Consensus Building in Group Decision-Making for the Risk Assessment of Wind Farm Projects

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Abstract—Infrastructure projects for harnessing renewable energy (e.g., wind farm projects) have recently gained popularity because of their low adverse impact on the environment. However, it is challenging to perform risk assessments for these projects because data are either scarce or of low quality. Therefore, risk assessments for renewable energy infrastructure projects must rely on expert knowledge and can be treated as multi-criteria group decision-making (MCGDM) problems. In group decision-making problems, consensus must be built between individual decision makers who each supply their own preference indices for decision alternatives. This paper introduces a novel technique for consensus building in MCGDM problems using the principle of justifiable granularity, thereby producing an interval-valued fuzzy set that represents the aggregated value of the preference indices assigned to decision alternatives by decision makers. The preference indices obtained from each expert are realized through the analytic hierarchy process (AHP). In this paper, the introduced MCGDM technique is used to assess risk for wind farm projects. First, a context-specific work breakdown structure for wind farm projects is developed. Second, construction work packages are ranked based on how much they contribute to the overall risk or uncertainty involved in achieving the project objectives of time, cost, quality, and safety.

Keywords— *wind farm projects, risk assessment, multi-criteria decision-making, AHP*

I. Introduction

Finding the right balance between efficiency, cost-effectiveness, and safety throughout an energy facility's life cycle depends on the proper construction, operation, and maintenance of that facility. Facilities that use energy resources are classified as *energy infrastructure*, which is defined as the "physical infrastructure required for producing, transforming, transmitting, distributing, and storing energy" [1]. Improving performance on energy infrastructure projects is a significant concern in many engineering disciplines, including construction, civil and electrical engineering. In order to improve performance, the numerous risks that energy infrastructure projects are exposed to throughout their life cycles need to be properly addressed. Renewable energy projects (i.e., projects intended to harness energy from renewable resources, such as solar panels and wind farms) have attracted much attention from academia in recent years, but it is challenging to assess risk on these projects because the data are either scarce or of low quality. Data scarcity and their low quality can be attributed to new technologies that are not commonly used on conventional energy infrastructure projects (e.g., oilsands projects), but that are necessary for renewable energy projects. Therefore, risk assessments for renewable energy projects must rely on expert judgment and can be treated as group decision-making problems. In order to perform comprehensive risk assessments for energy infrastructure projects, experts need to take into consideration the risks or uncertainties involved in achieving project objectives in terms of four different criteria: cost, time, quality, and safety. Thus, risk assessment problems for renewable energy infrastructure projects can be solved using multi-criteria group decision-making (MCGDM) techniques.

Developed by Saaty [2], the analytic hierarchy process (AHP) is a multi-criteria decision-making (MCDM) technique based on the pairwise comparison of decision alternatives, and it has a broad range of applications in decision-making problems [3]. However, this technique has limitations in terms of building consensus between decision makers, making its application to group decision-making problems challenging. Consensus can be described as an acceptable resolution of the decision outputs that is supported by a majority of decision makers; extreme decision outputs may be excluded. When using the AHP technique, consensus can be built by developing a methodology for aggregating the preference indices determined by different experts for each decision alternative. Previous research on aggregation methodologies for group decision-making using the AHP technique can be categorized into two groups [4]: 1) methodologies that focus on the aggregation of the elements of reciprocal matrices using the weighted geometric mean or the weighted median (see [5]) and 2) methodologies that focus on the aggregation of vectors produced by the AHP technique.

This paper has two objectives. The first is to develop a new technique for MCGDM as an extension of the AHP technique. This new technique aggregates the results produced by individual AHP models into interval-valued fuzzy sets of preferences. The interval-valued fuzzy sets, which represent consensus between the decision makers, are developed using the principle of justifiable granularity. This principle maximizes both the coverage of the intervals (including the largest number of individual preference indices) and their specificity (including the lowest level of uncertainty). The second objective of this paper is to assess the risks of wind farm projects using the newly developed MCGDM technique. To make this assessment, the work breakdown structure (WBS) of wind farm projects must first be developed. The new MCGDM technique is then used to rank the construction work packages (CWPs) based on how much they contribute to the overall risk or uncertainty involved in achieving project objectives in terms of cost, time, quality, and safety.

