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

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Abstract

Although many quantitative risk assessment models have been proposed in literature, their use in construction practice remain limited due to a lack of domain-specific models, tools, and application examples. This is especially true in wind farm construction, where the state-of-the-art integrated Monte Carlo simulation and critical path method (MCS-CPM) risk assessment approach has yet to be demonstrated. The present case study is the first reported application of the MCS-CPM method for risk assessment in wind farm construction and is the first case study to consider correlations between cost and schedule impacts of risk factors using copulas. MCS-CPM provided reasonable risk assessment results for a wind farm project, and its use in practice is recommended. Aimed at facilitating the practical application of quantitative risk assessment methods, this case study provides a much-needed analytical generalization of MCS-CPM, offering application examples, discussion of expected results, and recommendations to wind farm construction practitioners.

Keywords

Renewable energy; wind farm; construction; risk; risk assessment; CPM; Monte Carlo simulation

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 modeling 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 modeling 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.

2. Literature Review

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 2017). 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.

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.

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 S1. 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.

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 S1) 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 modeling 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 S1), 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).

MCS 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 S2). 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.

3. Methodology

MCS-CPM 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, modeling and quantification, decision-support, and sensitivity analysis. An overview of the methodology is provided in Figure 1. Model development, as well as a discussion of the results and practical implications of the method, are detailed as follows.

3.1 Input Data Preparation

3.1.1 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.

3.1.2 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 S2. 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.

3.1.3 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 S3. 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).

3.2 Modeling and Quantification

Once the input data are prepared, modeling 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 S1.

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).

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 S3: pre-construction work, foundation, turbine delivery, turbine assembly, collection system, mechanical completion, commissioning, and site rehabilitation.

4.1 Input Data Preparation

4.1.1 Construction Process Configuration and Regular Variability

Each of the work-packages was further partitioned into more detailed work-packages, as shown in Figure S3. Logical relationships between the work-packages and their durations were extracted from project plan documents, as shown in Table 1. 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 S3) and project experts.

4.1.2 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 2; detailed descriptions of each risk factor are available in Table S4. 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.

The probability of occurrence of each risk factor was evaluated linguistically using the scale in Table S5; average values of the numerical ranges, summarized in Table S5 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 2.

The probability distributions for cost and schedule risk impact were determined using the method introduced by Mohamed *et al.* (2020b) for input modeling of MCS in wind farm construction. First, the root causes/scenarios of the risk factors were determined and evaluated. An example for R2 is shown in Table 3; a complete list of the root causes of the risk factors and their evaluations are detailed in Table S6.

Second, the frequency of occurrence and adverse consequence of root causes/scenarios were evaluated subjectively using a fuzzy membership function, as shown in Figure S2. 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 2; mapping for all other risk factors

are shown in Figures S4 through S9. Finally, the correlation between the cost and schedule risk impact was evaluated subjectively as either weak ($\rho=0.15$), moderate ($\rho=0.45$), or strong ($\rho=0.8$), 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 4.

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).

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 modeling of the cost- and schedule-risk impact dependence. An example bivariate distribution for R2 is presented as Figure 3. Bivariate distributions for R6 and R7 are shown in Figures S10 and S11.

4.2 Modeling 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 modeling 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 Figures S12 and S13, 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).

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 4a. Average duration of the baseline project (P_{50}) was determined to be 281 days ($\sigma = 3$ days), with a 90% likelihood (P_{90}) that the duration of the baseline project would not exceed 285 days (Figure 4b). This resulted in a project completion date of April 22, 2021, and April 28, 2021, for P_{50} and P_{90} , respectively (Figure S14). Initially planned using a deterministic approach, the project was expected to be completed in 270 days. As is observed in Figure 6, 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 ($\sigma = 64$ days) (Figure 5). 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). 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 S15). 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.

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 ($\sigma = 64$ days) (Figure 6). 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 6). The time contingency varied between 0 and 375 days due to the long-tailed beta distributions for schedule impacts of risk factors.

