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

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Abstract

As worldwide goals for sustainable development expand, numerous countries are investing in renewable energy projects, particularly onshore and offshore wind farm projects, which have low adverse environmental impacts. The relative novelty of onshore wind farm projects worldwide means very few studies have been published and the literature lacks a comprehensive list of risks that affect such projects, although effective risk management for construction project relies heavily on successful risk identification. The first goal of this paper is to fill the research gap by identifying the work-package–level risks that affect onshore wind farm construction projects and developing a risk breakdown matrix suitable to these projects. However, the application of existing risk identification techniques in these projects is usually hindered by the lack of comprehensive research in the literature, scarcity of historical data, and high cost of acquiring expert knowledge. Consequently, the second goal of this paper is developing a new risk identification technique based on case-based reasoning and fuzzy logic suitable to onshore wind farm projects. The proposed technique identifies the risks associated with the onshore wind farm projects at the work-package level based on the similarities of these projects to the other types of construction projects. The application of fuzzy logic in the proposed technique allows users to assess the similarities between different types of projects using linguistic variables, and it facilitates the capture of partial similarities between the different types of construction projects. In addition to the novel risk identification technique, this paper presents a risk breakdown matrix of onshore wind farm projects representing 169 risk factors, which are mapped to 11 construction work packages of onshore wind farm projects. The results of this paper and the proposed risk identification technique are compared with conventional techniques, confirming that the proposed technique is suitable to novel types of construction projects like onshore wind farms. The main contributions of this paper are twofold: (1) proposing a new risk identification technique based on fuzzy case-based reasoning that suits novel types of construction projects with limited or no pre-existing knowledge; and (2) developing a generic risk breakdown matrix (RBM) for onshore wind farm projects to improve the risk management process.

Keywords: Risk identification; risk breakdown matrix (RBM); fuzzy case-based reasoning; onshore wind farm; renewable energy project; work-package–level risk

1. Introduction

The number of wind farm projects has been significantly increasing worldwide because of the ongoing trend toward developing infrastructure for renewable energy sources and the technological advancements achieved in the production of highly efficient wind turbines (REN21 2018). The global wind power capacity increased by 45 GW annually on average from 2013 until 2018, which makes wind farms the fastest-growing type of renewable energy projects, ahead of solar power, hydropower, and geothermal power projects (IRENA 2019). Despite its fast growth in production capacity, wind farm projects only produced 24 percent of world renewable energy in 2018 (IRENA 2019). To meet the global target of onshore wind power for 2030, the current capacity needs to be tripled (IRENA 2018). However, challenges associated with developing onshore wind farm projects, such as insufficient risk management practices, can cause a failure to deliver projects within budget and schedule (Fera et al. 2017), and may prevent this 2030 global target. Therefore, improving the risk management practice of onshore wind farm projects can facilitate forecasted growth by promoting wind farm development and successful delivery of projects within budget and on schedule.

According to the Project Management Institute (PMI 2016), the life cycle of construction projects can be divided into five phases: conception, design, construction, commissioning, and closeout. Among these, the construction phase consumes the largest portion of project budget and time; thus, the implementation of risk management practices during the construction phase is essential for the successful delivery of projects within budget and schedule, and failing to do so can negatively impact project objectives (Fera et al. 2012; Siraj and Fayek 2019). Risk identification is the first step in risk management, and successful risk identification results in the accurate assessment of threats and opportunities in onshore wind farm projects during the construction phase. According to Tchankova (2002), the risk identification step plays a leading role in effective risk management, and unccessful risk identification is one of the main reasons for risk management failure and, consequently, project cost overruns and delays. Thus, ample research in the literature focuses on risk identification for different types of construction projects. However, the relative novelty of onshore wind farm projects means they have not been sufficiently investigated in terms of the risks affecting them. Furthermore, the few studies conducted on these projects were primarily focused on project-level risks, and a research gap exists for identifying the work-package-level risks that affect onshore wind farm projects. Therefore, the first goal of this paper was to address the research gap by identifying the work-package-level risks that affect onshore wind farm projects and, consequently, developing the risk breakdown matrix (RBM) of such projects by relating each identified risk to the work-packages affected by the risk.

Many tools and techniques have been proposed for identifying risks associated with construction projects, including literature review (Siraj and Fayek 2019); the strengths, weaknesses, opportunities, threats (SWOT) technique (Gao and Low 2014); checklist analysis (Guo et al. 2019); and Delphi technique (Perrenoud 2018). While risk identification significantly impacts the successful delivery of construction projects, in the case of onshore wind farm projects, the application of traditional risk identification techniques is often hindered by the incomprehensive research literature, lack of historical data, and high cost of acquiring expert knowledge. Thus, the second goal of this paper is to address this challenge by developing a novel risk identification technique based on case-based reasoning (CBR) that suits the needs of novel types of construction projects, including onshore wind farm projects. CBR is an artificial intelligence technique for identifying the characteristics (e.g., risks) of an unknown or less-known phenomenon (e.g., onshore wind farm projects) based on its similarity to the other well-known phenomena (e.g., other types of construction projects) (Watson 1999).

CBR is widely used in different domains to solve different types of problems, including cyber security (Abutair et al. 2019), medical sciences (Marie et al. 2019; Ehtesham et al. 2019), and engineering (Tan 2006). Despite its application in a wide range of engineering problems, CBR lacks the capacity to capture the subjective uncertainty exhibited by different elements of real-world systems. Such limitation becomes more prominent in construction risk identification, where CBR cannot capture the subjectivity associated with assessing partial similarity between two types of construction projects (projects that are neither identical nor fully dissimilar). To address this challenge, CBR was integrated with fuzzy logic in this research, to develop fuzzy case-based reasoning (FCBR). Fuzzy logic is an artificial intelligence technique for capturing the subjective uncertainties of the real-world systems. The integration of CBR with fuzzy logic in the proposed risk identification technique enables the FCBR technique to capture the linguistically expressed expert knowledge and assess the similarity between the different types of construction projects, as well as capturing the partial similarities between different project types. The proposed FCBR was then implemented to identify risks associated with the construction of onshore wind farm projects at the work-package level and develop an RBM for such projects by mapping each risk to the construction work packages (CWPs) affected by the risk. The contributions of this paper are twofold: (1) proposing a new risk identification technique based on case-based reasoning and fuzzy logic that suits novel types of construction projects with limited or no pre-existing knowledge; and (2) developing a generic RBM for onshore wind farm projects to improve the risk management process.

The rest of this paper is organized as follows. The second section provides a literature review on risk identification for onshore wind farm projects and the applications of CBR and FCBR in construction research. The third section presents the research proposed technique for risk identification using FCBR. The fourth section presents risk identification of onshore wind farm projects and research results in the form of RBM. The fifth section presents a discussion on results, followed by the sixth section that presents conclusions and future research.

2. Literature Review

2.1. Risk identification of onshore wind farm projects

The International Organization for Standardization (ISO 2016) defines risk as “the effect of uncertainty on objectives”, which includes opportunities with positive impact as well as threats with negative impact. Construction projects are highly influenced by various risks because of their complex nature and numerous external factors affecting them (Siraj and Fayek 2019).

Therefore, researchers work to identify and assess risks that adversely affect construction projects and determine appropriate risk management practices.