The rest of this paper is structured as follows. Section II presents a brief introduction of the AHP technique and describes the challenges of group decision-making using the AHP technique. In Section III, the principle of justifiable granularity is described, the application of this principle for building consensus in group decision-making using the AHP technique is discussed, and the MCGDM technique developed in this paper is introduced. Section IV presents the WBS of wind farm projects and the results of the risk assessment for these projects. Finally, Section V discusses conclusions and suggests future research on this topic.

II. AHP and Its Application In Group Decision-Making

A. A Brief Introduction to the AHP Technique

The AHP is an MCDM technique developed by Saaty [2] that is based on the pairwise comparison of decision alternatives. According to Saaty [2], more accurate results are achieved when only two alternatives are evaluated at a time, as opposed to when all decision alternatives are compared simultaneously. Moreover, the AHP technique can be used to develop fuzzy membership functions that represent the linguistic or subjective uncertainties of real-world variables. It is challenging to address subjective uncertainties related to real-world systems through probability theory, but the application of fuzzy set theory enhances the ability of MCDM techniques for risk management to address these subjective uncertainties [6]. Particularly in risk management, the AHP is a pivotal part of analyzing uncertainties and risks [7]. In this paper, the collection of n alternatives $x_1, x_2, \dots, x_n$ is used for decision-making with the AHP technique. The degree of preference of the alternatives over one another (i.e., the results of the pairwise comparisons) are represented by the reciprocal pairwise comparison matrix $A = [r_{ij}],\ r_{ij} = \frac{1}{r_{ji}},\ i,j = 1,2,\dots,n$, where r_{ij} represents the result of pairwise comparison between the alternatives i and j and the elements of the main diagonal ($i = j$) are equal to 1. The degree to which one alternative is preferred over another is expressed using the nine-level linguistic scale provided in Saaty [2], as shown in Table 1.

Table 1. The linguistic scale of the AHP technique.

Grade	AHP linguistic scale
1	Equally essential
3	Moderately more essential
5	Strongly more essential
7	Demonstratively more essential
9	Extremely more essential
2, 4, 6, 8	Compromises/between

Once the reciprocal matrix A has been developed, the maximal eigenvalue λ_{max} and its corresponding eigenvector are determined using Equation 1:

$$(A - \lambda_{max} I)\, e = 0 \qquad (1)$$

where A is the reciprocal matrix, λ_{max} stands for the maximum eigenvalue of matrix A, and I is the identity matrix. The consistency of the reciprocal matrix is the consistency of the pairwise comparisons between the different alternatives. For example, if alternative J is more important than K, and alternative K is more important than L, then alternative J needs to be more important than L in a consistent reciprocal matrix. In a perfectly consistent reciprocal matrix, the maximum eigenvalue should be equal to the number of alternatives. Accordingly, the consistency index (*CI)* of the reciprocal matrix is determined by comparing the maximum eigenvalue of the reciprocal matrix with perfect conditions, as presented below.

