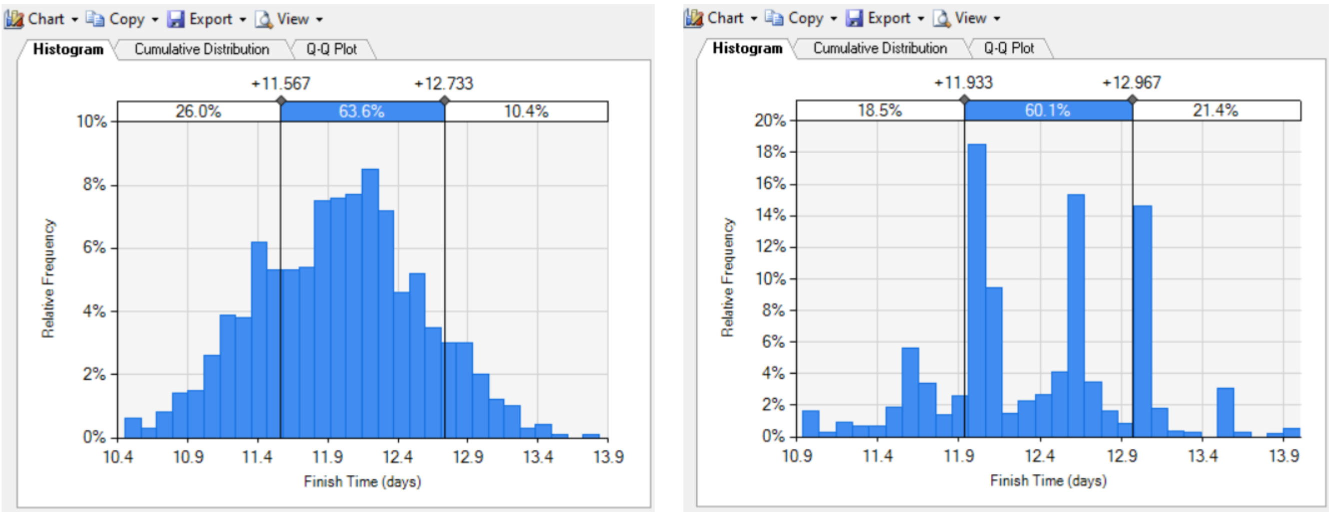
(**a**) (**b**)

Figure 6.11. Weather impact on compaction activity: (a) progress as productivity factor and (b) accumulated activity duration.



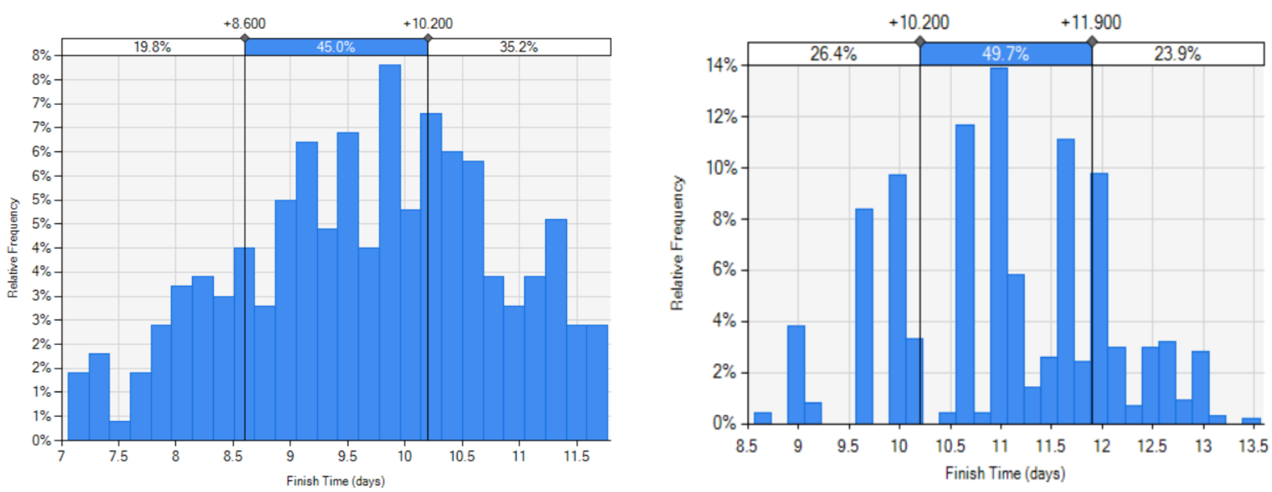
(**a**) (**b**)

Figure 6.12. Weather impact on substation excavation activity: (a) progress as productivity factor and (b) accumulated simulated activity duration.



(a) **(b)**

Figure 6.13. Finish time of compaction activity: (a) without weather impact and (b) considering weather impact.