In the risk identification step, construction risks are traditionally represented in the form of risk breakdown structure (RBS), which is a hierarchical structure of risks categorized based on their potential sources. Hillson et al. (2006) introduced the RBM as a new format for identifying and representing risks in construction projects. Although work breakdown structure (WBS) and RBS are noticeably similar, they illustrate two different structure of projects, namely, risks and activities. WBS constitutes the basic framework for the management of a project; likewise, RBS is used as a powerful tool in the risk management process (Hillson 2003; PMI 2016). Thus, a combined use of a project's WBS and RBS allows the project team to control and monitor the risk at a level of detail appropriate to the specific project context (Rafele et al. 2005). In an RBM, the hierarchical structure of risks is presented as in an RBS, and each risk is mapped to those work package(s) that are affected by the risk. An RBM can be presented in the form of matrices or diagrams, which formats can guide researchers and practitioners to an in-depth understanding of risks and their effects on CWPs, (Hillson et al. 2006) via the following:

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

In previous literature related to risk identification for onshore wind farm projects, researchers and practitioners specifically focused on construction risk identification of wind farm projects at the project-level. Fera et al. (2017) ranked 42 identified risks in wind farm projects based on their severity index determined using the analytic network process, which revealed that the quality of concrete curing has the highest severity on project objectives. However, they did not specify their risk identification technique. Enevoldsen (2016) did a comprehensive literature review of onshore wind farm projects in forest areas that focused on the construction, operation, and commissioning phases of onshore wind farm projects. The result revealed that construction is the highest risk-prone phase because of risks associated with land use (e.g., land ownership transferring, renting, etc.). Finlay-Jones (2007) conducted an extensive literature review to identify the risks affecting wind farm projects focused primarily on risks that affect project cost. He interviewed eight project managers in Australia who were experts in on- and offshore wind farm projects to validate the list of identified risks. Study results showed that delay due to weather conditions, transportation of large machinery and turbine components, and availability of labor and resource are the most severe construction-phase risks. This review shows that most prior research focused on onshore wind farm projects at the project-level and neglected the work-package level in the risk identification step. Accordingly, this research aims to develop a new risk identification technique based on FCBR that suits the challenges associated with risk identification of onshore wind farm projects. This paper also aims to fill the research gap for comprehensive risk identification for onshore wind farm projects by developing a generic RBM using the introduced risk identification technique.

2.2. Risk identification techniques

Many tools and techniques have been proposed for identifying risks associated with construction projects, including literature review (Siraj and Fayek 2019), the SWOT technique (Gao and Low 2014), checklist analysis (Guo et al. 2019), and Delphi technique (Perrenoud 2018). According to Siraj and Fayek (2019), the information-gathering techniques (e.g., literature review, questionnaire survey, expert interview) were more widely used than diagramming techniques (e.g., influence diagrams, cause-and-effect diagrams) because diagramming techniques do not consider the root causes of risk and their interdependencies. Among the information-gathering techniques, the literature review is the most commonly used technique, since it is straightforward and easily helps researchers to assess historical data from specific previous projects (Siraj and Fayek 2019). However, a lack of research makes it challenging to implement a literature review on novel infrastructure (Alavi and Nadir 2020).

Another popular information-gathering technique is acquiring expert knowledge through questionnaire surveys and expert interviews. Although expert knowledge is valuable as input for the risk identification process, it has some limitations. Expert knowledge is predominately based on experience, and according to Hubbard (2020) experience is a nonscientific sample of events because it is based on selective memory over the course of one's life, which results in bias. Further, humans tend to be inconsistent in using their experience to make decisions.

Because information-gathering techniques rely on expert knowledge or prior knowledge of projects acquired through the literature review or historical data, their application in risk assessment for novel types of construction projects is limited. As a result, knowledge-based techniques, such as artificial neural network and case-based reasoning, have gained popularity in this context. Researchers can use data from other types of projects as inputs to generate output for risk management for new types of construction projects. However, improper data management can cause failure in the risk management process (Rodriguez and Edwards 2014), and few studies have been conducted on the application of knowledge-based techniques for risk identification in construction projects.

To address the scarcity of data regarding knowledge-based techniques in risk identification for novel types of construction projects, Somi et al. (2020) introduced a new risk identification technique based on case-based reasoning and fuzzy sets. In their proposed technique, similarity between the novel project type and the other types of construction projects is determined, and then similarities that affect the novel construction type are identified. The proposed technique by Somi et al. (2020) has the following shortcomings: (1) it lacks the capacity to capture the subjective uncertainty involved in determining similarity between two projects (i.e., partial similarity), and (2) it lacks the flexibility to be modified by the experts based on the application context. The current paper addresses these research gaps by developing a new risk identification technique using fuzzy case-based reasoning that captures the partial similarities between different project types using fuzzy numbers, and experts can modify it using natural language. Although the use of fuzzy numbers to represent similarity between different cases increases the computational complexity of the proposed technique, the comparison of the results to the existing FCBR technique (Somi et al. 2020) shows improvement in terms of performance (i.e., number of risks identified) and flexibility of the model.

2.3. The applications of CBR and FCBR in construction

Kolodner (1992) introduced CBR as a new technique for solving problems based on previous knowledge about similar cases, which imitate the human reasoning process of applying knowledge acquired through previous experiences to new situations. In a comprehensive literature review of 91 papers from 1996–2015, Hu et al. (2016) found CBR applied to 17 construction areas and a high proportion of problems involving cost estimation and bidding. An et al. (2007) combined the analytic hierarchy process (AHP) with CBR to determine the relative importance of the characteristics used to compare construction projects, creating a hybrid CBR-

AHP model for forecasting the construction cost of residential buildings. They defined 9 attributes for residential buildings: gross floor area, number of stories, total unit, unit area, location, roof type, foundation type, usage of the basement, and finishing grades. Next, they used these weights to calculate the similarity index in the CBR technique. The CBR-AHP model needs expert opinions in order to define weights for each characteristics, which is a limitation for problems with many characteristics. Jin et al. (2016) expanded the application of CBR in estimating the duration of residential projects in the preliminary stage. In this model, similarity indexes are first calculated based on the similarity between each characteristic of problem case and previous cases (e.g., total floor area, foundation type, etc.) then used for calculating revised duration. They concluded that compared to the regression model (i.e., a statistical regression model developed to predict projects' duration based on their characteristics), their CBR model more accurately predicted actual duration.

Despite its numerous strengths for use in construction risk identification, CBR is not yet widely used in the construction risk management context. Goh and Chua (2009) applied CBR for construction hazard identification using a semantic taxonomy for representing each case to systematically retrieve similar information from previous cases. Goh and Chua (2010) expanded previous model using similarity indices to delete, add, and modify similar hazards from retrieved cases. Forbes et al. (2010) developed a CBR model for selecting appropriate risk management techniques in the built environment based on six characteristics of projects and the risks associated with them, including project phase, involving risks, risk owner, and the fuzziness, randomness, and incompleteness of the risk. Fan et al. (2015) broadened the application of CBR to the area of construction risk management, generating risk response strategies and their cost of implementation in subway construction projects. Given the above applications in construction, CBR shows great potential in solving construction problems. More importantly, CBR is not considered a black-box model (Richter and Weber 2013), where the expert can find the logic behind each reasoning made by the model. However, CBR does not have the capability to capture the subjectivity of the information and consequently cannot consider subjective information in the similarity calculation.