$$CI = \frac{\lambda_{max} - n}{n-1} \qquad (2)$$

where λ_{max} stands for the maximum eigenvalue of the reciprocal matrix and n represents the dimensionality of the reciprocal matrix (i.e., the number of alternatives). Because the reciprocal matrices of real-world decision-making problems are usually inconsistent to some extent, it is necessary to specify a threshold for maximum acceptable inconsistency in order to rule out reciprocal matrices that are extremely inconsistent. Per Saaty [8], the consistency ratio (CR) of a reciprocal matrix is determined by comparing the consistency index of the reciprocal matrix to the consistency index of a randomly generated matrix (*RI*) with the formula $CR = CI/RI$. The threshold for the maximum acceptable consistency ratio (CR) is specified to rule out any inconsistent reciprocal matrices. In this paper, the threshold for the maximum acceptable consistency ratio is less than 10% [2], [3], [9]. Any reciprocal matrix with a consistency ratio of 10% or higher is excluded from the decision-making process and the reciprocal matrix is reevaluated. If the difference between the preference indices of two alternatives is extremely small, the difference between those two alternatives will be ambiguous and they may not be distinguishable [10]. In such situations, the difference between the two alternatives is reevaluated in order to find out: 1) if the two alternatives are in fact distinguishable, in which case the choice for one alternative over the other may be made based on the personal preference of the decision maker rather than the results of the AHP technique, or 2) if the two alternatives should be combined into a single alternative. In this paper, the difference between the preference indices of any two alternatives should be greater than 0.05 for the two alternatives to be considered distinguishable alternatives in decision-making.

B. Group Decision-Making with the AHP Technique

Traditionally, collective intelligence is recommended as a way achieve accuracy in decision-making [11]. However, in group decision-making, different decision makers may make similar or completely opposite choices, since their decisions are based on various factors including educational background, personal preference, experience, the decision environment and even moral values [12]. Therefore, an essential part of solving group decision-making problems is the aggregation of the preference indices assigned to each decision alternative by different decision makers into one single preference index [13]. In this paper, p number of decision makers are involved in group decision-making, and they provide the reciprocal matrices $A_1, A_2, \dots, A_p$ that are used to evaluate the preference indices of n number of alternatives (refer to Section II). For each decision maker, the consistency level of the reciprocal matrix is determined as $C_1, C_2, \dots, C_p$. Next, for all the obtained reciprocal matrices, the vectors of the preference indices for n alternatives are determined as A, $P_1, P_2, \dots, P_n$. Then, as discussed in Section III, the preference indices for each alternative (P_i) are aggregated using the principle of justifiable granularity to build consensus between the decision makers.

III. The Aggregation of Preference Matrices Using the Principle of Justifiable Granularity

This section describes the methodology for building consensus between a group of decision makers whose decisions are presented as preference matrices that are developed using the AHP technique. In order to build such consensus, the preference matrices developed by decision makers are aggregated. The elements of the aggregated preference matrix are represented as type-2 fuzzy sets, where the preference index of each alternative is expressed as an interval rather than a crisp number. Type-1 fuzzy sets, defined over a discrete space of alternatives, return a crisp number for the preference index of each alternative, while interval-valued, or type-2, fuzzy sets return an interval for the preference index of each alternative. While using type-1 fuzzy sets only provides information about the preference index of the alternatives, using interval-valued fuzzy sets provides information about the preference indices of the alternatives and the level of agreement (or disagreement) between decision makers. Using interval-valued fuzzy sets is therefore preferable in this case since it provides more information than using type-1 fuzzy sets. Fig. 1 represents an example of the triangular membership function of interval-valued fuzzy sets.

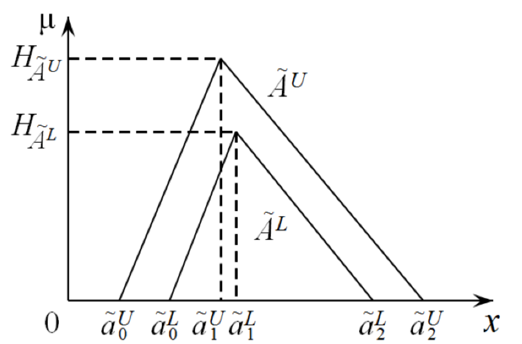

Fig. 1. Example of a triangular membership function of interval valued fuzzy sets.

