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Framework for Risk Identification of Renewable Energy Projects Using Fuzzy Case-Based Reasoning

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Abstract: Construction projects are highly risk-prone due to both internal factors (e.g., organizational, contractual, project, etc.) and external factors (e.g., environmental, economic, political, etc.). Construction risks can thus have a direct or indirect impact on project objectives, such as cost, time, safety, and quality. Identification of these risks is crucial in order to fulfill project objectives. Many tools and techniques have been proposed for risk identification, including literature review, questionnaire surveys, and expert interviews. However, the majority of these approaches are highly reliant on expert knowledge or prior knowledge of the project. Therefore, the application of such tools and techniques in risk identification for renewable energy projects (e.g., wind farm and solar power plant projects) is challenging due to their novelty and the limited availability of historical data or literature. This paper addresses these challenges by introducing a new risk identification framework for renewable energy projects, which combines case-based reasoning (CBR) with fuzzy logic. CBR helps to solve problems related to novel projects (e.g., renewable energy projects) based on their similarities to existing, well-studied projects (e.g., conventional energy projects). CBR addresses the issue of data scarcity by comparing novel types of construction projects to other well-studied project types and using the similarities between these two sets of projects to solve the different problems associated with novel types of construction projects, such as risk identification of renewable energy projects. Moreover, the integration of fuzzy logic with CBR, to develop fuzzy case-based reasoning (FCBR), increases the applicability of CBR in construction by capturing the subjective uncertainty that exists in construction-related problems. The applicability of the proposed framework was tested on a case study of an onshore wind farm project. The objectives of this paper are to introduce a novel framework for risk identification of renewable energy projects and to identify the risks associated with the construction of onshore wind farm projects at the work package level. The results of this paper will help to improve the risk management of renewable energy projects during the construction phase.

Keywords: risk identification; case-based reasoning (CBR); fuzzy case-based reasoning (FCBR); renewable energy projects

1. Introduction

Internationally, the incidence of renewable energy projects has been increasing due to technological advancements in the production of highly efficient electromechanical systems (e.g., solar panels and wind turbines). There have also been significant reductions in the construction costs of these projects, stemming from advancements in construction equipment and methods [1,2]. On average, the global power generation capacity from renewable sources has increased by 155 GW annually from 2013 until 2018 [1]. Seventy percent of this annual growth corresponds to the development of new wind farm and solar power plant projects, which makes them the fastest-growing type of renewable energy projects, followed by hydropower and geothermal power projects [1]. Despite their growth, renewable energy projects, excluding hydropower, only produced five percent of the global power generation capacity in 2018 [3]. To meet the 2050 global target for renewable energy power generation capacity, the current annual growth must double in size [4]. In order to improve this trend, researchers and practitioners need to address the challenges associated with the development of renewable energy projects, which include risk management of these projects across their lifecycle. Improving risk management practices for renewable energy projects can reduce their construction time and costs, resulting in increased investment.

According to the Project Management Institute (PMI) [5], the lifecycle of construction projects can be divided into five phases: conception, design, construction, commissioning, and closeout. Among these five phases, the construction phase consumes the largest portion of the project budget and time [6]. Therefore, implementation of risk management practices during the construction phase is essential for the successful delivery of projects on time and within budget; failing to do so can lead to negative impacts on project objectives [7]. The first step in the implementation of risk management practices is risk identification. Although a number of tools and techniques currently exist for construction risk identification (e.g., literature review, surveys, and expert interviews), these tools and techniques often rely on the literature or experts to acquire knowledge about the specific type of construction project being studied [7]. Therefore, challenges may arise when identifying the risks associated with novel types of construction projects due to the lack of comprehensive literature, scarcity of historical data, and need to collect expert knowledge.

Among those techniques, case-based reasoning (CBR) is best suited to construction projects, which are novel in terms of project type or construction method, and that have not been comprehensively studied in the literature. CBR addresses the issue of data scarcity by comparing novel types of construction projects to other well-studied project types and using the similarities between these two types of projects to solve the problems associated with novel types of construction projects, such as risk identification of renewable energy projects [8]. CBR is widely used in different domains to solve novel problems based on knowledge about previous cases. For example, De and Chakraborty [9] used CBR for helping car mechanics diagnose car faults. Abutair, Belghith, and AlAhmadi [10] used CBR to develop a model for phishing detection, where the CBR model was developed using a small sample size of phishing data. The model developed by Abutair, Belghith, and AlAhmadi [10] showed higher accuracy in comparison to machine learning techniques (e.g., artificial neural networks, Bayesian additive regression trees, and logistic regression) with the small sample size for training.