CBR has been combined with fuzzy set theory (Zadeh 1965) in order to capture the subjectivity and imprecision that exists in real-world systems (Richter and Weber 2013). Zuo et al. (2014) used fuzzy set theory in the retrieval phase of a CBR model for reinforced concrete structures, in which the user assigns weights to the key characteristics of the problem case in linguistic terms ("Very Important," "Important," "General," "Not Important," and "Not to Be Considered"). Then, these fuzzy weights are used to calculate similarity between characteristics. Zima (2015) developed an FCBR model for cost estimation that defines cases using 15 characteristics, next represents each by linguistic terms that are determined as triangular fuzzy numbers, and then retrieves cases based on the defuzzified value of similarity indices. Lu et al. (2016) combined fuzzy rule-based systems (FRBS) with CBR in modelling to forecast precipitation. In their model, the most similar rule (i.e., the rule with the highest membership degree) is only activated in the fuzzy rule-based system. They also compared the fuzzy CBR with the stand-alone application of CBR and FRBS, which showed that FCBR is more accurate in predicting the level of precipitation. There is a research gap in the existing variations of FCBR, a technique that relies heavily on expert knowledge for capturing subjective uncertainty involved in the real-world problems. This paper addresses the research gap by calculating the similarity between the different cases based on fuzzy distance measures and using fuzzy numbers to represent these values and capture the partial similarity between cases in the real-world problems. This paper also uses the proposed FCBR process and existing data about different types of construction projects to identify the risks associated with novel construction project types.

3. The Proposed FCBR Technique for Risk Identification

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

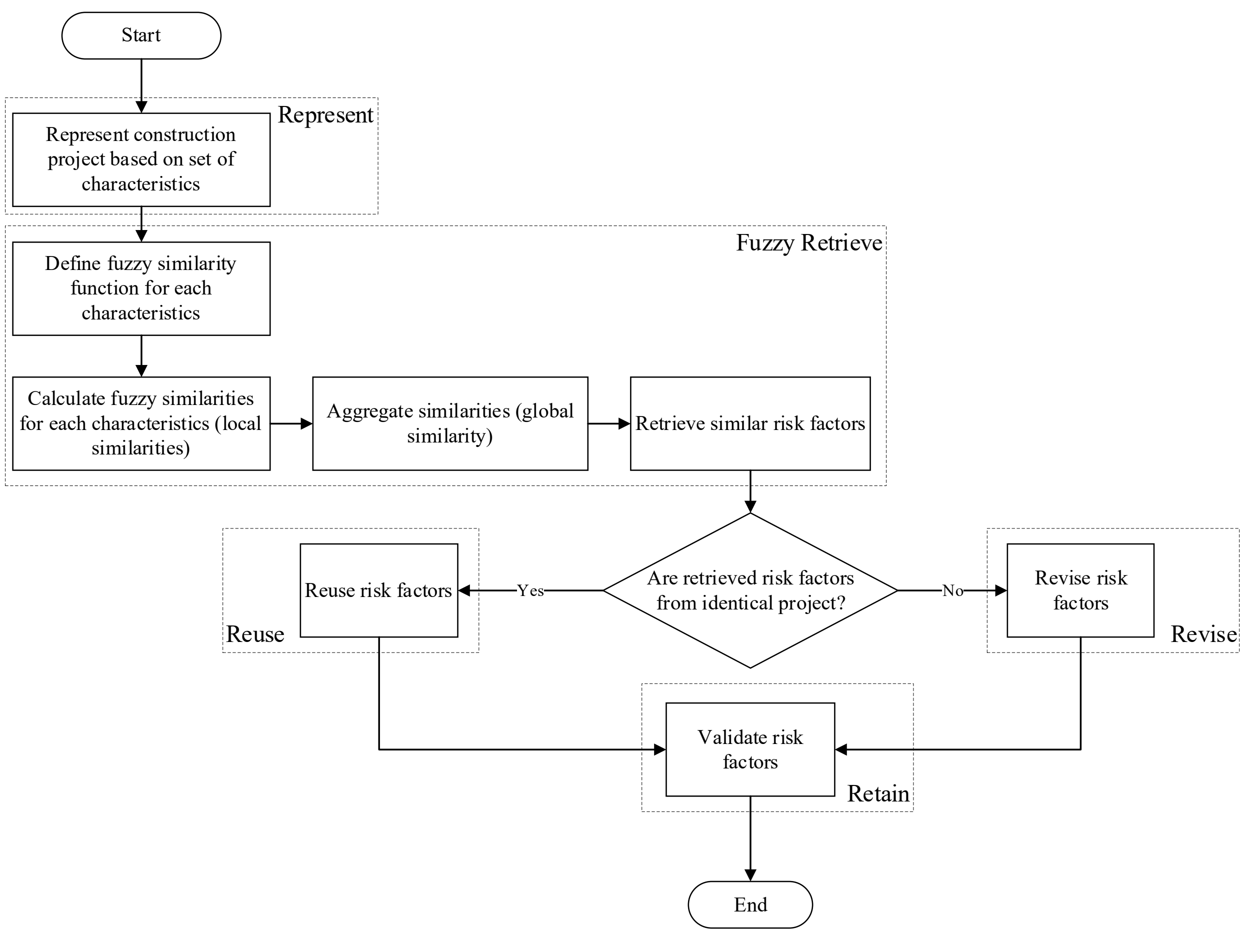

Fig. 1. Research methodology for implementing FCBR in risk identification.

The following subsections further discuss the five steps of the methodology. It should also be noted that prior to the implementation of the proposed risk identification technique, a database was needed that comprised the characteristics of different types of construction projects, the construction work-packages involved in their construction, and their associated risks at the work-package-level. Moreover, the database is not limited to one type of construction project (e.g., hydropower projects), and it can cover all the different types of construction projects because the application of fuzzy logic in the proposed technique allows the capture of partial similarities between different project types. Fig. *2* presents the flow of information between the database and the different steps of the methodology and illustrates how the proposed technique uses project characteristics and previously identified risks for the novel type of construction project studied.

3.1. Case representation

Generally, in the CBR approach, different cases (i.e., construction projects in this paper) are represented by a set of characteristics or attributes, which are selected based on the scope of the problem. For representation of complex cases, which cannot be directly represented by a few characteristics or attributes, the local–global principle is used, which is based on the presumption that complex cases are built up hierarchically, starting from basic elements at the bottom of the hierarchy to comprehensive elements at the top (Richter and Weber 2013). To implement the local–global principle in case representation, each case is first decomposed into its basic elements. For example, in this paper the characteristics of construction projects are decomposed into project type and CWP involved in the project. Then, the similarity between the basic elements of different cases, called local similarity, is calculated. Next, local similarities are aggregated to calculate the overall similarity between the two cases, called global similarity.