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 7). The average cost contingency for the project was 444 691 CAD ($\sigma = 840 337$) CAD (Figure 7), with a 90% likelihood (P_{90}) that the cost contingency would not exceed 2 000 000 CAD (Figure 7). Due to a low probability of risk factors' occurrence, a 70% likelihood (P_{70}) that the cost contingency would be zero was observed.

A tornado diagram, which visualizes risk factor rankings based on their mean simulated risk impact of all runs, was extracted from *SimphonyProject.NET* (Figure 8). Results suggest that project completion delays have the largest potential cost impact, while COVID-19-related delays have the largest potential schedule impact.

A joint time-cost contingency scattergram was generated from the data of each simulation iteration (Figure 9). Each iteration was plotted as estimated project completion (x-axis) versus cost contingency (y-axis). The green lines (Figure 9) represent baseline (i.e., no risk) values of project duration and cost. The gathering of points at the horizontal green line (Figure 9) can be explained

by the finding that there is a 70% likelihood that the cost contingency will be zero (Figure 7). The scattergram also reveals that the completion date of the project is moderately correlated with cost contingency (Figure 9).

The impact of risk on the critical path of the project and criticality of the activities was examined. Table S7 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.

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.

5.1 Sensitivity to Probability of Occurrence

Sensitivity of the model to probability of occurrence values was examined (Figures 10a and b) based on ten scenarios (Table S8). In the original model, the average value of the range associated with the linguistic term (Table S5) 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 S5 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

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 11a 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 12). Here, cost and schedule values were consistently elevated when impacts were correlated (Figure 12). Therefore, considering the impacts of cost and schedule as dependent is recommended to ensure that contingencies are not underestimated—especially in large risk models.

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 *SymphonyProject.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 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.

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 modeling (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, *SymphonyProject.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 *SimphonyProject.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.

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Competing Interests

The authors declare there are no competing interests.

Contributors' Statement

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Data Availability Statement

All data used in the study were provided by a third party. Direct requests for these materials may be made to the provider as indicated in the Acknowledgments. Models and code that support the findings of this study are available from the corresponding author upon reasonable request and with permission from the partner indicated in the Acknowledgements.

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Figure Captions

Fig. 1. Case study methodology.

Fig. 2. Probability distribution for (a) cost and (b) schedule impact of R2.

Fig. 3. Bivariate impact probability distribution of R2.

Fig. 4. Baseline project (i.e., no risk) duration as a (a) probability density function and (b) cumulative distribution function.

Fig. 5. Project duration considering risk impact as a cumulative distribution function.

Fig. 6. Time contingency as a cumulative distribution function.

Fig. 7. Cost contingency as a cumulative distribution function.

Fig. 8. Tornado risk diagram.

Fig. 9. Joint cost-time contingency.

Fig. 10. Sensitivity of (a) cost contingency and (b) project duration, as a cumulative distribution function, with respect to probability of occurrence.

Fig. 11. Sensitivity of (a) cost contingency and (b) project duration, as a cumulative distribution function, with respect to cost-schedule impact correlation.

Fig. 12. Simulated risk impact of (a) R2 and (b) R6.

TABLES

Table 1. 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

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

Table 2. 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 3. Root causes of risk factor R2 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

Table 4. Parameters of distributions for cost and schedule risk impact

ID	Cost Impact				Schedule Impact				ρ^1
	Lower	Upper	α	β	Lower	Upper	α	β	
R1	Triangular (50 000, 250 000, 100 000)				Pert (30, 365, 90)				0.8
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	-