In Fig. 1, $\tilde{A}^L$ and $\tilde{A}^U$ represent the triangular membership functions for the lower and upper limits, respectively, of the interval-valued preference indices. $H_{\tilde{A}^L}$ and $H_{\tilde{A}^U}$ represent the height of the triangular membership functions for the lower and upper limits, respectively, of the interval-valued preference indices. The minimum, core and maximum values of the triangular membership function for the lower of the interval-valued preference indices are $\tilde{a}_0^L$, $\tilde{a}_1^L$ and $\tilde{a}_2^L$, and $\tilde{a}_0^U$, $\tilde{a}_1^U$ and $\tilde{a}_2^U$ are the minimum, core and maximum values for the upper limit of the interval-valued preference indices. The alternatives and their membership degrees are expressed on the x axis and the μ axis, respectively.

In this paper, the interval-valued fuzzy sets representing the preference indices of alternatives are developed through the following steps. In the first step, the preference indices determined by each decision maker are normalized as follows.

$$e_i' = \frac{e_i - e_{min}}{e_{max} - e_i} \quad (3)$$

where e_i' stands for the normalized value of the preference index for alternative i, e_i stands for the original value of the preference index and e_{min} and e_{max} represent the minimum and maximum preference index, respectively.

In the second step, the aggregation of the preference index for each decision alternative i is determined by $A_i = [e'_1, e'_2, \dots, e'_p]$, where e_j' represents the normalized preference index determined by decision maker j and p stands for the number of decision makers. In the third step, the consistency indices (CI_j) of the reciprocal matrices are determined as discussed in Section II (refer to (2)), and the consistency of each reciprocal matrix j is calculated as $C_j = 1 - CI_j$ in order to weight the preference indices determined by the decision maker j. Thus, the aggregation of preference indices for decision alternative i is determined by $A_i = [(C_1, e'_1), (C_2, e'_2), \dots, (C_p, e'_p)]$, where C_j stands for the consistency of the reciprocal matrix developed by decision maker j. In the fourth step, the principle of justifiable granularity is used to determine the interval-valued fuzzy sets representing the preference indices of alternatives, in which the preference index of each alternative is represented by an interval $[e^-, e^+]$. In order to determine the values of e^- and e^+ for each alternative, the weighted median of the preference indices of each alternative is determined using (4).

$$e_i^* = argmin\ \sum_{j=1}^{p} C_j \left| e_{j,i} - e_i^* \right| \quad (4)$$

where e^* stands for the weighted median of the preference indices of alternative i, C_j stands for the consistency of the reciprocal matrix determined by decision maker j and $e_{j,i}$ represents the value of the preference index determined for alternative i by decision maker j. Next, the lower and upper bounds of the interval-valued preference index of each alternative is determined by maximizing the coverage and the specificity of the interval simultaneously. Since there is a conflict between maximization of the coverage and maximization of the specificity, the composite index of the two measures—determined as the product of the two expressions—is maximized [14]. Thus, the lower and the upper bounds of the interval-valued preference index of the alternative i (i.e., e_i^-, e_i^+) are determined using (5) and (6), respectively.

$$e_i^- = argmax\ \ Cov(e_i^-).Sp(e_i^-) \quad (5)$$

$$e_i^+ = argmax\ \ Cov(e_i^+).Sp(e_i^+) \quad (6)$$

where $Cov(e_i^-)$ stands for the coverage of the lower bound of the interval-valued preference index of alternative i and $Sp(e_i^-)$ stands for the specificity of the lower bound of the interval-valued preference index of alternative i. $Cov(e_i^+)$ and $Sp(e_i^+)$ can be similarly defined for the upper bound of the interval. The values of coverage and specificity for the lower and upper bounds of the interval-valued preference index of alternative i are calculated using (7) and (8), respectively [14], [15], [16].

$$Cov(e_i^-) = \sum_{j=1}^{p} C_j \qquad when\ \ e^- < e_p < e^* \quad (7)$$

$$Cov(e_i^+) = \sum_{j=1}^{p} C_j \qquad when\ \ e^* < e_p < e^+ \quad (8)$$

The specificity of the lower and upper bounds of the interval-valued preference index of alternative i are calculated in the following form [14], [15], [16].