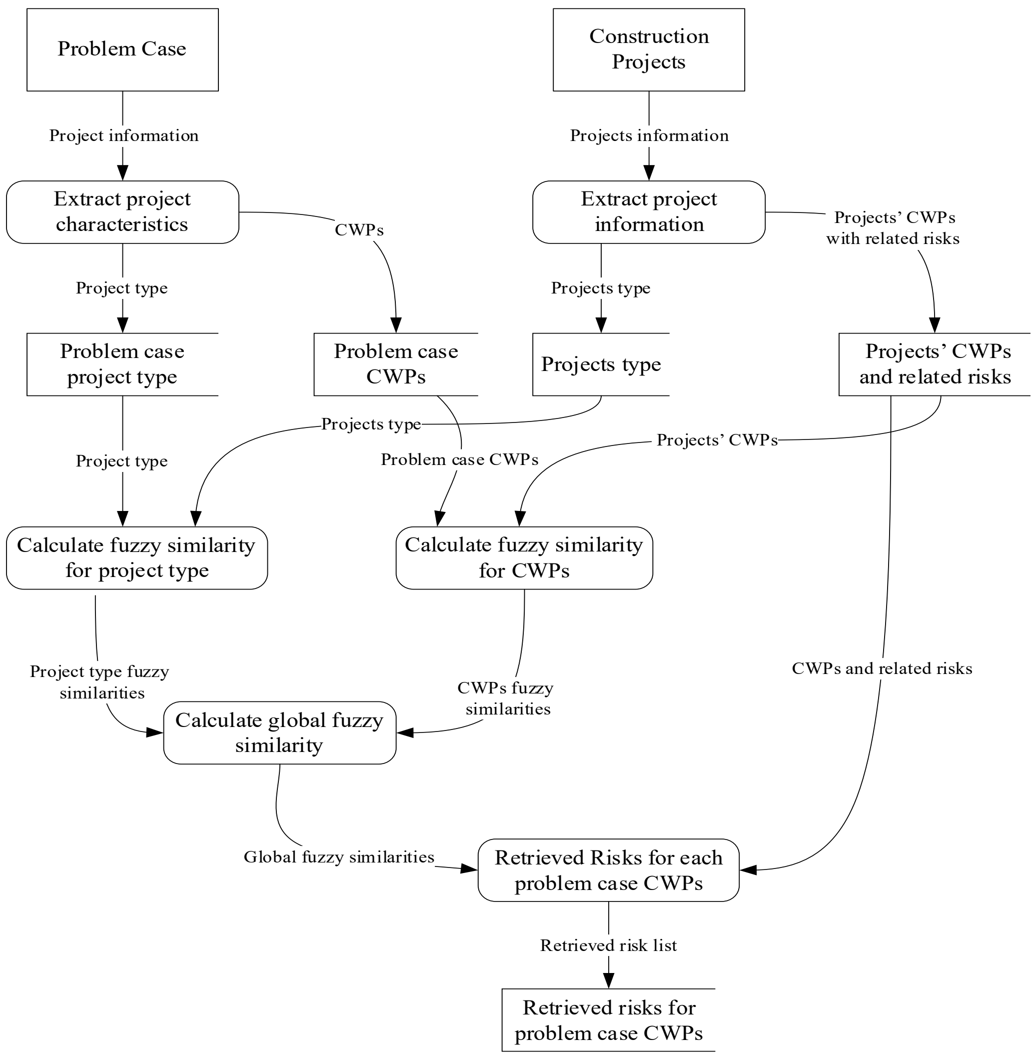

Fig. 2. Data flow diagram of the proposed risk identification technique.

Details of the calculations for local similarity indices and calculations of global similarity are provided in Section 3.2. One aggregation method is the product method, which simply multiplies the local similarities to determine the global similarity (Goh and Chua 2009). The product method is a non-compensatory aggregation technique, in which a very low evaluation in one criterion is not compensated by very high evaluations in other criteria. In this paper, a non-compensatory aggregation technique is used, since very low similarity in one aspect of projects can make them completely distinct; thus, the risks related to one project type may be irrelevant to another project type.

In the case study discussed in this paper, the local-global principle was applied for case representation using two characteristics: project type, and CWPs of onshore wind farm projects. The project type characteristic is represented using hierarchical representation, in which cases are represented in the form of a taxonomy, and the similarity between cases is determined based on their location in the taxonomy (Richter and Weber 2013). The taxonomy of construction projects is developed using the Central Product Classification (United Nations 2015) and presented in Figure 3.

This taxonomy starts with level 1 as all construction, level 2 is general concepts of construction sectors (e.g., buildings and civil engineering works) and is broken down into three more levels of categorization, with the lowest level being specific types of construction projects, such as electrical generating plants, restaurants, and embankments. Details regarding the calculations of the similarity between different types of construction projects using the taxonomy are discussed in Section 3.2.1.

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

3.2. Fuzzy Retrieve

In the case retrieval step, the project under study is compared to other construction project types based on two local characteristics and similarity between types. Similarity functions are

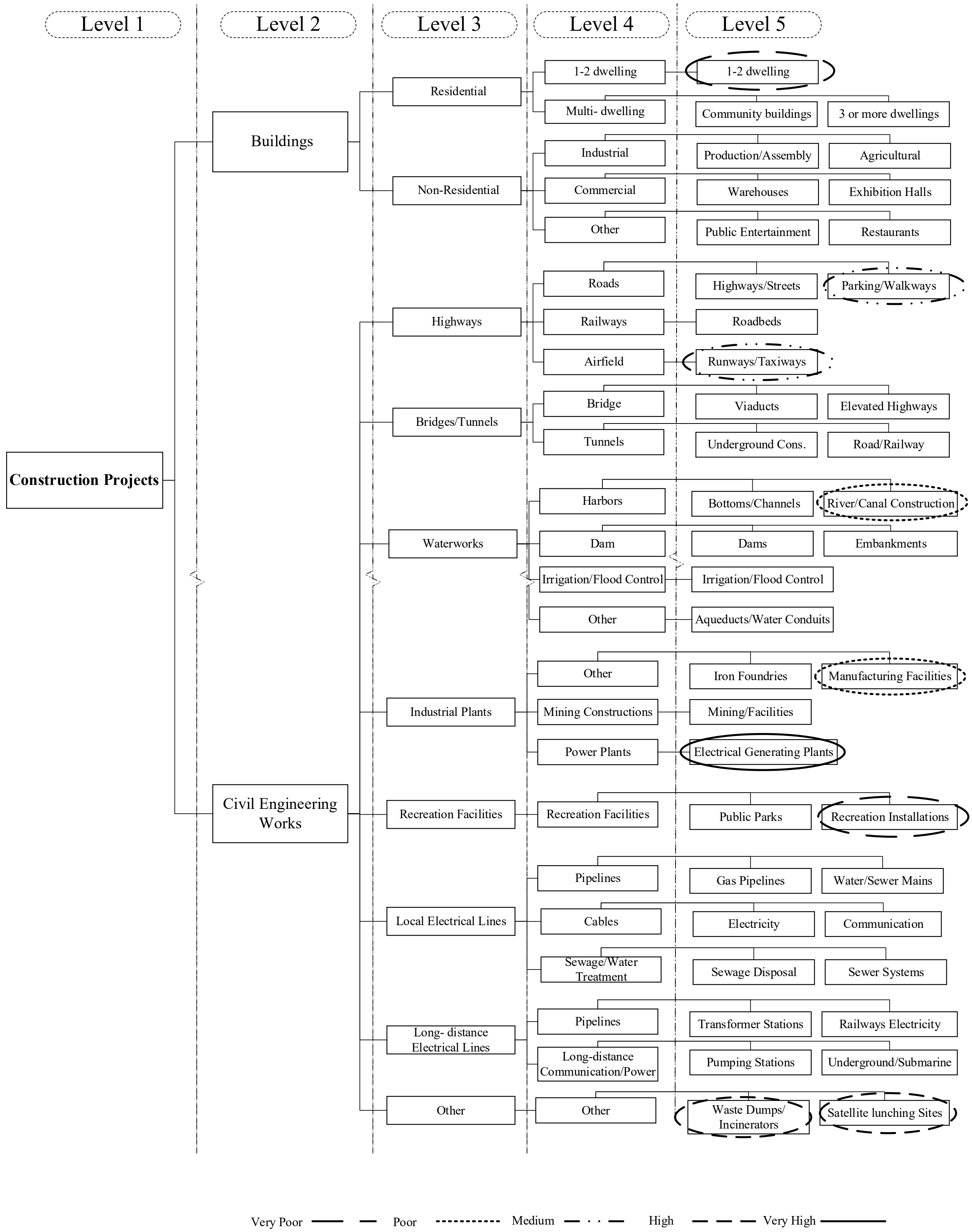

Fig. 3. Taxonomy of construction project types.

selected based on the type of information represented by each characteristic (e.g., numeric value, text, image), and the similarity index may be 0 for distinct cases, 1 for identical cases, or a value in the range of (0,1) for non-identical cases. Since determining the similarity between two types of construction projects is a subjective assessment, crisp similarity indices are not appropriate representation where the compared projects have partial similarity, and fuzzy numbers are used instead. The application of fuzzy logic allows users to assess the similarities between different types of projects using linguistic variables, and it also facilitates the capture of partial similarities between the different types of construction projects.