¹Where ρ = assigned correlation value

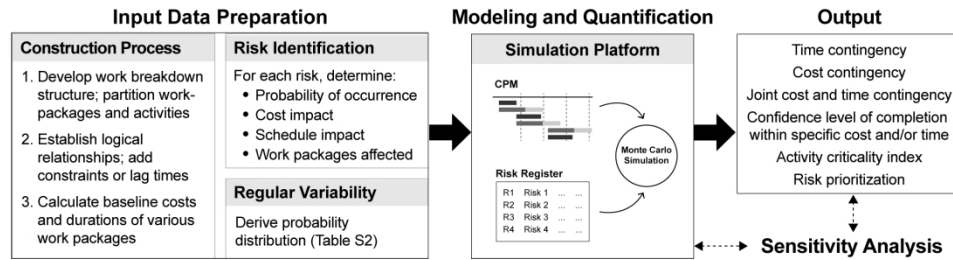


Figure 1. Case study methodology

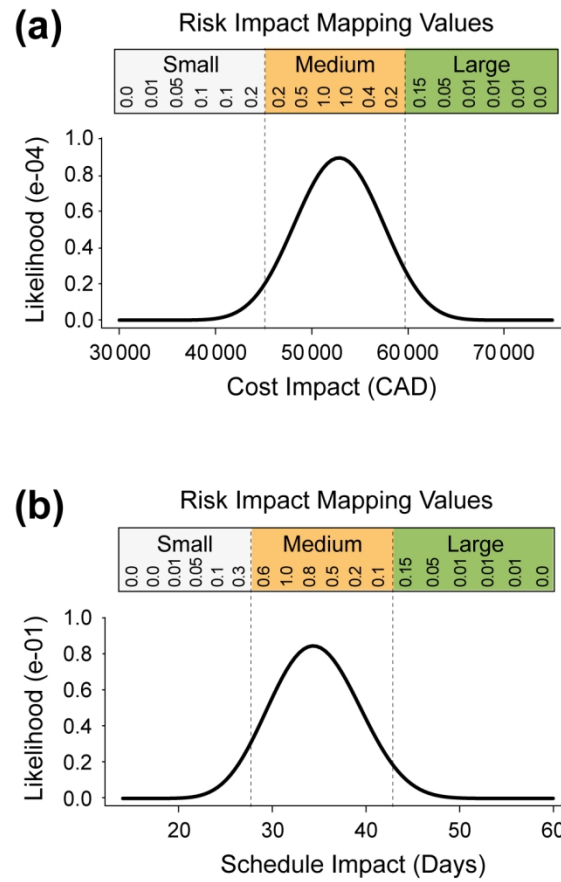


Figure 2. Probability distribution for (a) cost and (b) schedule impact of R2

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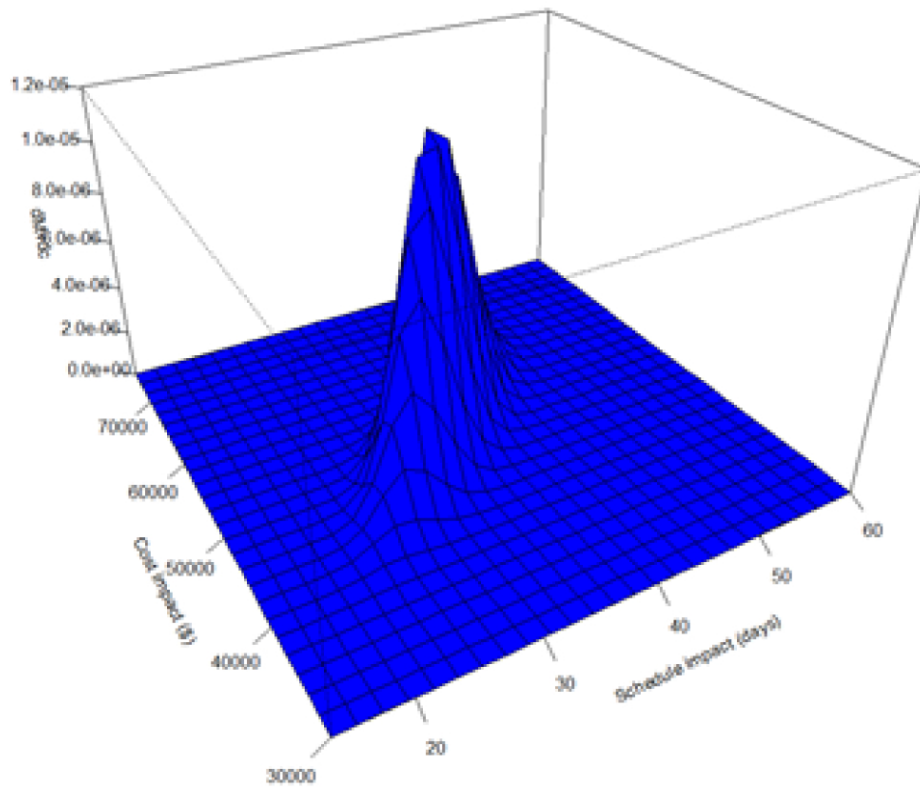