The few applications of CBR in construction contexts reveal that there are similarities among construction projects, or lessons learned, which can be used to solve problems in novel cases [11]. A few examples of the applications of CBR in construction include the model developed for predicting the cost of residential building projects [12], as well as the model developed for safety risk management [13]. However, CBR has not yet been used for construction risk identification. The contribution of this paper is the implementation of CBR integrated with fuzzy logic for identifying the risks associated with the construction of renewable energy projects at the work package level. The proposed risk identification technique identifies the risks associated with these projects by reviewing other well-studied types of construction projects and using the similarity that exists between renewable energy projects and these other types of construction projects. The integration of CBR with fuzzy logic, known as fuzzy case-based reasoning (FCBR), enables this risk identification technique to capture the subjective uncertainty that exists in determining the similarities between different types of construction projects using linguistic terms. Moreover, in this paper, the applicability of the proposed risk identification technique is tested by implementing it to identify the risks associated with the construction of onshore wind farm projects at the work package level.

2. Literature Review

2.1. Literature Review on Risk Identification Methods

Many researchers have attempted to identify and assess risks that affect construction projects, as well as determine appropriate risk management practices for reducing adverse effects on project objectives. According to PMI [5], the first step in the risk management process is risk identification. Common techniques for risk identification include literature review, surveys, expert interviews, and the use of historical project data [7]. Park et al. [14] conducted an interview survey with experts selected from 15 construction management firms to identify organizational-level risk factors affecting projects during the construction phase. Kassem, Azry Khoiry, and Hamzah [15] conducted a survey on risk factors influencing the oil and gas industry in Yemen; the authors identified a number of factors affecting time and cost objectives of projects. Siraj and Fayek [7] conducted a comprehensive literature review based on 130 existing studies and identified 571 project-level risk factors for construction projects. Xing et al. [16] developed a knowledge-based model for safety risk identification on metro construction projects, which used an ontology from previous metro construction projects.

These examples demonstrate that there is a limitation in existing risk identification techniques, where such techniques are highly reliant on expert knowledge or prior studies conducted on the same type of projects. Consequently, the application of common risk identification techniques in renewable energy projects is challenged by the limited availability of historical data and a lack of comprehensive research in this context. This paper addresses this research gap by developing a new framework for risk identification of renewable energy projects using CBR and fuzzy set theory.

2.2. Literature Review on the Application of Case-Based Reasoning in Risk Management

Hu et al. [11] conducted a comprehensive literature review on the application of CBR in construction from 1996 until 2015. The authors found 17 application areas for CBR in the construction domain; construction risk management was shown to be a common application area [11]. Goh and Chua [17] applied CBR in construction hazard identification, where a semantic taxonomy was used for representing each case in order to systematically retrieve similar information from previous hazards. In addition, Goh and Chua [18] expanded their model to use similarity indices to delete, add, and modify similar hazards from retrieved cases. Later, Lu, Li, and Xiao [19] developed a similar CBR model to Goh and Chua [18] in order to analyze the safety risks of subway construction projects. The two models developed by [17] and [19] rely on expert judgement to add, remove, or modify the hazards that threaten construction projects based on the similarities that exist between these projects. Zou, Kiviniemi, and Jones [13] used natural language processing (NLP) in CBR to increase the accuracy of CBR for safety risk management of construction projects. Zou, Kiviniemi, and Jones [13] used a bag-of-words model to represent cases (i.e., safety hazards and incidents); the similarity between different cases was calculated based on the frequency of the words used to represent each incident. Fan, Li, and Zhang [20] broadened the application of CBR methods to the area of construction risk management; the authors used CBR for generating risk response strategies. The model enables experts to retrieve risk response strategies for subway construction and suggests the best strategy for each risk, based on similarities to previous risk response strategies and their implementation cost. Moreover, Forbes, Smith, and Horner [21] developed a CBR model for selecting an appropriate risk management strategy based on previous projects. Despite its numerous strengths for construction risk identification as demonstrated by the examples, CBR is not widely used in the construction risk management context yet, as the total number of CBR applications in the risk identification area is six, based on Hu et al. [11] research.