$$Sp(e_i^-) = 1 - \frac{|e^- - e^*|}{|e_{min} - e^*|} \quad (9)$$

$$Sp(e_i^+) = 1 - \frac{|e^+ - e^*|}{|e_{max} - e^*|} \quad (10)$$

IV. The Risk Assessment of Wind farm Projects Using the Proposed Multi-Criteria Group Decision-Making Technique

The definition of energy infrastructure projects (see Section I) is used to develop the context-specific WBS of wind farm projects, as presented in Fig. 2. In this paper, the WBS is developed through an extensive literature review and the investigation of two actual wind farm projects that are located in Canada. Further information about these wind farm projects is publicly available at [17], [18].

Wind Farm Project 1: The Port Ryerse Wind Power Project, which is located east of the hamlet of Port Ryerse in Norfolk County, Ontario, is developed by Boralex Inc. (Boralex) in association with UDI Renewables Corporation (UDI). This project includes four Siemens SWT 3.0 113 wind turbine generators. The 3.0 MW turbines are customized to a nameplate capacity of 2.5 MW for this project. The total maximum installed nameplate capacity of all four turbines does not exceed 10 MW. Other basic components of the project include step-up transformers located adjacent to the base of each turbine (steps up voltage from approximately 0.69 kV to 27.6 kV), a 27.6 kV underground collector system, fiber optic data lines, a distribution substation, a permanent parking lot (if required), a meteorological tower and turbine access roads.

Wind Farm Project 2: The second wind farm project is located in the Township of West Lincoln in the Niagara region of Ontario and is owned by IPC Energy. The project consists of five Vestas V-100 18 MW wind turbines producing a nameplate capacity of 9 MW. The undertaking includes three phases: construction, operation and maintenance, and decommissioning of the facility and its associated infrastructure.

The context-specific WBS for wind farm projects, as shown in Fig. 2, represents CWPs at the third level, which are briefly described as follows:

Pre-Construction Activities: This CWP includes three main tasks, namely clearing (trees, existing structures, etc.), stripping and removal of topsoil, and site preparation.

Surveying: Land surveys are done to identify the exact location of important structures such as turbines, access roads, etc. The positions of other structures necessary for construction, such as temporary crane pads and laydown areas, are also specified during surveying.

Turbine Foundation: This CWP includes construction activities such as excavation, formwork construction, concrete delivery, steel reinforcement installation, concrete pouring, curing, hauling, backfilling, and compaction. The construction of this CWP may differ at each wind turbine, depending on the location of each foundation and its accessibility to other site facilities (e.g., access roads, etc.).