Figure 3. Bivariate impact probability distribution of R2

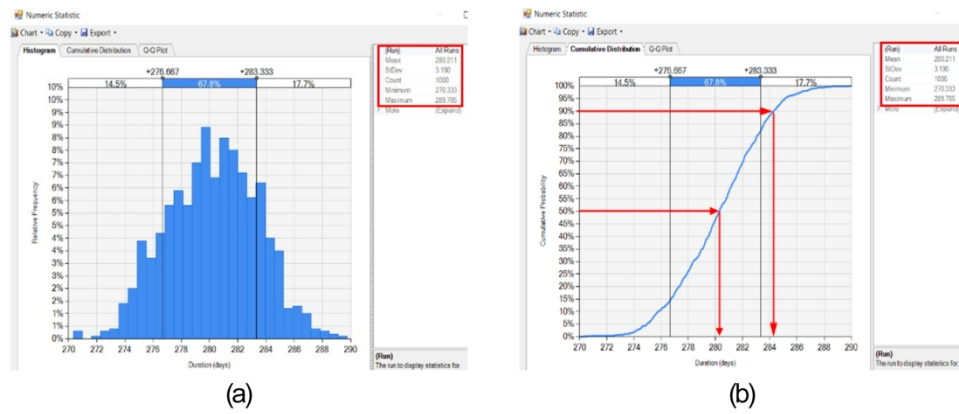


Figure 4. Baseline project (i.e., no risk) duration as a (a) probability density function and (b) cumulative distribution function

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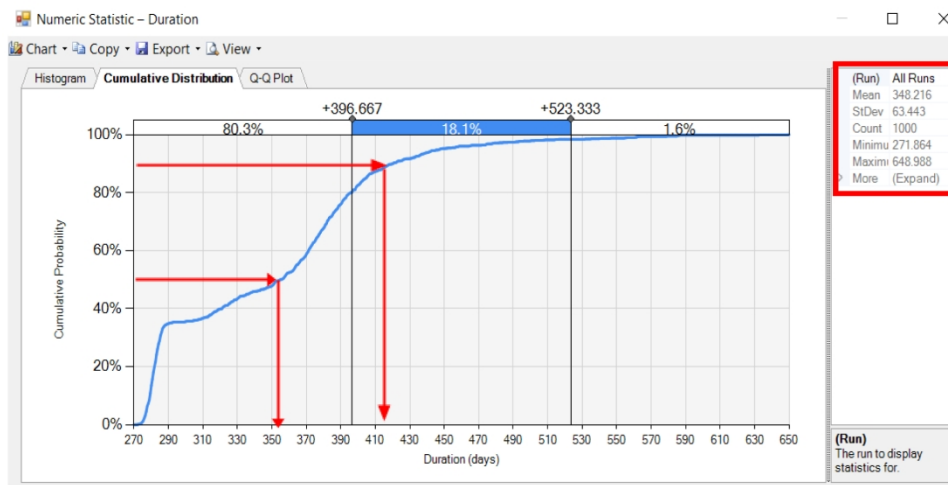


Figure 5. Project duration considering risk impact as a cumulative distribution function