(a) **(b)**

Figure 6.14. Finish time of excavation activity: (a) without weather impact and (b) considering weather impact.

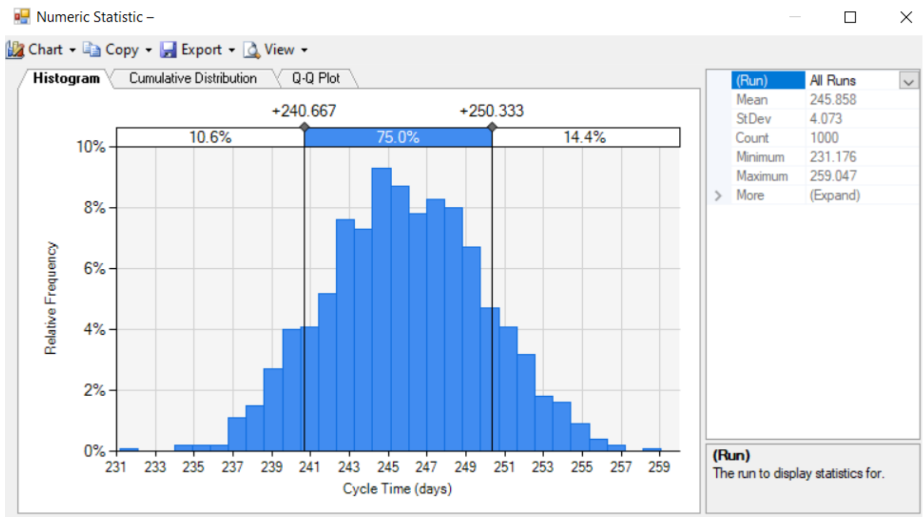


Figure 6.15. Project duration after considering weather impact for first lookahead update.

Similar to the first update period, weather conditions during the second update period were favorable (Table 6.7)ranging between 14.9°C and 24.6°C, wind speeds remaining below 6.16 m/s, and no precipitation. Nine activities had been initiated during the first update period, of which two were still ongoing. Progress information is detailed in Table 6.9.

Table 6.9: Progress of project activities at day 14.

Activity	Weather-Sensitive?	Progress (%)	Actual Duration (Days)	Remaining
Scrape topsoil section 1	No	100	6	0
Scrape topsoil section 2	No	100	5	0
Compact subsoil of section 1	Yes	100	6	0
Scrape topsoil section 3	No	In Progress	2	Tri (3, 5, 4)
Compact subsoil of section 2	Yes	In Progress	3	Tri (2, 4, 3)
Add geotextile layer of section 1	No	100	3	0
Excavation of substation area	Yes	100	11	0
Gravel layer of substation	No	100	4	0

Actual durations were used for completed activities. For in progress activities, a discrete task was used for the completed portion of the activity, and the remaining portion was modeled as continuous task to allow consideration of weather effects. In addition to the in progress activities, seven weather-sensitive activities were initiated during the second update period. As expected, the favorable weather conditions had a minimal impact on productivity, resulting in a simulated project duration of 245 days ($\sigma = 4$; Figure 6.16). A high-level summary of the results for update periods 1 and 2 is provided in Table 6.10.

Table 6.10: High-level summary of results for update periods 1 and 2 of case study.

Period	**Impact on**		**Project Duration**	**Corrective Action**
	Productivity [1]	**Total Project Duration**		
Baseline	-	-	246 days ($\sigma = 4$)	-
1	<10%	Minimal	246 days ($\sigma = 4$)	None required
2	<10%	Minimal	245 days ($\sigma = 4$)	None required

[1] Weather-sensitive activities.

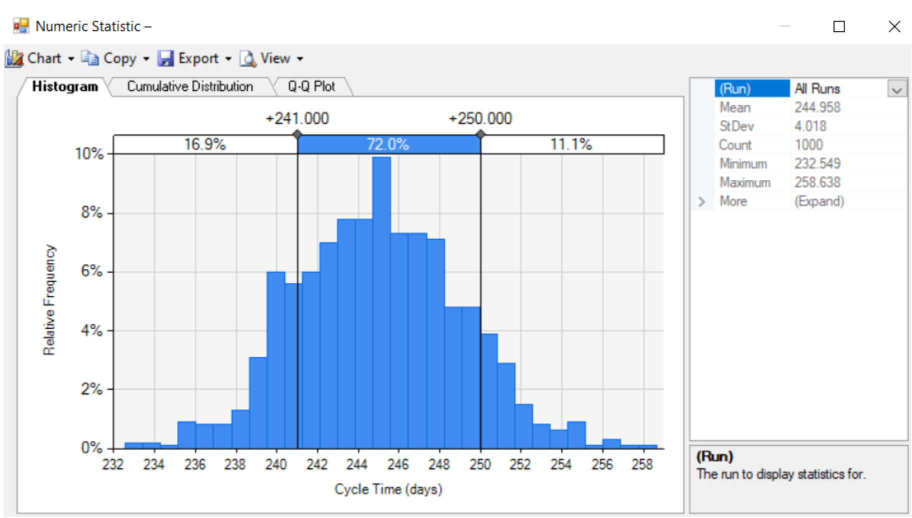


Figure 6.16. Project duration after considering weather impact for second lookahead update.