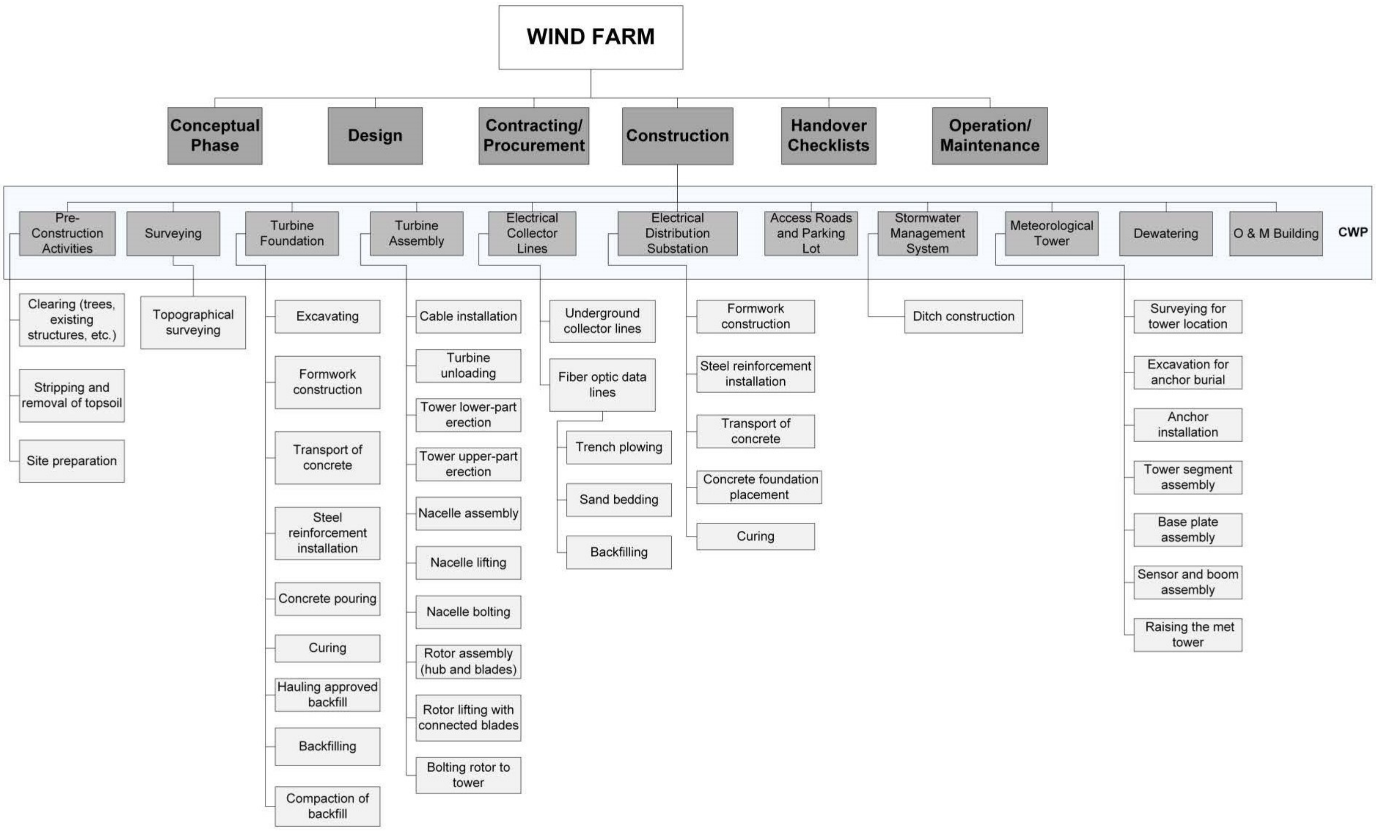

Fig. 2. Work breakdown structure (WBS) for wind farm projects.

Turbine Assembly: This CWP involves all the activities required for the assembly of the wind turbines, including cable installation, unloading turbines, tower lower-part erection, tower upper-part erection, nacelle assembly, nacelle lifting, nacelle bolting, rotor assembly (hub and blades), and rotor lifting and bolting.

Electrical Collector Lines: Underground collector lines and fiber optic data lines are put into place for the interconnections and distribution systems that are below ground. This CWP involves all activities required to install the electrical collector and optic data lines, including trench plowing, sand bedding and backfilling. The construction activities included in this CWP may differ depending on the construction method selected for installing the collector and data fiber lines (i.e., open-cut/trenching versus closed-cut).

Electrical Distribution Substation: This CWP involves the construction of the electrical distribution station building and includes activities such as formwork construction, steel reinforcement installation, transport and placement of concrete, and curing for reinforced concrete structures. The construction activities included in this CWP may differ depending on the structure type of the electrical distribution station building (i.e., concrete structure versus steel structure).

Access Roads and Parking Lot: Access roads connect the site entrance to an existing municipal road. They are built specifically to provide access for construction services.