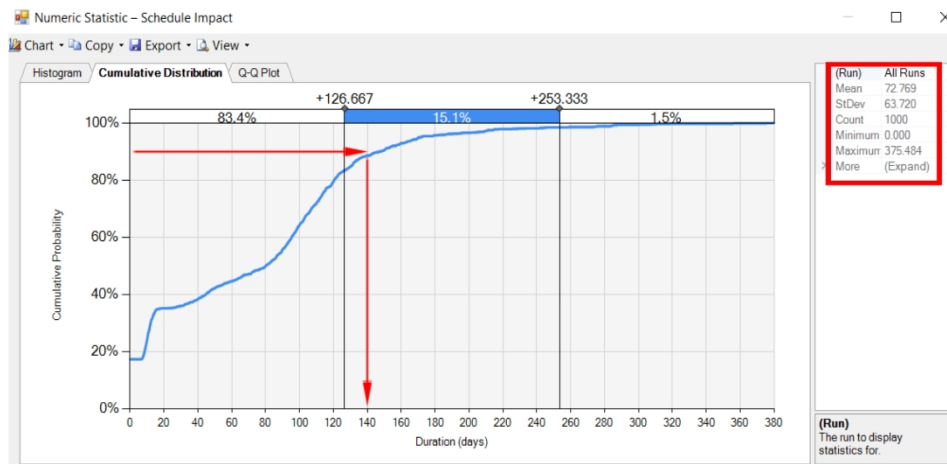


Figure 6. Time contingency as a cumulative distribution function

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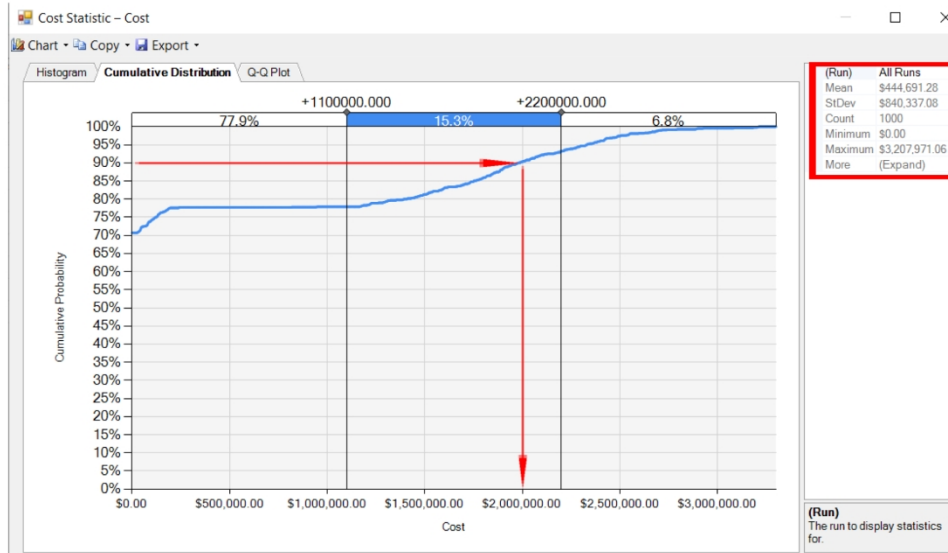


Figure 7. Cost contingency as a cumulative distribution function

Risk	Cost Impact (in CAD)	Schedule Impact (in Days)
Project completion delay	435 756.49	8.794
Bombs in the project area	6 874.16	6.594
Concrete foundation issues	691.48	0.262
Installation errors (Other)	550.11	0.083
Unexpected poor site geology	502.20	0.161
Blade erection failure	316.83	0.056
COVID-19-related delays	0.00	47.115
Limited experience	0.00	5.358