In this study, five triangular fuzzy numbers are used to represent the similarity between project types in linguistic terms. These fuzzy numbers are based on previous studies conducted by Etemadinia and Tavakolan (2018) and Khatwani et al. (2015) and represented in Figure 4 and Table 1. Using linguistic terms to represent similarity improves the performance of FCBR in this study by (1) helping experts to more easily interpret the framework reasoning process (i.e., transparency) and (2) allowing experts to provide similarity between two cases using linguistic terms, which results in greater flexibility of the model as needed.

Table 1. Triangular fuzzy numbers.

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

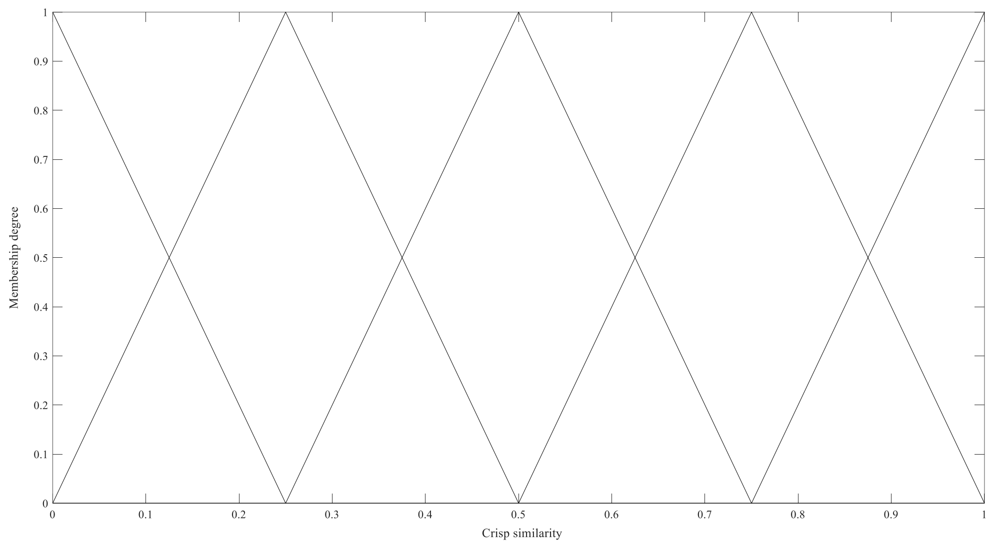

Fig. 4. Triangular fuzzy numbers for similarity.

3.2.1. Project type similarity

The structure-oriented similarity function is used for the project type characteristic; it is also called "path-oriented similarity," since the path between two project types in the hierarchy determines their similarity. In addition to the position of projects in the taxonomy of construction projects (Figure 3), the similarity between two project types is determined based on the deepest common predecessor (DCP) between them. DCP has five possible similarity values represented by fuzzy numbers, as shown in Table 1 and Figure 4: 1= "Very Poor," 2 = "Poor," 3 = "Medium," 4 = "High," and 5 = "Very High." The structure-oriented similarity function used for determining the similarity between two types of construction projects is represented in Equation (1).

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

where DCP(p_p, s_p) = 1 refers to two types of construction projects that share exactly one level of taxonomy (i.e., the very highest level), such as "restaurant building" or "satellite launching sites." Similarly, DCP(p_p, s_p) = 2, 3, 4, or 5 = can be defined for a pair of construction projects that share 2, 3, 4, or 5 levels of taxonomy, respectively.

3.2.2. CWP similarity

The counting similarity function is used for the CWP characteristic; the number of common elements between two sets determines the similarity of the two CWPs. To determine similarity, each CWP of a wind farm project is decomposed into its constituent activities. Next, the similarity function counts the number of construction activities in common between two CWPs and the number of construction activities specific to each. In this paper, the well-known Tversky similarity method is used to calculate the similarity between two CWPs, or sets *P,* and *S*, as presented in Equation (2).

$$T_{Sim}(S,P) = \frac{(s \cap p)}{(s \cap p) + \alpha(s - (s \cap p)) + \beta(p - (s \cap p))} \tag{2}$$

where *S* and *P* are the two CWPs for which similarity is being assessed; $s \cap p$ is the number of common activities between the two CWPs; and the parameters α, β are weights for defining the importance of exclusive activities of *S* and exclusive activities of *P*. The value of the parameters α, β are assumed to be $\alpha = \beta = 0.5$ (Richter and Weber 2013). Next, in order to determine the appropriate fuzzy number to represent the similarity between two CWPs, the distance between T_{Sim} (see Equation [2]) and the five triangular fuzzy numbers is calculated using the fuzzy distance measure introduced by Xie et al. (2019). The distance between two trapezoidal fuzzy numbers $\tilde{A} = (a_1, a_2, a_3, a_4; w_{\tilde{A}}), \tilde{B} = (b_1, b_2, b_3, b_4; w_{\tilde{B}})$ is calculated using Equation (3), where $w_{\tilde{A}}, w_{\tilde{B}} \in [0,1]$ stands for the height of the fuzzy numbers $\tilde{A}$ and $\tilde{B}$, respectively.

$$S(\tilde{A}, \tilde{B}) = se * sw \tag{3}$$

where

$$se = \begin{cases} e^{-|a_1 - b_1|}, & a_4 = a_1 \text{ and } b_4 = b_1 \\ e^{-(k+z+h+lr)/w}, & Otherwise \end{cases} \tag{4}$$

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

$$k = |(a_4 - a_1) - (b_4 - b_1)|$$

$$z = \max(|a_1 - b_1|, |a_4 - b_4|)$$

$$w = \max\ (a_4 - a_1, b_4 - b_1)$$

$$h = |(a_3 - a_2) - (b_3 - b_2)|$$

$$l_r = \max(|a_2 - b_2|, |a_3 - b_3|)$$

and

$$sw = \frac{\min(w_{\tilde{A}}, w_{\mathrm{B}})}{\max(w_{\tilde{A}}, w_{\mathrm{B}})}.$$

After the distance between the similarity index, T_{Sim}, and the triangular fuzzy numbers is calculated, the fuzzy number with the smallest distance is selected to represent the fuzzy similarity, C_{Sim}, between the two CWPs. The fuzzy distance measure can then be applied to crisp numbers – $a_1 = a_2 = a_3 = a_4$, or T_{Sim} in this case – as well as triangular fuzzy numbers – $a_1 < a_2 = a_3 < a_4$, the five fuzzy numbers that represent the fuzzy similarity indices.