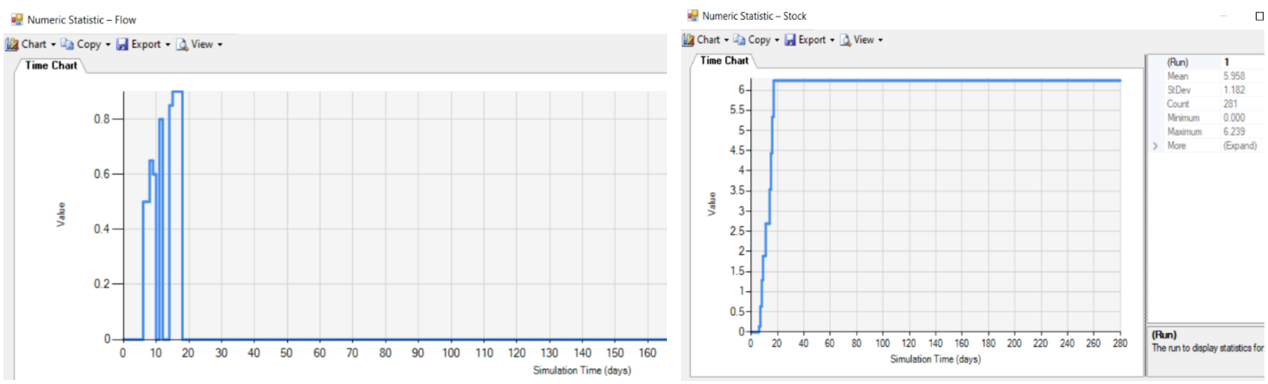
6.4.3.1 Framework Evaluation

In addition to validating the model's logic (detailed in Section 6.4.2.1), the framework was validated through two additional tests: a sensitivity analysis and a face validation of the output results (Sargent 2013). First, the sensitivity of the model to changes in weather conditions was examined. In contrast to favorable weather conditions observed in the case study, the sensitivity analysis input unfavorable weather data into the simulation model (Table 6.11). Here, air temperatures were below 0°C, with average wind speeds ranging between 2 and 20 m/s and precipitation present on 7 of the 14 days.

Table 6.11: New weather parameters for first 14 days.

Days Since Start	Average Temperature (°C)	Average Precipitation (mm/h)	Average Wind Speed (m/s)
1	–10.0	1.00	2
2	–3.5	2.00	4
3	–7.7	3.50	2
4	–8.0	1.50	3
5	–9.4	4.00	5
6	–9.4	2.00	6
7	-8.9	0.00	7
8	–12.1	0.00	8
9	–16.8	5.00	9
10	–1.1	0.00	14
11	–1.9	0.00	15
12	0.0	0.00	20
13	–1.9	0.00	8
14	–1.8	0.00	6

The daily productivity factor of compaction ranged from 0.5 to 0.9, in turn extending the duration of compaction from an average simulated planned duration of 6 days (Figure 6.17b) to a simulated weather-impacted duration of 11 days, which is reflected in the finish time of the activity in Figure 6.18. Altogether, the unfavorable weather conditions during the first 14 days alone caused an overall project delay of 5 days, resulting in a simulated project duration of 251 days (σ = 4) (Figure 6.19). Also, Figure 6.17a demonstrates that the sensitivity analysis results were consistent with expected outcomes, with unfavorable weather conditions resulting in longer activity durations and delayed project completion dates.



(a) **(b)**

Figure 6.17. Weather impact on compaction activity: (a) progress as productivity factor and (b) accumulated activity duration.