2.3. Literature Review on Fuzzy Case-Based Reasoning

Existing research demonstrates that CBR has been combined with fuzzy set theory in order to process the subjectivity and imprecision that exists in real-world systems [22]. Lu et al. [23] combined fuzzy rule-based systems (FRBSs) and CBR to create a fuzzy CBR (FCBR) model, which was used to forecast precipitation rates based on previous weather data. In contrast to the common FRBS approach, where all activated rules are aggregated, in the model developed by [23], only those rules with the highest membership degree in the input space are selected. Lu et al. [23] also compared the FCBR model to the stand-alone applications of CBR and FRBS. The results showed that FCBR was more accurate in predicting precipitation levels. Zima [24] improved the CBR model for cost estimation by integrating fuzzy set theory with CBR to process linguistic terms, which were used to represent different types of construction projects. In their study, Zima [24] defined each construction project by 15 characteristics, each of which was represented by linguistic terms; triangular fuzzy numbers were used to assign weights to the characteristics. Next, Zima [24] determined the fuzzy similarity between the different projects, and the project with the largest defuzzified similarity value was retrieved. Zuo et al. [25] used fuzzy set theory in the retrieval phase of the CBR model they developed to retrieve the accidents in reinforced concrete structures, based on the similarities between different structures. Zuo et al. [25] assigned weights to the key characteristics of the cases using linguistic terms (i.e., very important, important, general, not important, and not to be considered). These fuzzy weights were then used to calculate the similarity between different types of structures. The aforementioned applications of FCBR confirm that the fuzzy set theory can effectively process the subjectivity of case characteristics, as well as the similarities between the cases. This paper aims to introduce a framework based on FCBR to identify risks associated with the construction of renewable energy projects, where the similarities between different types of projects are measured as fuzzy numbers. There are two main advantages of FCBR over conventional CBR. First, FCBR improves the transparency of the model by allowing the user to track the reasoning behind the decisions, which are all represented in linguistic terms; second, an expert can add his/her knowledge into the FCBR model by changing the linguistic terms that represent similarities, which results in greater flexibility. Unlike the two aforementioned applications of FCBR [23,24], the FCBR framework presented in this paper does not rely solely on expert knowledge for determining the similarities between the different cases. The proposed FCBR framework relies on project information, such as construction work packages (CWPs) and project types, to determine the similarity values; it then allows experts to adjust these similarity values to reflect the problem context.

3. The Proposed Framework for Risk Identification of Renewable Energy Projects

3.1. Fuzzy Case-Based Reasoning

FCBR is a technique for systematically retrieving information about an unknown case, based on its similarities to other well-studied cases. For the risk identification of construction projects, the FCBR model used in the present research assumes that similar CWPs have similar risk factors, according to previous research on the application of CBR in risk management. This section presents steps for implementing the proposed FCBR, followed by a detailed explanation of each step.

CBR is applied in five steps: case representation, retrieval, reuse, revision, and retention [22]. Applying fuzzy set theory in retrieval steps evolves CBR into FCBR. In the first step, cases are represented by a set of characteristics and solutions. These characteristics should be relevant and useful for solving the problem at hand. In general, the characteristics used to represent cases are identified by considering the scope of the problem (e.g., work package-level risk identification) in order to extract similar solutions (e.g., work package-level risk factors). In the case retrieval step, the represented case is compared to other cases, based on its characteristics and specific fuzzy similarity functions. This step helps to determine the fuzzy similarity (fuzzy number) between the problem case and other cases by capturing the subjective uncertainty that exists in the CWPs. Using a retrieval method, similar cases are retrieved, and these cases are further processed in the next two steps. In the reuse step, cases identical to the problem case are extracted. Though the problem case might not be fully similar to any other cases, due to the uniqueness of the problem, the retrieved cases are analyzed in the revision step. The extracted information from similar cases is modified or removed, based on the similarity between the problem case and the retrieved cases. The output of the reuse and revision steps is a list of results that were extracted from different retrieved cases relevant to the problem case. Finally, the results are validated using different methods (e.g., expert validation, comparison to real-world results, etc.) before they are added to the database.

3.2. Methodology for Risk Identification of Renewable Energy Projects Using Fuzzy Case-Based Reasoning

The proposed framework was used to identify the work package-level risk factors for renewable projects using FCBR. This framework also distinguishes work packages affected by each risk, which provides the user with an organized structure for representing risk identification results, called a risk breakdown matrix (RBM). Each step is discussed below.