3.2.3. Global similarity

The global similarity is determined by aggregating the two local similarity indices, $C_{Sim,}$ and P_{Sim}, using the product aggregation method. Total similarity S is defined by Equation (5) (Richter and Weber 2013):

$$S = C_{Sim} \otimes P_{Sim} \tag{5}$$

Fuzzy multiplication (represented as ⊗ in Equation [5]) uses one of two approaches. The α-cut approach is widely used in many different applications because of its computational simplicity, but it causes overestimation of uncertainties in the resulting fuzzy number (Gerami Seresht and Fayek 2019). In recent applications, the extension principle approach is therefore preferred, since it can eliminate the problem of overestimating uncertainty. Gerami Seresht and Fayek (2019) developed a computational method for implementing fuzzy arithmetic operations on a triangular fuzzy number using two t-norms: product t-norm and Lukasiewicz t-norm. Both result in a fuzzy number with a lower level of uncertainty compared to the α-cut approach, and the Lukasiewicz t-norm is more sensitive than the product t-norm to changes in the input fuzzy numbers. Therefore, this study uses the product t-norm. Also, the computational method proposed by Gerami Seresht and Fayek (2019) for implementing fuzzy multiplication on triangular fuzzy numbers is used to determine the global similarity index.

Once the global similarity index for each identified risk is calculated, risks are retrieved that have an index higher than a prespecified threshold, known as the retrieval threshold. In this study, the retrieval threshold (RT) was set to “Medium” similarity, meaning that any risk with a global similarity of “Medium” or higher is retrieved as a potential risk in onshore wind farm construction. Equation (6) calculates the fuzzy distance between the global similarity index of each risk S_j and the retrieval threshold RT.

$$d(S_j, T) = \frac{\sum_{i=1}^{n} |\mu_S(x_i) - \mu_T(x_i)|}{n} \quad (6)$$

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

3.3. Reuse

In the reuse step, retrieved cases are reused in one of two ways: (1) risks retrieved from identical cases (i.e., with full similarity to the project being studied) are selected and transferred to the retain step with no revisions; and (2) risks retrieved from partially similar cases are reviewed and revised by the user/expert before being transferred to the retain step. In CBR, determining cases with full similarity (i.e., identical cases) is straightforward, being indicated by the full global similarity S = 1. However, determining full similarity between cases in FCBR is challenging due to the characteristic of fuzzy multiplication, where $x \otimes x = x \Leftrightarrow x = (1,1,1) or\ (0,0,0)$, as there are no fuzzy numbers, such as 1 and 0 in crisp numbers, where $x^2 = x$. In FCBR, if the local similarity between two cases is assessed to be the maximum value, "Very High" for both the project type and CWPs' characteristics, the global similarity between the two cases is not "Very High". In the proposed technique, this challenge is addressed by defining a threshold for full similarity between two cases, named identicality threshold (IT).

In the case study of the risk identification of onshore wind farm projects (see Section 4), IT was set to "High" similarity, meaning that any risk with a global similarity of "High" or "Very High" is directly transferred to the retain step. The value of the RT was selected through a trialand-error process based on the following considerations: if more than 20% of the risks retrieved are irrelevant to onshore wind farm projects, the value of the retrieval threshold needs to be increased; and if very few risks (i.e., less than 10 risks per work package) retrieved and/or the list of risks is not comprehensive, the value of the retrieval threshold needs to be decreased. In this study, the retrieval threshold was set to "Medium" to retrieve any risk factor with the value of local similarities equal to "High" or higher to onshore wind farm projects. Retrieved risks with a global similarity less than "High" were revised before being considered as a risk that affects onshore wind farm projects.

3.4. Revise

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

3.5 *Retain*

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

4. Results, Case Study: Onshore Wind Farm Projects

4.1 *Developing a database for the proposed risk identification technique*

Through an extensive literature review, a database was developed in Microsoft Excel® to store the risks associated with the target construction projects, which have one or more CWP(s) in common with the onshore wind farm projects. For this purpose, first, the CWPs of onshore wind farm projects were extracted from Hao et al. (2019), which identified the following 11 CWPs: pre-construction activities, surveying, turbine foundation, turbine assembly, electrical collector line, electrical distribution substation, access road and parking lot, stormwater management system, meteorological tower, dewatering, and operation and maintenance (O & M) buildings. Next, two common scientific databases, Scopus® and Google Scholar®, were searched. The name of each CWP was searched in Scopus® to find any journal articles, conference papers, or technical/engineering reports that in its keywords, abstract, or title that include both the CWP name and at least one of the four following terms risk identification, risk management, risk assessment, or construction risk. The same search methodology was used with Google Scholar®, but it lacks advanced search options in Google Scholar® for searching within specific sections of the documents, so the aforementioned terms were searched for within whole documents. Searches in Scopus® and Google Scholar® were not limited to a specific time frame, meaning the upper limit for the publication date is 2020 (i.e., the time of conducting this research), and the earliest paper found was published in 1990. A total of 37 articles were found that identify risks associated with the CWPs of onshore wind farm projects, yielding a database inclusive of 347 risks collected from 15 different types of construction projects that have common CWPs. Table 2 presents the list of 37 articles, the types of construction projects studied, and risks identified by each article. This model can use risk data (e.g., identified risks, the severity of risks) from different project types (e.g., subway, road, building, and hydropower projects). However, in this study, a literature review is used to collect different project data as input to the model.

Table 2. List of retrieved cases for each CWP.

CWP	**Type of Project** (References)
Pre-construction activities	**Onshore wind farm project** (Manwell et al. 2006); **hydropower project** (Baroudi and McAnulty 2013); **highway project** (Diab et al. 2017; Vishwakarma et al. 2016); **water importation and pipeline project** (Kershaw et al. 2009); **electricity transmission project** (Sidawi 2012)
Surveying	**Pipe jacking construction project** (Cheng and Lu 2015); **highway project** (Diab et al. 2017); **electricity transmission project** (Sidawi 2012)
Turbine foundation	**Subway projects** (Fan et al. 2015; Zhou and Zhang 2011; Zhou et al. 2017); **onshore wind farm project** (Hassanzadeh 2012); **road construction project** (Amey Comsulting PLC 2016); **bridge construction project** (Issa and Ahmed 2014); **infrastructure projects-general** (Hosny et al. 2018, Hussein and Goble 2000); **hydropower project** (Stantec 2017)

CWP	**Type of Project** (References)
Turbine assembly	**Onshore wind farm project** (Chou and Tu 2011, Mustafa and Al-Mahadin 2018); **windmill construction project** (Sanders and Shapira 2011); **on- and offshore wind farm projects** (Canada Wind Energy Association 2018); **infrastructure projects-general** (Marquez et al. 2014)
Electrical collector lines	**Transmission and distribution line construction** (Albert and Hallowell 2013); **highway project** (Zayed et al. 2008)
Electrical distribution substation	**Onshore wind farm project** (Hassanzadeh 2012, Canada Wind Energy Association 2018); **hydropower project** (Stantec 2017); **transmission and distribution line construction** (Albert and Hallowell 2013); **UHV power transmission construction** (Zhao and Guo 2014)
Access road	**Highway project** (Creedy et al. 2010; Tawalare 2019; Vishwakarma et al. 2016; Zayed et al. 2008)
Stormwater management	**Infrastructure projects-general** (United States Environmental Protection Agency 1991, Government of Western Australia 2012, Infrastructure Health & Safety Association 2019); **public utilities projects** (Jannadi 2008)
Meteorological tower	**Telecommunication tower project** (Davies 2011, Rosu et al. 2018); **modular construction** (Li et al. 2013); **Infrastructure projects-general** (Marquez et al. 2014)
Dewatering	**Infrastructure projects-general** (Government of Western Australia 2012)
O & M building	**Modular construction project** (Li et al. 2013); **building projects** (Canadian Home Builders' Association 1988, Enshassi et al. 2008, Valipour et al. 2017)

4.2 Implementing the FCBR technique for risk identification

Following the methodology introduced for proposed risk identification technique, as discussed in section 3.1, the local characteristic of project type was represented using the taxonomy of construction project types (see Figure 3). Next, the WBS of onshore wind farm projects was extracted from Hao et al. (2019) to identify the CWP involved in these projects and their relevant activities. Then, the global similarity index was calculated as discussed in Section 3.2.3, thus completing the case retrieval step. To automate the process of risk retrieval, a function is developed in MATLAB® programming language. As noted in section 3.2, RT was set to

“*Medium*”, and IT was set to “*High*”. For further clarification, Figure 5 and Figure 6 are presented illustrating global fuzzy numbers for two different thresholds in the turbine foundation work package.