Figure 8. Tornado risk diagram

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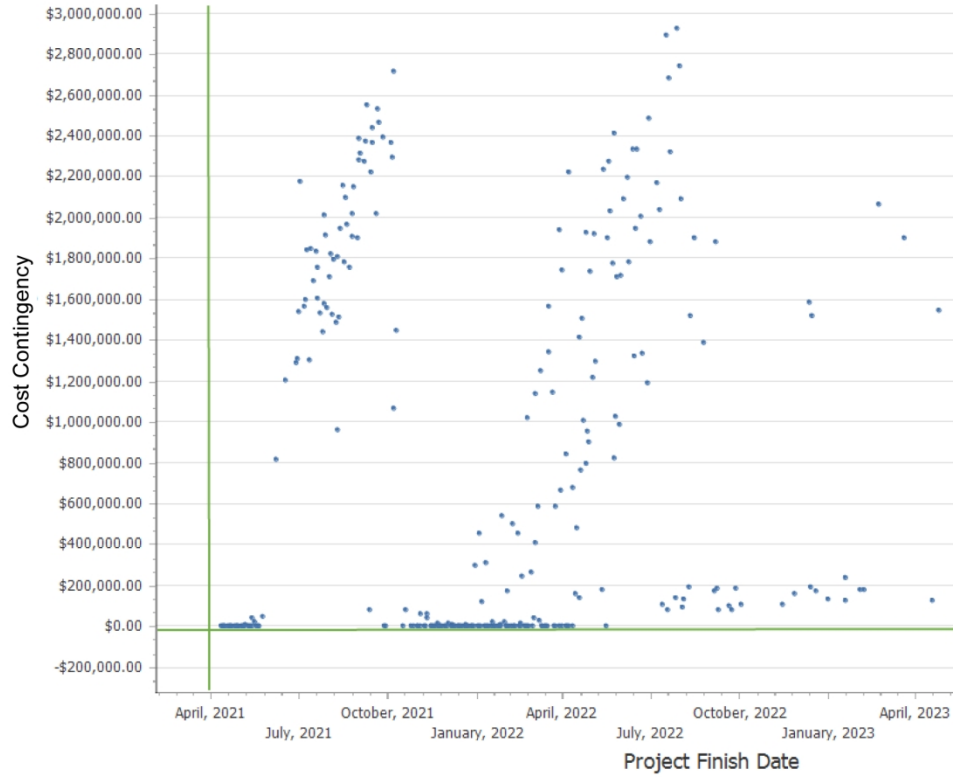


Figure 9. Joint cost-time contingency

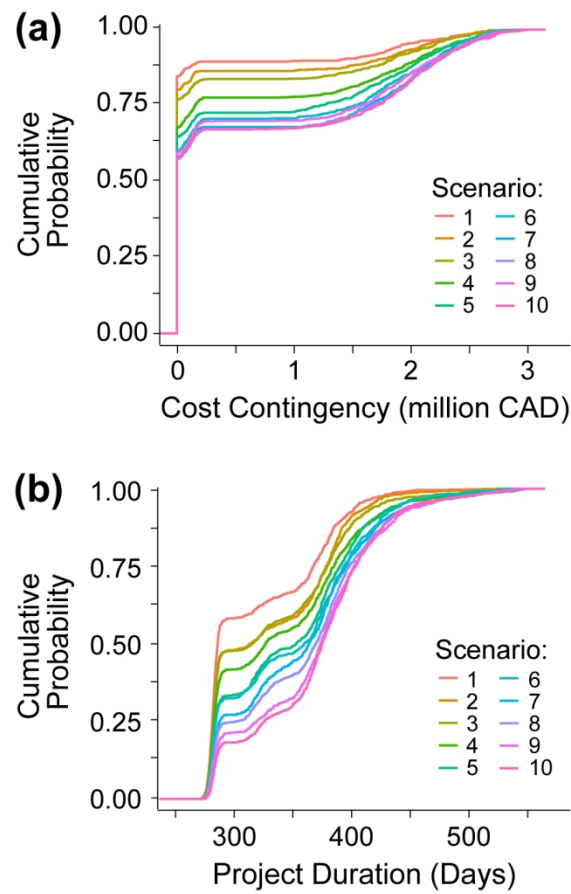


Figure 10. Sensitivity of (a) cost contingency and (b) project duration, as a cumulative distribution function, with respect to probability of occurrence