Stormwater Management System: This CWP involves the construction of ditches in order to avoid stormwater damage to incomplete construction works or the exposed surfaces of site facilities.

Meteorological Tower: This CWP involves the construction of the meteorological tower building, which is accomplished through the following activities: excavation for anchors, anchor installation, assembly of meteorological tower segments, base plate installation, sensor and boom installation, and erection of the meteorological tower.

Dewatering: Dewatering activities include removing unwanted water that may come as a form of stormwater runoff or ground water that manifests when performing excavations.

O&M Building: The operation and maintenance building CWP includes the construction of a building to host the facilities required for the operation and maintenance of the wind farm project, as well as the provision of a workspace for the on-site management, engineering, and technician teams who are responsible for the operation and maintenance of the facility.

In order to evaluate the risks associated with each CWP using the MCGDM technique introduced in this paper, a questionnaire survey was designed to acquire expert knowledge. The questionnaire asks experts to compare each pair of CWPs in terms of their contribution to the overall risk or uncertainty involved in achieving the project objectives in terms of cost, time, quality, and safety. Fig. 3 presents an example of questionnaire survey questions.

In order to rank the CWPs presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project cost** objective, compare the **"pre-construction activities"** CWP to each of the CWPs listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Pre-construction activities										Surveying works
										Turbine foundation
										Turbine Assembly
										Electrical collector lines
										Electrical distribution substation
										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O & M Building

Fig. 3. Questionnaire survey example.

A total 15 responses were collected from construction researchers and used to evaluate the risks associated with each CWP using the MCGDM technique introduced in this paper.

While the four criteria for decision-making—project cost, time, quality and safety—are equally weighted, the interval-valued preference index of each CWP (i.e., the decision alternative) is determined as presented in Table 2. As discussed in Section III, the interval values of the preference indices represent 1) the amount of risk each CWP contributes to the overall risk or uncertainty involved in achieving the project objectives and 2) the variability of the preference index given to each alternative by each different decision maker. The interval-valued preference indices are used to rank the CWPs in descending order, as shown in Table 2, where a higher preference index is associated with a higher level of risk contributed by the CWP. While the preference index for each CWP is calculated as a crisp interval (i.e., a non-fuzzy interval), interval ranking methods are used to rank the CWPs. Sengupta and Pal [19] discussed the three types of interval ranking problems: (1) non-overlapping intervals, in which there is no overlap between any pair of intervals; (2) partially overlapping intervals, in which there are overlaps between different intervals but none of the intervals are completely overlapped (i.e., covered) by others; and (3) overlapping intervals, in which some of the intervals are completely overlapped by others. According to Sengupta and Pal [19], non-overlapping intervals can be ranked using transitive relation, as presented below for two intervals $A = [a_L, a_R]$ and $B = [b_L, b_R]$.

$$A < B \Leftrightarrow a_R < b_L \qquad (11)$$

Since the transitive relation is not applicable to the ranking of partially overlapping and overlapping intervals, Sengupta and Pal [19] suggested using the midpoint and/or the width of intervals for ranking. There are also more complicated approaches for ranking partially overlapping and overlapping intervals using the probability theory; these approaches consider each interval a uniform distribution and use probabilistic relationships to rank them [19]. In this paper, the CWPs are ranked based on the geometric mean (GM) of their interval-valued preference index, as Sheen [20] suggested that ranking generalized fuzzy numbers by GMs is "computationally simple" and "logically sound." According to Sheen [20], when ranking generalized fuzzy numbers by GMs, an alternative with a higher GM is ranked higher, and when there are two alternatives with an equal GM, the number with a lower geometric variance is ranked higher.