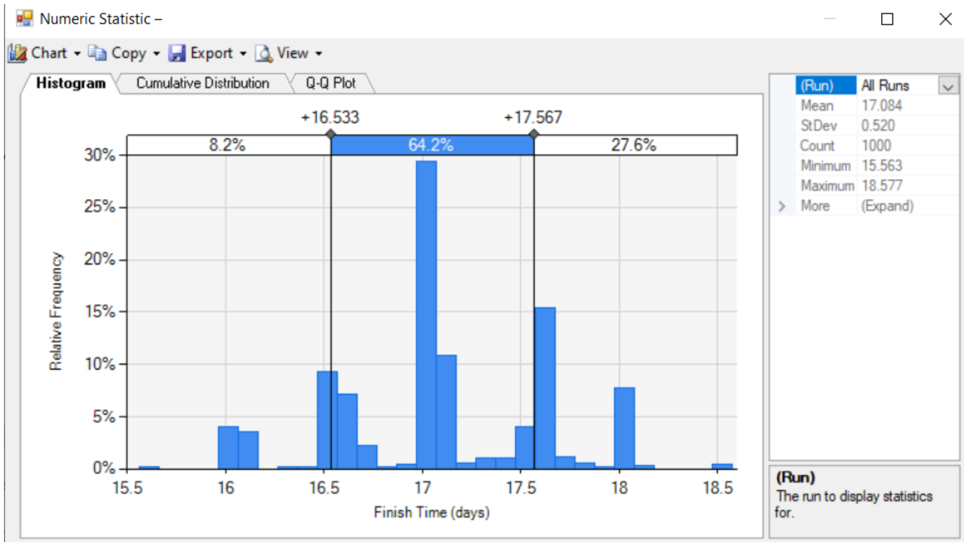


Figure 6.18. Finish time of compaction activity under new weather parameters.

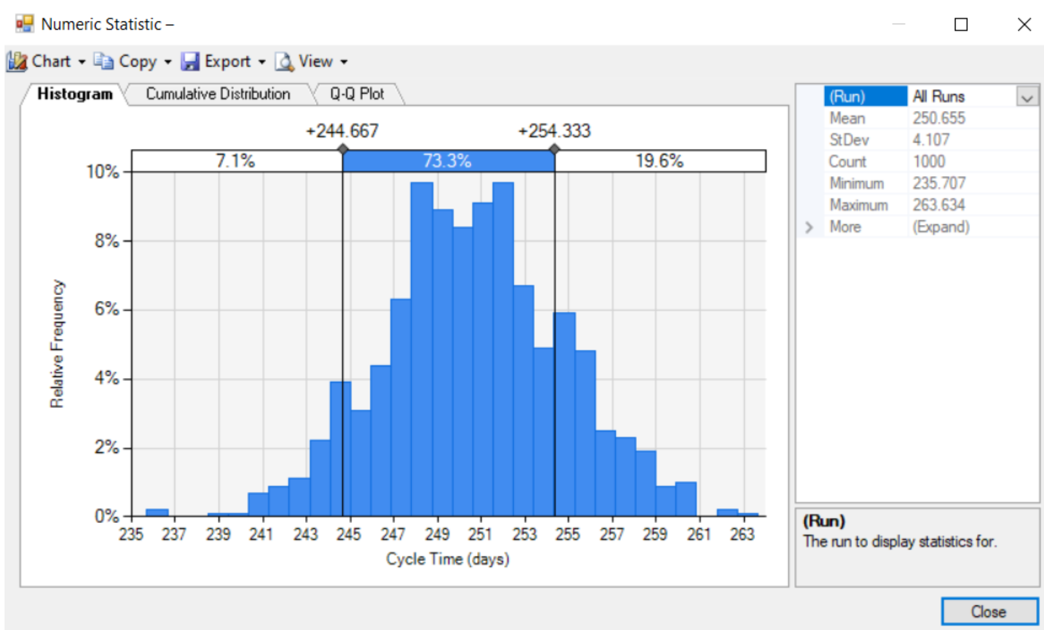


Figure 6.19. Project duration under impact of new weather parameters.

Table 6.12 presents a comparative summary of the first lookahead update period and the baseline schedule. Notably, poor weather conditions, causing a 50% reduction in the productivity of weather-sensitive activities, resulted in a 5-day delay in project completion time. Corrective actions would be required to mitigate the impact of the delay on overall project duration.

Table 6.12: High-level summary of results for update period 1 of sensitivity analysis.

Period	**Impact on**		**Project Duration**	**Corrective Action**
	Productivity 1	**Total Project Duration**		
Baseline	-	-	246 days (σ = 4)	-
1	<10%	Minimal	246 days (σ = 4)	None required

[1] Weather-sensitive activities.

Face validation was also used to assess the advantages and applicability of the proposed method. Results of the case study and sensitivity analysis were presented and discussed with the subject matter experts described in Table 6.5 The experts confirmed that the results generated by the framework were reasonable and consistent with what is expected in practice. They agreed that the framework solves existing challenges with lookahead scheduling that are not currently addressed by existing commercial scheduling software and that results generated by the proposed framework can be used to enhance and further support existing decision-making. For example, in the unfavorable weather conditions of the sensitivity analysis, the delay expected by the short-term weather forecast could prompt practitioners to double the resources available by increasing the number of shifts or working weekends during the short-term lookahead period to compensate for the (almost 50%) loss in productivity.

To further enhance the benefits of the method, the experts noted that, in its current form, the framework was not easy-to-use—particularly by practitioners who may not be familiar with simulation. The development of a graphical user interface for the system was recommended by the experts to facilitate application of the framework in industry.