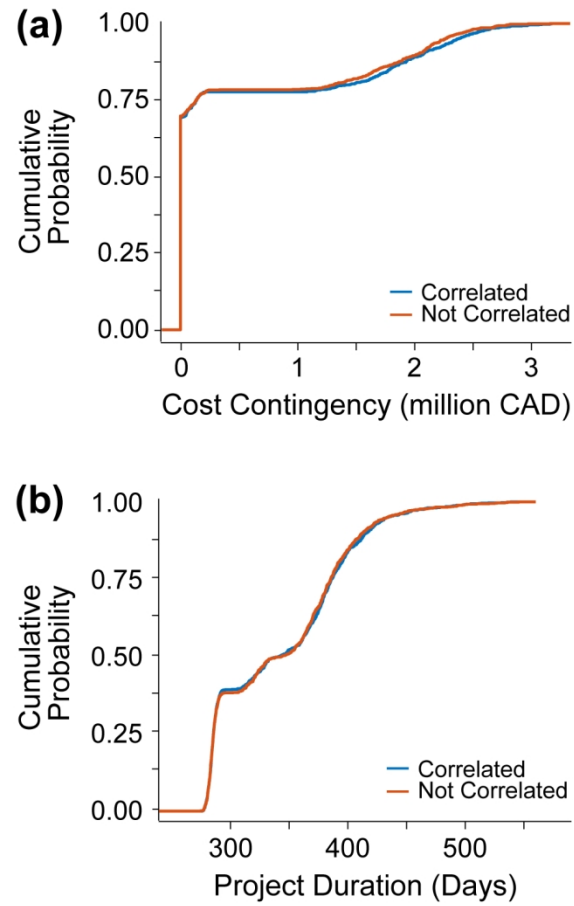


Figure 11. Sensitivity of (a) cost contingency and (b) project duration, as a cumulative distribution function, with respect to cost-schedule impact correlation.

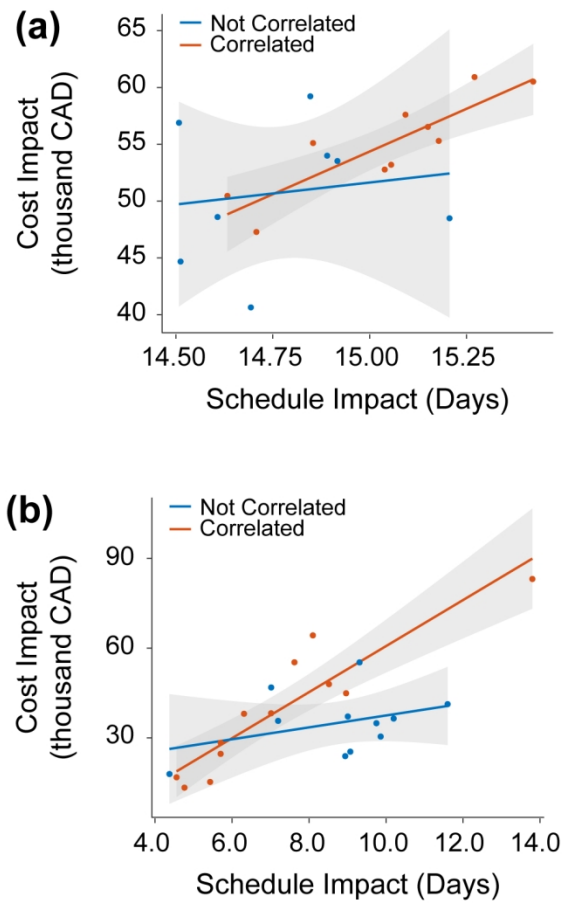


Figure 12. Simulated risk impact of (a) R2 and (b) R6