3.2.1. Case Representation

In this step, FCBR was used to identify risk factors associated with each CWP. The problem case (i.e., the project with unknown risk factors) and other cases (i.e., projects with identified risk factors) can be characterized as a description of the project, such as project type, project CWPs, location of the project, total cost, and duration of CWPs. Solutions for previous projects can be defined as associated risks of CWPs. However, in the present research, only project type and CWPs were chosen as characteristics of the cases. Project location, total cost, and duration of CWPs were ignored since there were limited data available about the cost and duration of CWPs in each project type. The location of projects was also ignored, since this paper aims to develop a comprehensive list of construction risk factors for renewable energy projects, as opposed to identifying context-specific risk factors for a particular location. Finally, case representation was completed by storing previous cases in a database for retrieval and retention.

There are many techniques to represent complex cases and knowledge (i.e., image, speech, text, attribute-value, etc.) when using FCBR. The complexity of risk identification in construction research was addressed in this paper through the characterization of projects by two attributes, project type and CWPs. In addition, complexity can be reduced by using the local-global principle to simplify the representation of each case. The local-global principle is based on the idea that complex cases are built up in a systematic way, starting from basic elements. Cases first are broken down into elements, and the similarity between elements is then calculated (i.e., local similarity) and aggregated to simplify the similarity calculation between the two complex cases (i.e., global similarity). Aggregation may be implemented using a number of different methods, such as a weighted average. In order to implement the local-global principle, each case must be decomposed into its structuring elements or characteristics. Each element or characteristic, hereafter referred to as sub-class, may be decomposed further into detailed sub-classes. In the present work, construction projects were characterized by two sub-classes, project type and their CWPs. CWPs can be further characterized by two detailed sub-classes, the risk factors that affect the CWP, and the construction activities included within the CWP.

3.2.2. Case Retrieval

In CBR, the similarity between different cases is an essential function used for retrieval. In this paper, two different types of similarity measures, structure-oriented and counting, are used to determine the similarities between the two project characteristics (i.e., project type and CWPs) [22]. For

- Structure-oriented similarities: The structure in which the knowledge or concept is presented plays a key role in this type of similarity. Structure-oriented similarities are symbolically (versus metrically) distance-oriented. This type is sometimes called path-oriented similarity because it is reliant on the paths of a given structure (e.g., taxonomy).
- Counting similarities: Using this measurement type, certain occurrences in a representation are counted with possible weights. This*n similarities.

Project Type Similarity

In order to determine the similarity between two different types of construction projects (e.g., hydropower plants and onshore wind farm projects), a taxonomy of construction projects was developed using Central Product Classification (CPC) [26]. This hierarchy starts from general concepts of construction project types (e.g., buildings and civil engineering works) and is further broken down to the lowest-level elements, which include specific construction project types (e.g., onshore wind farm projects and solar power plant).

In this paper, the similarity between two given types of construction projects was determined using a structure-based similarity index. The similarity was determined based on the position of the two projects in the taxonomy presented in Figure 1, as well as the deepest common predecessor (DCP).

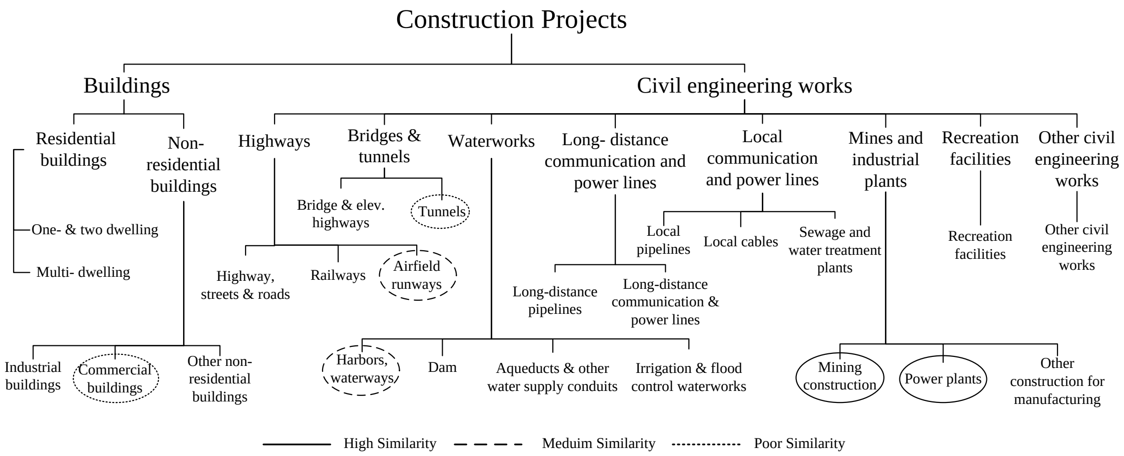

Figure 1. Taxonomy of construction project types.