6.5 Discussion

To address these limitations, a combined discrete-event and continuous simulation method that allows practitioners to more effectively assess and understand the impact of short-term weather uncertainty on construction activities during lookahead scheduling was developed and applied to a case study of a real onshore wind farm project. As expected, favorable weather conditions experienced during the tested lookahead periods resulted in a negligible impact on the productivity of weather-sensitive activities (10% reduction in planned productivity; Table 6.10), which translated into an overall project delay of less than 1 day. The results of the case study, together with the validation experiments, demonstrated the ability of the proposed framework to address the four barriers limiting the performance of existing methods. Specifically, the proposed framework was shown to be capable of: (1) considering additional weather parameters, (2) considering all construction activities and their criticality, (3) integrating short-term weather forecast data, and (4) integrating as-built and progress information into the lookahead scheduling process. The results of the sensitivity analysis, which demonstrated a 50% reduction in productivity (Table 6.12) as a result of poor weather conditions, confirmed the responsiveness of the proposed framework.

This study has advanced the state-of-the-art by addressing four key research gaps, which have limitedthe application of existing methods to lookahead scheduling in wind farm construction. First, the proposed method is capable of considering the impact of three weather parameters (i.e., wind, precipitation, and temperature) on onshore wind farm projects. This is in contrast to the work of (Atef et al. 2010; Guo et al. 2017b), which were limited to wind speed. Second, the proposed simulation model is capable of modeling all construction activities of an onshore wind project. Conversely, the models designed by Atef et al. and Guo et al. remained limited to wind turbine construction (Atef et al. 2010) and (Guo et al. 2017b). Third, the simulation model uses an innovative combined discrete-event simulation and continuous simulation approach to facilitate modeling of both non-sensitive and weather-sensitive activities of onshore wind projects. While a combined discrete-event/continuous simulation approach was used to model a variety of construction operations, such as pipeline construction (Shahin et al. 2011) and (Shi and Abourizk 1998), tunneling construction (Shahin et al. 2014), and building construction (AbouRizk and Wales 1997), this study represents the first application of this approach to model weather-sensitive construction activities in onshore wind projects. Fourth, the proposed framework allows the integration of both short-term weather forecasts and as-built activity durations to enable decision-support at a granular level. This is in contrast to previous studies by Guo et al. and Zhou et al., which focused on the development of wind farm construction scheduling at a master scheduling level (Atef et al. 2010; Guo et al. 2017b). Importantly, while the proposed simulation model was developed for wind farm construction operations, the methodological approach used to develop the simulation model (described in Section 6.3.2.1) can be applied to other project types.

Proactive scheduling approaches for offshore wind farms were also explored. Kerkhove and Vanhoucke (2017) proposed a mathematical optimization model for proactive scheduling of offshore wind projects subject to weather conditions. Similar to previous studies summarized in

Table 6.1, the model proposed by (Kerkhove and Vanhoucke 2017) made use of a Markovian weather generator model that relied on historical data of weather parameters, focused only on the planning phase of offshore wind farm projects, and considered only two weather parameters (i.e., wave height and average wind speed).

A comparison of the proposed framework with previous models developed to assess the impact of weather conditions on productivity of different types of construction projects is summarized in Table 6.13.

Table 6.13: Comparison of proposed framework with previous studies.

Item	**Research Study**																
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**	**O**	**P**	**Current Study**
Reliance on historical weather data	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	x
Flexibility of the method to analyze additional weather parameters during execution	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✔
Consideration of as-built and progress information	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✔
Consideration of short-term weather forecasts	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✔

Note: A= (Guo 2000); B= (Pan 2005); C= (Guo et al. 2017b); D= (Zhou et al. 2021); E= (El-Rayes and Moselhi 2001); F= (Apipattanavis et al. 2010); G= (Ballesteros-Pérez et al. 2017); H= (Ballesteros-Pérez et al. 2018); I= (Ballesteros-Pérez et al. 2015); J= (Atef et al. 2010); K= (Shahin et al. 2014); L= (Zhang et al. 2018); M= (Jung et al. 2016); N= (Larsson and Rudberg 2019); O= (Shahin et al. 2011); P= (Marzoughi et al. 2018)

6.5.1 Practical and Managerial Implications

While methods designed to consider the impact of historical weather data during the planning stages of construction were developed (as detailed in Table 6.1), the impact of short-term fluctuations in weather conditions on productivity were not addressed in previous studies. Indeed, current commercial scheduling software, such as Primavera and Microsoft Project (“Microsoft Project | Project Management Software | MS Project” n.d.), lack the capability to consider the impact of short-term weather on productivity. Consequently, construction companies often use an intuitive, subjective approach to consider the impact of weather during lookahead scheduling, which often results in the development of unrealistic lookahead schedules and the inability to identify and implement timely corrective actions to mitigate potential weather-related delays.