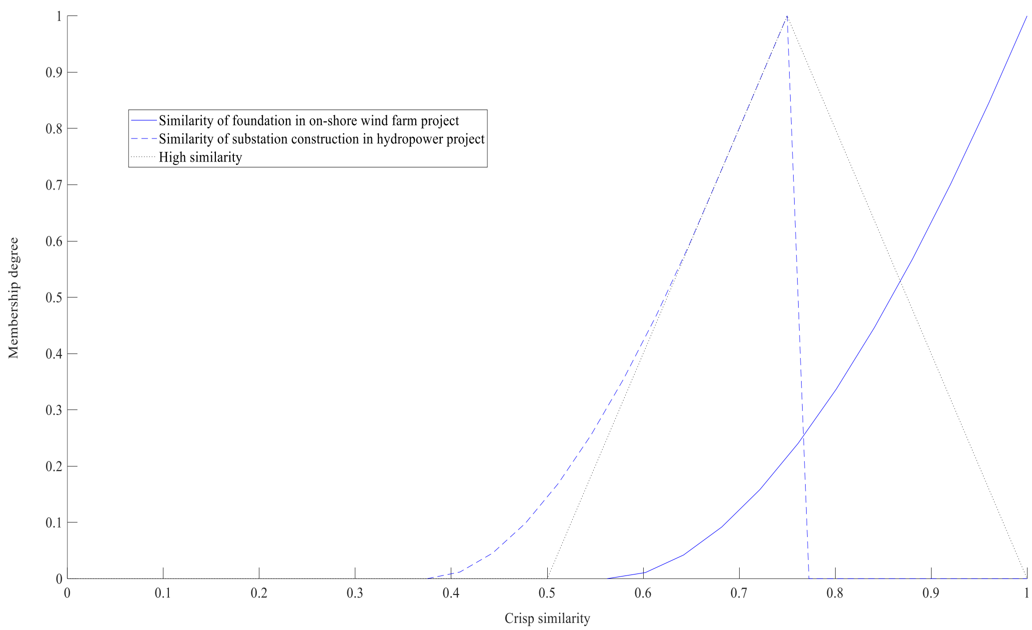

Fig. 5. Retrieved cases for high fuzzy threshold.

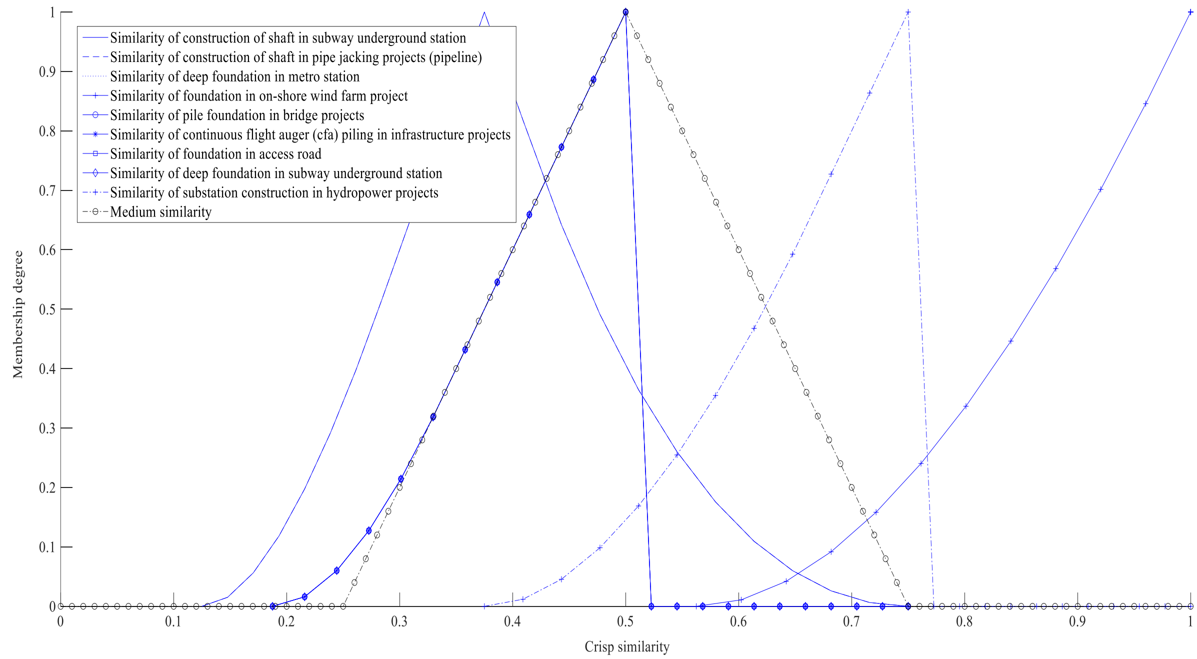

Fig. 6. Retrieved cases for high fuzzy threshold.

IT was set to "*High*", and RT was set to "*Medium*," which resulted in retrieving 2 identical cases and 9 similar cases, respectively. It should be note that those 7 similar and non-identical cases need to be revised according to the scope of the project; and all retrieved cases for turbine foundation are related to foundation work packages in different projects, namely, subway, bridge, road, industrial buildings, and onshore wind farm projects. Following the implementation of the proposed risk identification technique, a total of 169 risks were identified for the 11 CWPs of onshore wind farm projects as presented in Table 3.

Table 3. List of risk factors associated with CWP in onshore wind farm projects.

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

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

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

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

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

The results of this study reveal that among the 11 CWPs of onshore wind farm projects, the largest number of risks are associated with "turbine foundation" with 61 risks. Moreover, the risks that are common among several CWPs are: "harsh weather conditions," which affects 8 CWPs; and "lack of skilled workers," which affects 6 CWPs.

Piney (2003) suggested checking the risk factors against the scope of each CWP to validate the list of risks identified per CWP. In this paper, the proposed method was used to validate the risks identified for onshore wind farm projects; for illustrative purposes, two CWPs, "electrical distribution substation" and "meteorological tower," were used to demonstrate the validation process of the RBM presented in Table 3.

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

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

5. Discussion

The use of FCBR for developing the proposed risk identification technique enables the user/expert to customize the linguistic terms and fuzzy numbers for different project types. It also enables the user/expert to understand the reasoning behind the risk identification process and to justify the selection of each risk. Table 4 presents a comparison of the proposed risk identification technique with some other common risk identification techniques (noted in section 1).

Table 4. Comparison of proposed FCBR risk identification technique to other techniques.