The DCP represents the number of levels of the taxonomy that the two types of construction projects have in common. There are three possible values for DCP, 1, 2, and 3, which are represented by three fuzzy numbers, low, medium, and high similarity, as shown in Table 1.

Table 1. Fuzzy triangular numbers for the project and construction work packages (CWPs) similarity.

Linguistic Term	**Triangular Fuzzy Number**	
	Project Similarity (P_{Sim})	**CWPs Similarity (C_{Sim})**
Very Low	-	[0.0, 0.0, 0.25]
Low	[0.0, 0.0, 0.5]	[0.0, 0.25, 0.5]
Medium	[0.0, 0.5, 1.0]	[0.25, 0.5, 0.75]
High	[0.5, 1.0, 1.0]	[0.5, 0.75, 1.0]
Very High	-	[0.75, 0.75, 1.0]

CWPs Similarity

In order to determine the similarity index between the CWPs of onshore wind farm projects and those from other types of construction projects, each CWP of renewable energy projects was decomposed into its constituent activities. These actives were identified through an extensive literature review. Next, the Tversky similarity measure [22] was used to calculate the similarity of two CWPs, p and s, as presented in Equation (1).

$$T_{Sim}(s,p) = \frac{(s \cap p)}{(s \cap p) + \alpha(s - (s \cap p)) + \beta(p - (s \cap p))} \tag{1}$$

where s and p are the two CWPs where similarity is being assessed; $s \cap p$ is the number of common activities between the two CWPs; and the parameters α and β are weights for defining the importance of two criteria, exclusive activities of s and exclusive activities of p. Next, in order to capture the subjectivity of the similarity index, T_{Sim}, five fuzzy numbers were defined to represent the similarity between two given CWPs, as shown in Table 1. The fuzzy distance between the crisp similarity index, T_{Sim}, and the five triangular fuzzy numbers was then determined using the fuzzy distance measure. Next, the fuzzy number with the smallest distance to the crisp similarity index was selected to represent the fuzzy similarity of the two CWPs. In order to determine the fuzzy numbers that represent the similarity value, the fuzzy distance between T_{Sim} and each of the five fuzzy numbers was calculated. A number of different measures have been proposed in the literature for calculating the distance between trapezoidal fuzzy numbers. In this paper, the fuzzy distance measure proposed by Wei and Chen [27] was used, which determines the fuzzy distance between two trapezoidal fuzzy numbers of $A(a1, a2, a3, a4)$ and $B(b1, b2, b3, b4)$, as shown in Equation (2).

$$C_{Sim}\left(\widetilde{A},\widetilde{B}\right) = \left(1 - \frac{\sum_{i=1}^{4}|a_i - b_i|}{4}\right) \times \frac{\min\left(P\left(\widetilde{A}\right), P\left(\widetilde{B}\right)\right) + 1}{max\left(P\left(\widetilde{A}\right), P\left(\widetilde{B}\right)\right) + 1} \tag{2}$$

where,

$$P\left(\widetilde{A}\right) = \sqrt{(a_1 - a_2)^2 - 1} + \sqrt{(a_3 - a_4)^2 - 1} + (a_3 - a_2) + (a_4 - a_1) \tag{3}$$

$$P\left(\widetilde{B}\right) = \sqrt{(b_1 - b_2)^2 - 1} + \sqrt{(b_3 - b_4)^2 - 1} + (b_3 - b_2) + (b_4 - b_1) \tag{4}$$

It should be noted that trapezoidal fuzzy numbers are the general form of both crisp numbers (T_{Sim} in this case) and triangular fuzzy numbers (the five fuzzy numbers representing fuzzy similarity indices).

Total Similarity

The total similarity (i.e., global similarity) of cases was determined by aggregating the two local similarity indices, C_{Sim} and P_{Sim}, using the weighted product aggregation method. The weighted product method is a non-compensatory method for aggregation since a low-value in one criterion cannot be compensated by other criteria. The total similarity S is defined as follows:

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

Fuzzy multiplication was used to calculate total similarity since the similarity indices were fuzzy numbers. For fuzzy multiplication, the approximate α-cut method was chosen for its simplicity. Finally, the total similarity was defuzzified using the center of area (COA) method, and the cases with a total similarity more than the user-defined threshold of 0.5 were retrieved for the next steps.