This study aimed to improve lookahead scheduling practices through a simulation-based approach that is capable of considering short-term weather information along with as-built information. This study demonstrated the practicality and benefits of the proposed approach. Specifically, the simulation-based approach was capable of generating a variety of results that can be used to support decision-making in practice by:

1) Obtaining the expected productivity (Figure 6.11a and Figure 6.12a) and duration (Figure 6.11b and Figure 6.12b) of weather-sensitive activities based on short-term weather forecasts, thereby increasing the representativeness of lookahead schedules over existing methods. With a more representative prediction of activity durations, practitioners are able to allocate resources (e.g., labor, material, and equipment) to activities that may be experiencing unexpected delays in productivity. For example, if a simulated activity duration is delayed by 4 days due to unfavorable weather, the

project team may choose to proactively extend working days to include weekends during the lookahead period. Or, if the weather is forecasted to cause work stoppages during the second week of the lookahead period, practitioners may choose to proactively double the number of shifts during the first week when weather conditions are expected to be favorable. Targeted actions such as these not only keep the project on schedule but may also prevent irreversible delays that can lead to disputes.

2) Obtaining probabilistic completion times (Figure 6.13a and Figure 6.14a) of individual activities based on short-term weather forecasts. By obtaining a probabilistic completion time, the project team is able to make more informed decisions about what types of corrective actions they can—and are interested in—pursuing. For example, if a weather-sensitive activity has a high likelihood of being delayed due to unfavorable weather, the project team may decide to postpone delivery of material for subsequent activities to avoid crowding the worksite.

3) Obtaining a probabilistic completion duration of the entire project (Figure 6.15) in consideration of as-built and short-term weather forecasts. The impact of lookahead weather delays on the overall project schedule will depend on the total float of the affected activities and whether or not the activities are on the critical path. Delay of certain activities may result in a considerable delay of the overall project, while others may not affect project duration at all. The ability to easily and quickly quantify the impact of weather-related activity delays in a specific lookahead period

on the overall project duration will help the project team determine the amount of mitigation effort needed to resolve the delay. For example, a delay in the pouring of the concrete foundations for multiple turbines may result in the same activity-level delay as a weather-related delay in installation of the substation drainage. However, a delay in pouring concrete foundations may have a tremendous impact on subsequent activities (and material deliveries) that depend on the completion of the foundation to begin. In contrast, delays in drainage installation for the substation will not impact other activities, thereby minimally impacting overall project duration. The effort expended by the project team to mitigate each delay, therefore, will vary tremendously (Table 6.10 and Table 6.12).

4) Obtaining confidence levels for completing the project within a specific duration (Figure 6.15). Due to the consideration of stochastic activity duration, together with short-term weather forecast impact, outputs of the framework are stochastic and represented by a probability distribution. The probabilistic nature of the outputs provides practitioners with more insightful information, allowing the project team to base their decision on their specific level of confidence.

Using the outputs of the proposed approach, practitioners can proactively schedule their construction tasks in response to a weather-related impact on activity and project durations, thereby enhancing construction progress, reducing weather delays and related claims, and improving the likelihood of project success. While the motivation for adopting enhanced control and monitoring strategies is often the avoidance of unexpected delays and costs, the implementation of effective project control strategies can enable practitioners to capitalize on potential opportunities that may otherwise go unnoticed. Using the proposed framework, the impact of favorable weather conditions (e.g., a warmer than average lookahead period) that result in increased productivity can be easily quantified and identified. It is anticipated that the timely access of such information—made possible by the proposed framework—may allow project managers to better plan construction activities and the delivery of needed materials to capitalize on accelerated schedules, allowing for a shortening of overall project durations.

The findings of this study have highlighted several key recommendations for practitioners performing lookahead scheduling in onshore wind farm construction:

1) Uncertainty arising from weather risk must be quantified as thoroughly and accurately as possible to maximize the likelihood of completing the project within the duration defined in the project contract.
2) It is recommended to begin construction activities during a period characterized by favorable weather conditions to minimize the impact of weather on the productivity of activities early in the project, thereby reducing the number of subsequent activities impacted by early weather-related delays.
3) The impact of adverse weather should be integrated with project lookahead scheduling to more accurately predict the productivity of individual activities and the entire project.
4) Simulation-based approaches provide a better understanding and evaluation of weather impacts on individual activities and the entire project. Moreover, simulation-based

approaches have the capability to consider stochastic duration of activities (as opposed to deterministic durations), allowing these systems to model other variables (in addition to weather) and allowing practitioners to choose their desired level of confidence when making decisions.

5) The proposed simulation-based approach allows practitioners to more quantitatively, rapidly, and easily assess the mitigation effort required to adjust the project schedule.