Method / **Criterion**	Literature review	Expert interview	Delphi method	SWOT method	CBR	Proposed technique based on FCBR
Capturing subjective uncertainty	–	–	–	–	–	✓
Low reliance on historical data of the project	–	✓	✓	✓	✓	✓
Quantitative analysis	–	–	–	–	✓	✓
Low reliance on expert knowledge	–	–	–	–	✓	✓

Less challenging process	✓			✓	✓	✓
Flexibility to customize method for different project types and stages	✓	✓	✓	–	–	✓
Considering all identified risks of other project types.	–	✓	✓	–	✓	✓

The proposed technique is less challenging than the literature review method, because once a database is developed for FCBR, the same database can be re-used for other types of projects, which is not the case for the literature review. Moreover, for the risk identification of novel construction projects, the proposed technique is superior to the literature review method since it deals with challenges associated with historical data scarcity by using historical data collected from all different types of construction projects. Acquiring expert knowledge is time-consuming and expensive, so the proposed technique's low reliance on expert knowledge makes it faster and cheaper to implement compared to methods that rely solely on expert knowledge, namely expert interview, Delphi, and SWOT. The proposed technique also captures subjective uncertainty by defining similarities between two cases using linguistic terms. As a result, FCBR can define the partial similarity between projects, which means that it considers a wider range of projects and generates more comprehensive results compared to CBR.

Compared to the FCBR risk identification technique introduced by Somi et al. (2020), the proposed technique in this study first uses the extension principle to eliminate the problem of overestimation of uncertainty in global similarity. Further, using fuzzy distance measures and fuzzy thresholds of similarity and identicality rather than crisp ones enhances the model performance, since it avoids information loss due to the defuzzification of fuzzy numbers (Pedrycz 2017). Figure 6 illustrates that using fuzzy thresholds instead of crisp value results in retrieving cases that are more similar to the target case, such as the construction of shaft cases. The cases graphically have defuzzifed values less than 0.5, but using fuzzy distances results in retrieval of those cases. Moreover, fuzzy thresholds increase the flexibility of the model by allowing the user/expert to use linguistic terms to modify the model.

For further investigation regarding the validity of the proposed risk identification technique and to illustrate its flexibility, sensitivity analysis was performed to determine the sensitivity of the results to the changes in the parameters of the Tversky similarity index, presented in Equation (2) (see Section 3.2.2). The two parameters of the Tversky similarity index are $\alpha, \beta \in [0, 1]$; to test the sensitivity of the proposed technique per these parameters, the values of α and β were changed between the two extreme points: $\alpha = 0.0$ and $\beta = 1.0$; and $\alpha = 1.0$ and $\beta = 0.0$. Then, for each case, CWPs that were found to be similar to onshore wind farm projects were retrieved from the database. The results are presented in Table 5.

Table 5. Different retrieved cases regarding α, β in Tversky similarity.

Tversky parameters values	Retrieved CWPs	Fuzzy CWP similarity
Scenario 1: $\alpha = 0.0$ $\beta = 1.0$	Deep foundation in metro station	Very High
	Foundation in onshore wind farm project	Very High
	Pile foundation in bridge projects	Very High
	Continuous flight auger (CFA) piling construction in all infrastructure projects	Very High
	Foundation in access road	Very High
	Excavation in electrical transmission and distribution projects	Very High
	Deep foundation in subway underground station	Very High

	Substation construction in hydropower projects	Very High
Scenario 2: $\alpha = 1.0$ $\beta = 0.0$	Construction of shaft in subway underground station	Very High
	Construction of shaft in pipe jacking projects (pipeline)	Very High
	Deep foundation in metro station	Very High
	Foundation in onshore wind farm project	Very High
	Pile foundation in bridge projects	Very High
	Continuous flight auger (CFA) piling construction in all infrastructure projects	Very High
	Foundation in access road	Very High
	Deep foundation in subway underground station	Very High
	Substation construction in hydropower projects	High

Per Section 3.2.2, to compare two CWPs S and P, α and β are the two parameters for defining the importance of exclusive activities of S and exclusive activities of P, respectively. In other words, for $\alpha = 0.0$, $\beta = 1.0$, the Tversky similarity index ignores the exclusive activities involved in CWP S and not involved in CWP P, which is the case when S is more general (i.e., of a higher level in WBS) compared with CWP P. Conversely, for $\alpha = 1.0$, $\beta = 0.0$, the Tversky similarity index ignores the exclusive activities involved in CWP P and not involved in CWP S. According to the results presented in Table 5, a higher value for α results in retrieving more cases, where 9 cases were retrieved in scenario 1, and 8 cases were retrieved in scenario 2. However, a small value for β can cause negligence regarding the characteristics of the CWPs involved in other types of construction projects and would calculate a biased similarity value. Furthermore, using $\alpha = 0.5$, $\beta = 0.5$ results in the same retrieved cases (refer to Table 3) but with lower similarity values.

In addition to the theoretical contributions of this paper, the proposed risk identification technique provides a practical tool for risk identification practices in real-world construction projects. For successful and efficient implementation of the proposed technique in practice, two things need to be developed: a large database of construction projects with a structured hierarchy of characteristics that determine the similarity of the projects, and a comprehensive risk list of the construction projects included in the database. The development of such a database within an organization facilitates the risk identification process for multiple projects, making the process more efficient. Moreover, the development of an open-source, online database (e.g., a data repository) is also recommended in order to enable different users to contribute to the database and to develop the most comprehensive set of project types and construction risks.

6. Conclusions and Future Work

Risk identification is the first stage in risk management practice, and the successful delivery of construction projects is highly dependent on the precise identification of the risks associated with them. However, construction risk identification is challenging in novel types of construction projects, since these projects are not comprehensively studied in the literature and limited historical data are available for them. To address this challenge, a new risk identification technique is introduced in this paper that uses FCBR to determine the similarity between novel types of construction projects and projects that are well-studied in the literature and identifies the risks associated with novel types of construction projects based on such similarities. To confirm the applicability of the proposed technique, it was used to identify risks associated with the construction of onshore wind farm projects. Despite the scarcity of historical data and lack of ample research on these projects, an RBM consisting of 169 risk factors was developed for the construction of onshore wind farm projects. Moreover, this paper advances the state-of-art of

FCBR by using fuzzy numbers to define similarities between the different cases to: (1) improve the interpretability of the model by using linguistic terms for the reasoning process; and (2) increase the flexibility of the model by allowing the user/expert to use linguistic terms to modify the model. The findings of this paper reveal that the capacity of FCBR for capturing partial similarity between two cases improves the model's accuracy and comprehensiveness compared to CBR.

This study represented validation by comparing the scope of each CWP with identified risks. In future research, a survey will be conducted with construction experts to validate the RBM developed for onshore wind farm projects and assess the accuracy of the proposed technique based on the construction experts' opinions. Moreover, to further validate the proposed technique, the results of this study will be compared with other types of information-based techniques such as ontology-based risk identification. In this paper, the proposed risk identification technique solely relied on two characteristics to determine similarities. In future research, other characteristics of construction projects will be utilized and a hierarchy of project characteristics will be developed for determining the similarities in the proposed risk identification technique. Finally, the proposed risk identification technique will be extended by implementing weighted aggregation methods for determining global similarity between different types of construction projects. The application of weighted aggregation methods increases the flexibility of the proposed technique by incorporating the relative importance of each local characteristic in calculation of the global similarity index. Following the aforementioned theoretical extensions to the proposed risk identification technique, it will be applied to other kinds of renewable energy projects, including solar panel projects, and RBMs will be developed for those projects.

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