As presented in Table 2, the results of the analysis show that the top three CWP contributors to project risk or uncertainty are the turbine foundation, the meteorological tower and turbine assembly. The turbine foundation has the highest aggregated preference index, the highest preference index in terms of the cost and quality criteria and the second highest preference index for the safety criterion. The high preference index of this CWP (i.e., turbine foundation) stems from the uncertainty involved in its associated activities such as excavation, which is extremely dependent on unseen underground conditions. The CWP for the meteorological tower has the second highest aggregated preference index and the highest preference index in two individual criteria: time and safety. The high preference index of this CWP in the safety criterion stems from the involvement of heavy construction equipment, such as cranes, in the execution of activities such as anchor installation, assemblies and raising the meteorological tower. The use of heavy construction equipment also elevates the preference index of this CWP for the time and cost criteria. Finally, the CWP for turbine assembly has the third highest aggregated preference index and the second highest preference index for the cost criterion.

Table 2. Ranking of CWPs of wind farm projects based on their contribution to project risks or uncertainties.

CWP	Interval-Valued Preference Index			Rank
	Lower Limit	Upper Limit	GM	
Turbine foundation	0.732	0.867	0.800	1
Meteorological tower	0.533	0.741	0.637	2
Turbine assembly	0.524	0.737	0.631	3
Electrical collector lines	0.450	0.637	0.544	4
Electrical distribution substation	0.388	0.589	0.488	5
O & M building	0.349	0.547	0.448	6
Stormwater management system	0.291	0.467	0.379	7
Surveying works	0.243	0.471	0.357	8
Access roads	0.250	0.444	0.347	9
Pre-construction activities	0.215	0.418	0.316	10
Dewatering	0.202	0.335	0.269	11

V. Conclusions and Future Work

The AHP is a widely accepted MCDM technique that is used in a variety of engineering applications. However, making decisions in group settings using the AHP technique is challenging because this technique is not capable of building consensus within a group of decision makers. This paper's first contribution is to extend the application of the AHP technique for MCGDM by introducing a new methodology for building consensus using the principle of justifiable granularity. The introduced methodology provides the results of decision-making (i.e., preference indices of alternatives) as type-2 fuzzy sets, which represent 1) the preference index of each alternative and 2) the variability of the preference indices given to each alternative by different decision makers. The lower and upper bounds of the interval-valued preference index need to be determined by satisfying two contradictory conditions. First, the lower and the upper bounds of the intervals need to be far enough away to maximize the inclusion of decisions (i.e., maximize the coverage). Second, the lower and upper bounds need to be close enough together to deliver a sound semantic (i.e., maximize specificity). The methodology presented in this paper shows that these two contradictory conditions can be satisfied simultaneously by maximizing the composite index of the two measures, which is the product of the coverage and the specificity of the intervals.

The MCGDM technique developed in this paper is applied to the risk assessment of wind farm projects. Traditional techniques for the risk assessment of construction projects (e.g., the Monte Carlo simulation technique) usually rely on the availability of historical data. However, the risk assessment of renewable energy infrastructure projects (e.g., wind farm projects) relies extensively on expert judgment because data are either scarce or of low quality due to the novelty of the technologies used in these projects. This paper's second contribution is the implementation of the developed MCGDM technique, using expert judgment, to the assessment of risks associated with construction wind farm projects. This is accomplished as follows. First, the WBS of wind farm projects is developed through an extensive literature review and the investigation of two real case studies. Next, using the introduced MCGDM technique, the CWPs (i.e., decision alternatives) of wind farm projects are ranked based on how much they contribute to the overall risk or uncertainty involved in the achieving the project objectives in terms of cost, time, quality, and safety (i.e., the decision criteria). The results of the risk assessment reveal that the three CWPs that have the most impact on overall risks or uncertainties associated with project success are the turbine foundation, the meteorological tower and turbine assembly. These three CWPs therefore need to be carefully planned and monitored on wind farm projects. In future research, the MCGDM technique introduced in this paper will be extended to ascertain the weights of decision criteria prior to the preference indices of the alternatives in order to improve accuracy. In addition, the extended technique will be applied to the risk assessment of wind farm projects to obtain a more accurate and comprehensive overview of the risks associated with each CWP.

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