6.5.2 Limitations

A few limitations of this study should be considered prior to applying the proposed framework. First, triangular distributions and Dark Sky API were used because of their simplicity and for illustrative purposes. While more sophisticated methods capable of enhancing input modelling of activity durations and weather forecasting should be explored and applied, methods for improving input modelling is beyond the scope of this study. Second, because of the novelty of wind farm construction, few historical projects were available for review. While the model is intended to be universal, innovations in wind farm construction practices or organization-specific differences may exist. It is recommended that practitioners thoroughly review the WBS and if-then rules to ensure consistency with their operations and modify the WBS and if-then rules to suit their specific needs as required. Finally, while the functionality of the model was demonstrated using a real 40-MW onshore wind project, favorable weather parameters at the start of construction resulted in a negligible impact on activity and project durations, limiting the ability of the authors to compare model-derived outputs with real results under more unfavorable (i.e., extreme) conditions. Nevertheless, the sensitivity of the model to unfavorable weather conditions was demonstrated through a sensitivity analysis, where unfavorable weather conditions resulted in notable and expected activity and project-level delays.

6.5.3 Future Works

Given the limited availability of historical data in wind farm construction, research such as the study presented here, would greatly benefit from the implementation of data collection strategies designed to quantitatively derive relationships between weather conditions and productivity. These strategies would not only improve the accuracy of the productivity-weather relationships but would also provide the opportunity for future research in this area to be compared to historical outcomes of real projects, thereby improving validation of future models and increasing practitioner confidence. Future research should also focus on modelling the effect of extreme weather events, such as lightning, and how these rare, yet intense, occurrences affect project schedules. Finally, as proposed by the subject matter experts, future work should also focus on the development of a graphical user interface that would facilitate implementation of the method by users with limited simulation knowledge. Development of a graphical user interface would also reduce the effort required to code the model for large and complex projects.

6.6 Conclusion

Adverse weather is one of the most critical and challenging schedule-related risk factors in wind farm construction due to the wind-prone locations of these projects. Weather delays in wind farm construction must be monitored as accurately as possible, as predictable weather conditions are not entitled to time extensions in construction contracts. Current methods, however, only account for weather during the early scheduling stages, using historical weather data to estimate the impact of weather on project duration. However, a method capable of considering variability in short-term weather forecasts for lookahead scheduling during the execution phase of wind farm construction projects had yet to be developed. In this study, a combined discrete-event and continuous simulation model was proposed with the aim of fulfilling this need by developing a practical estimation method for predicting the impact of short-term weather forecasts on activity durations and project schedules during project execution. By addressing existing research gaps, the proposed approach was able to integrate short-term weather forecasts and as-built data to generate outputs that are logical and capable of providing much needed decision-support to practitioners. The method proposed facilitates the ability of practitioners to monitor adverse weather impacts on project durations in the time-frame required to exert effective correct actions capable of proactively mitigating weather-induced delays and subsequent related claims.

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Chapter 7 : Conclusion

7.1 Research Conclusions

This research outlined the development of decision support system (DSS) to improve risk management practices in onshore wind projects. It focused on addressing the research gaps identified in literature and current industry practice pertaining to the risk identification and assessment processes. The developed DSS can by emulated and implemented to any onshore wind project. Also, it can be applied to other types of projects such as mining following the proposed methodology after careful investigation of required inputs and data preparation for each component of the DSS.

Chapter 2 provided an in-depth understanding of the critical risk factors affecting the construction phase of onshore wind projects in Canada. Experts working in the Canadian wind energy industry were surveyed, and their evaluations of the risk factors in terms of their probability and impact on project objectives (i.e., cost, time, quality, and safety) were collected. The responses were analyzed using fuzzy AHP and fuzzy TOPSIS multi-criteria approach. Results indicated that managerial risk factors were the most critical risk factors followed by adverse weather.

Chapter 3 developed an ontological approach that enables the identification of context-specific risk factors based on the contextual characteristics of a project in an automated manner. The ontology-based approach allowed the integration of risk factor information and project context information semantically. This approach was designed to reduce the burden on project managers when identifying risk factors for a new project, reducing effort and time and increasing accuracy. A risk ontology was developed for onshore wind projects to facilitate the identification process based on contextual information.

Chapter 4 proposed a method to improve input modelling for simulation-based risk assessment through the implementation of a fuzzy-based multivariate analysis approach. This approach allows experts to express their detailed subjective knowledge in a granular manner, thereby overcoming the existing limitations of historical data unavailability, correlations between risk factor impacts, and expert biases. The ability of the fuzzy-based multivariate approach to develop a statistical distribution for a risk factor impact was demonstrated in the illustrative example provided, and the functionality of the proposed approach was confirmed following its application to an onshore wind project. The method was implemented in a simulation platform, SimphonyProjects.NET, for risk assessment.