3.2.3. Reuse, Revise, and Retain

In the reuse phase, for those retrieved solutions with full similarity (i.e., an aggregated similarity index of 1; $S = 1$), the risks were extracted with no revisions. In contrast, in the revise step, those risks extracted from non-identical cases (i.e., an aggregated similarity index of less than one and equal or greater than 0.5, $0.5 \leq S < 1$) were revised and adopted based on the scope of the problem project by construction experts. Finally, the list of risk factors was validated using expert knowledge before adding it to the database of factors affecting construction projects, which will be used as a "previous case" in future problems.

4. Case Study: Application of the Proposed Framework in Onshore Wind Farm Projects

The proposed method was applied to the CWPs of onshore wind farm projects. The meteorological tower of onshore wind farm projects was chosen to represent the problem case. The application of FCBR in this paper identified 14 work package-level risk factors affecting the aforementioned CWP, which are shown in Figure 2.

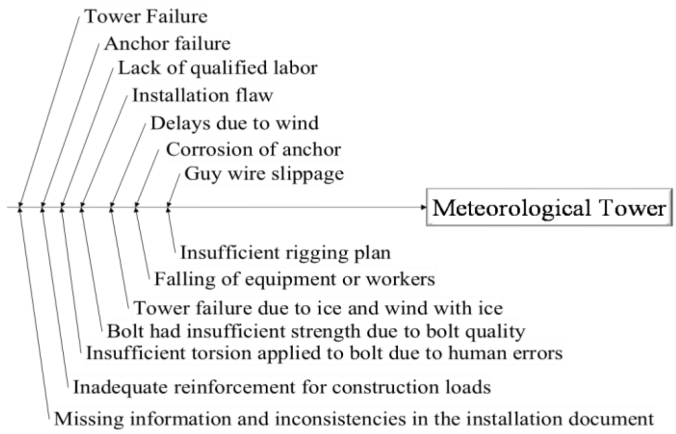

Figure 2. Result of fuzzy case-based reasoning (FCBR) for the meteorological tower.

Case representation was accomplished by identifying the CWP of onshore wind farm projects from the literature and then characterizing these projects using their project type and their CWPs. The CWPs used to represent onshore wind farm projects in this paper were adopted from the research conducted by Hao et al. [28].

The literature review technique was used to construct a database from previous cases (i.e., risk factors that affect other types of construction projects). The name of the CWP was searched in Scopus and Google Scholar databases to find any scholarly articles or technical reports identifying risk factors affecting the CWP under analysis. For Scopus, searches were completed on articles that included the name of the CWP and at least one of the four terms, "risk identification," "risk management," "risk assessment," and "construction risk," within the article keywords, abstract, or title. For Google Scholar, the same keywords were used, but the entire contents of the articles were searched. In addition to scientific articles, technical/engineering reports were also searched in Google Scholar and the Scopus databases. The searches in Scopus and Google Scholar were not limited to a specific time frame or publisher name.

In the retrieval step, MATLAB® was used to facilitate automatic retrieval. First, Equations (1) and (2) were used to calculate the similarity between the CWPs of an onshore wind farm project with other construction projects. The project similarity was then calculated, based on the value of DCP for the comparison of onshore wind farm projects with the other types of construction projects, using the taxonomy of construction projects presented in Figure 1. Next, the approximate α-cut approach was used to aggregate the local similarities, as shown in Equation (5). Finally, the CWPs of other construction projects with a global similarity index of $0.5 \leq S \leq 1$ were retrieved for the CWP of wind farm projects (i.e., metrological tower).