Chapter 5 proposed a domain-specific risk assessment approach for onshore wind projects. Evidence from literature demonstrated that industry practice uses simple techniques for quantitative risk assessment. Therefore, the domain-specific approach allows experts to easily apply and adapt available simulation techniques. A domain-specific MCS-CPM integrated approach was proposed for assessing risk factors of onshore wind projects. The previously developed fuzzy-based multivariate method was used for input modelling preparation of MCS-CPM. The method was implemented in a simulation platform, SimphonyProjects.NET, for risk assessment. The functionality of MCS-CPM method for risk assessment of onshore wind projects was demonstrated through application to a case study of onshore wind project.

Chapter 6 proposed a combined simulation approach for analyzing and understanding the short-term weather impact on project schedules. The proposed approach allows project managers to incorporate the short-term adverse weather forecast in lookahead planning of construction activities for an onshore wind project. This approach allows project managers to take corrective actions and make informed decisions in a timely manner. The functionality of the proposed approach was demonstrated through application to a case study of an onshore wind project. Results confirmed the ability of the method to properly analyze and understand the effects of adverse weather on both individual activities and overall project duration.

7.2 Academic Contributions

This research study has resulted in the development of several academic contributions:

1) Providing a systematic and thorough analysis of risk factors affecting construction of onshore wind projects in Canada, in addition to identifying critical risk factors using a hybrid multi-criteria approach that uses linguistic scales represented by fuzzy numbers to assess the probability and differential impacts (i.e. cost impact, time impact, safety impact, and quality impact) of risks.
2) Development of a context-driven approach that considers the specific characteristics of a project for accurate identification of project risks.
3) Providing an integrated simulation approach for assessment of risks in onshore wind projects that considers both the cost and time aspects of risks.
4) Advancing the Monte Carlo – critical path method by considering the correlation

between the cost and schedule impacts of risk factors.

5) Advancement of input modelling for Monte Carlo simulation, which allows experts to subjectively establish the probability distribution of risk factors' impact using fuzzy logic and multivariate analysis.
6) Providing a simulation-based approach that allows decision makers to assess the weather impact dynamically and accurately on project performance by considering short-term weather.

7.3 Industrial Contributions

The main industrial contributions of this research are summarised as follows:

1) Providing wind energy industry practitioners with a comprehensive list of the most common risks affecting onshore wind projects, in addition to prioritizing these factors in terms of their severity on project objectives.
2) Alleviating the need for time-intensive document review for risk identification by risk analysts and project managers following application of the proposed risk ontology.
3) Providing a proactive, weather simulation-based tool for project managers in onshore wind projects that allow decision-makers to take mitigation and corrective actions in a timely manner.
4) Providing meaningful simulation results and guideline to assist practitioners in performing risk analyses during both the planning and execution phases of

construction.

7.4 Limitations

Although the results presented in previous chapters support the use of the developed approaches, the findings should be interpreted in consideration of certain limitations:

- Although the risk ontology developed in Chapter 3 was designed to identify all types of risk factors (e.g., economic, environmental, and political), publicly-available data were limited to environmental risk factors. Collection of data related to other types of risk factors will enrich the ontology.
- Data collected for building the risk ontology in Chapter 3 were extracted manually from project documents; however, the risk ontology can be supported with a natural language process-based model capable of extracting the required information from documents.
- The fuzzy membership functions used in fuzzy computations in Chapter 4 were triangular and trapezoidal in shape. Other non-linear memberships were not investigated in this research, which may affect the results. Therefore, further investigation should be conducted.
- The combined simulation model proposed in Chapter 6 was built such that the underlying relationships between weather parameters and labor productivity was determined based on previous research studies, which may differ from one country to another or from one company to another. Also, the effect of other

weather parameters, such as lightning, was not considered in this study.

7.5 Envisioned Future Directions

This section reveals possible future research directions stemming from this research work.

- A tremendous amount of risk-associated data embedded within project documentation, such as change orders, claims, and project contracts, is generated and documented throughout the lifecycle of a project. A potential source for identifying risk factors is to review documents, such as contracts or lessons learned, related to the current or similar projects.
- This study proposed a domain-specific simulation for risk assessment to promote the use of advanced quantitative methods by industry practitioners. However, special purpose simulation models that can be developed for specific types of projects should be investigated to promote and encourage the use of advanced risk models by industry practitioners.
- Current practices for risk identification from project documents is conducted manually. Text analytics can be investigated to automate the document review process for risk identification, which can reduce the burden on project managers. Also, this text analytics module can be integrated with the risk ontology to fully automate the identification process.
- Decision making in risk assessment is often affected by the attitude or appetite of

the risk analyst. Future research should focus on addressing the impact of risk appetite on risk mitigation strategies, and how risk appetite can be incorporated in the decision-making process.

- The domain specific risk assessment model was developed based on the critical path method. Future research should focus on investigating the expansion of the model by replacing the simple representation of activity duration with a more sophisticated simulation model. Thus, the overall risk model can contain sub-models for activities that require detailed investigation.
- The decision support system in this thesis was developed for onshore wind projects, therefore future research should focus on investigating how this DSS can be replicated in other types of projects.

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