5. Discussion

In order to verify the applicability of the proposed risk identification technique, the risks identified using the proposed technique for the construction of meteorological towers of onshore wind farm projects were compared to those risks that threaten the construction of tall towers (e.g., telecommunication towers, cellular towers), which were identified through a comprehensive review by Davies [29]. The structural design and construction of meteorological towers are similar to those of telecommunication and cellular towers, where there is a very high ratio of tower height to tower width. These characteristics make these structures vulnerable to structural risks caused by horizontal forces (i.e., wind force, earthquakes). Thus, the results of the proposed risk identification technique for meteorological towers are compared to the structural risks that threaten telecommunication and cellular towers [29] to determine if the proposed technique identifies the structural risks that are relevant to tall towers. In this paper, 14 risk factors were identified for the construction of meteorological towers; however, Davies [29] only identified five risk factors: construction errors, ice, special wind, aircraft accident, and anchor failure. While the results of the proposed risk identification technique cover four out of the five risk factors identified by Davies [29], they also identify 10 additional risks that affect the construction of meteorological towers. Moreover, the risk factors presented in this paper are more detailed as compared to those identified by Davies [29]. For example, the risk factor "construction errors" identified by Davies [29] is further detailed in the results of the proposed risk identification technique as follows: "insufficient torsion applied to the bolt due to human errors," "insufficient rigging plan," and "missing information and inconsistencies in the installation document." Finally, the proposed risk identification technique is more efficient as compared to the literature review technique used by Davies [29]. In his research, Davies [29] conducted a comprehensive review of the literature from 1960 to 2011 using content analysis. In this paper, the proposed risk identification technique automatically retrieved similar literature and identified the risks associated with the construction of meteorological towers by considering similarities between project types.

The proposed FCBR model identified 14 work package-level risks for onshore wind farm projects (see Figure 2). In comparing this paper with that of Somi, Gerami Seresht, and Fayek [30], which used CBR for risk identification of onshore wind farm projects, the proposed FCBR model identified more risk factors (14) than the CBR model (11) [30]. This difference is due to the fact that Somi, Gerami Seresht, and Fayek [30] used a crisp CBR, where only the cases with full similarity (i.e., a similarity index of one) were retrieved. In contrast, the FCBR model has the capacity to retrieve cases with partial similarity (i.e., a similarity index less than one). Moreover, the CBR model by Somi, Gerami Seresht, and Fayek [30] was highly reliant on the expert judgment during the retrieval step, whereas the proposed FCBR method used previous project characteristics to retrieve similar cases. Some risk factors were common between the results of the proposed FCBR model and those of Somi, Gerami Seresht, and Fayek [30] (e.g., delays due to wind and falling equipment or workers) since both models retrieved cases with the full similarity. Moreover, some risk factors were retrieved by the FCBR model which were not mentioned in the previous research by Somi, Gerami Seresht, and Fayek [30], such as "anchor failure" and "Insufficient torsion applied to bolts due to human errors." These risk factors were retrieved from the telecommunication tower project, which was not considered in the CBR model since the CBR model only considers projects with full similarity. These differences stem from the fact that the FCBR model described in this paper retrieved cases with partial similarity.

6. Conclusions and Future Steps

Risk identification is the first stage in the risk management process and a key to the successful delivery of construction projects. However, identifying the risks associated with novel types of construction projects is challenging since these projects are not comprehensively studied in the literature and have limited historical data. To address this challenge, this paper introduces a new framework to identify the risks associated with novel types of construction projects, including renewable energy projects, based on the similarities that exist between these projects and other types of construction projects. Accordingly, the proposed risk identification technique improves the accuracy of risk identification for novel types of construction projects, for which limited literature, historical data, or expert-knowledge exist. This paper also contributes to the existing body of knowledge on the risk identification of renewable energy projects by identifying 14 risk factors that are associated with the construction of meteorological towers in onshore wind farm projects at the work package level. The results of this research show that the proposed FCBR model is an appropriate method for risk identification of renewable energy projects since they are novel types of construction projects that have not been comprehensively researched. Moreover, the comparison of the results to other research that used literature review to identify the risks associated with similar types of structures (i.e., telecommunication and cellular towers) reveals that the proposed technique is more efficient and identifies the risks associated with construction projects at a more detailed level. The proposed risk identification technique helps researchers and practitioners to use the data acquired from other types of projects to identify risk factors associated with novel types of construction projects. Moreover, the results of this paper help construction researchers and practitioners with risk identification of onshore wind farm projects. In future research, all the risk factors that affect the construction of onshore wind farm projects will be identified at the work package level, and the list of identified risks will be validated by expert knowledge acquired through interview surveys. These risks will then be prioritized based on their severity by using multi-criteria decision-making techniques. In addition, the application of other fuzzy similarity indices will be investigated to better mimic the human decision-making process. The application of different aggregation methods will also be investigated to improve the accuracy of the retrieval steps by assigning weights to different criteria (local similarity), where a given local similarity index is more important than the other similarity indices.

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