

Consensus Building and Optimization in Group Decision-Making for the Risk Assessment of Wind Farm Project

by

Yajie Hao

A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in

Software Engineering and Intelligent Systems

Department of Electrical and Computer Engineering
University of Alberta

© Yajie Hao, 2020

Abstract

Infrastructure projects for harnessing renewable energy (e.g., Wind Farm Project) have recently gained popularity because of their low adverse impact on the environment. However, the risk assessment of the Wind Farm Project involves numerous challenges since historical data for these projects are either scarce or of low quality. Therefore, risk assessments for renewable energy infrastructure projects must heavily rely on the expert assessment of different risk factors associated with achieving project objectives in terms of cost, time, quality, and safety. Accordingly, the risk assessment of the Wind Farm Project needs to be tackled as a multi-criteria group decision-making problem, which necessitates building consensus between individual decision-makers who each supply their preference indices for decision alternatives (i.e., risk factors).

In group decision-making problems, consensus must be built between individual decision-makers whom each supply their preference indices for decision alternatives. In this study, a new multiple criteria group decision-making technique is introduced for the risk assessment of the Wind Farm Project by building consensus among decision-makers—who have determined their decision alternative preferences representing the aggregated preference indices of decision alternatives as to the principle of justifiable granularity type-2 fuzzy numbers, thereby producing an interval-valued fuzzy set that represents the aggregated value of the reference indices assigned to decision alternatives by decision-makers.

The preference indices obtained from each expert and linguistic conflicts are realized and clarified through the analytic hierarchy process. Moreover, the introduced multiple criteria group decision-making technique is used to assess risk for Wind Farm Project. Then, the construction work packages are ranked based on how much they contribute to the overall risk or uncertainty involved in achieving the project objectives for time, cost, quality, and safety. Due to insufficient real experts' knowledge, data is much more valuable, and the principle of justifiable granularity selects and elevated the consensus of decision-making problems, which excludes the extreme preference of experts. Partial preferences of experts can be elevated higher through the exploration and elevation of the multiple criteria group decision-making consensus, which relies on the constraints of randomization and particle swarm optimization, the elevation of information granule, and its corresponding granularity includes more experts' preferences without losing too much preciseness. The main objectives of the thesis are aiming at the collection of consensus through the principle of justifiable granularity and the exploration and elevation of consensus.

Preface

This thesis was supervised by Professor. Witold Pedrycz. Chapter 3.2, Chapter 3.3, and Chapter 5.2 of this dissertation have been submitted to the "2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE) " by Yajie Hao, Dr.Nebiyu Siraj Kedir, Dr.Nima Gerami Seresht, Professor Witold Pedrycz, Professor Aminah Robinson Fayek. The name of the conference is "*Consensus Building in Group Decision-Making for the Risk Assessment of Wind Farm Project.*"

I participated in the literature review, the data processes of the Analytic Hierarchy Process for analyzing infrastructure risks, the aggregation of preferences of Multiple Criteria Group Decision-Making, and its partial result analysis. Professor Witold Pedrycz and Professor Aminah Robinson Fayek were the main idea developers and also the validators for manuscript and concept formation. Other chapters with further exploration were developed and explored by me.

Acknowledgments

To begin with, it has been my honor to work with the extremely gracious Professor Witold Pedrycz for both the development of the ideas and the writing of this thesis. He has been an example of unremitting exploration with an attitude toward rigorous scientific research. His patience and encouragement have supported me through many hardships in my Master's research. I am grateful for the constant guidance from him.

Secondly, I would like to thank Dr. Nima Gerami Seresht and Professor Aminah Robinson Fayek. The advice given to me by them has been hugely useful. It has been a pleasure for me to work together with them in one group.

In addition, I would like to thank my parents for their concerns, supports, and understanding. Their love has helped me overcome a lot of hardship during my graduate study.

Finally, I am grateful to the staff at the Department of Electrical and Computer Engineering, who has been friendly and offered support, especially Professor Marek Reformato, Pinder Bains, and Amy Ouyang. I am grateful for their help with the administration in the department.

Yajie Hao
University of Alberta
August 2020

Table of Contents

Chapter 1	Introduction.....	1
Chapter 2	Background.....	4
2.1	The Wind Farm Project	4
2.2	The Analytic Hierarchy Process	7
2.3	The Multiple Criteria Group Decision-Making.....	12
2.4	The Principle of Justifiable Granularity	14
2.5	The Fuzzy Logic and Type-2 Fuzzy Set.....	16
2.6	The Particle Swarm Optimization	19
2.7	Conclusion	20
Chapter 3	The Uncertainty Captured by AHP.....	21
3.1	The Structure of AHP	21
3.2	The Uncertainty of the Linguistic Variables Captured by AHP.....	22
3.3	The Establishment of the Reciprocal Pairwise Comparison Matrix.....	23
3.4	Conclusion	27
Chapter 4	The Consensus Building for MCGDM Problem	28
4.1	The Traditional Methodologies in MCGDM Problem	28
4.2	Consensus Collection for MCGDM problem.....	29
4.3	Conclusion	33
Chapter 5	The Principle of Justifiable Granularity and Aggregation for Preferences. 34	
5.1	The Information Granule for the Principle of Justifiable Granularity	34
5.2	The Principle of Justifiable Granularity Determine the Interval Type-2 Fuzzy Set for Consensus	36
5.3	5.3 The Aggregation and Ranking for Consensus	41
5.4	Conclusion	43

Chapter 6	Exploration and Elevation of Consensus by Particle Swarm Optimization	44
6.1	Constraints for the Exploration of Optimized Consensus through Particle Swarm Optimization	45
6.2	Exploration for Flexibility and Optimized Consensus	48
6.3	Elevation of Consensus for MCGDM Problem.....	51
6.4	Conclusion	64
Chapter 7	Summary and Further Study	66
7.1	Summary.....	66
7.2	Further Studies.....	67
References.....	错误!未定义书签。	

List of Tables

Table 2.2.1 The Linguistic scale of the AHP technique	10
Table 2.2.2 The Random Consistency Index for Different Dimension of Reciprocal Pairwise comparison Matrix.....	11
Table 3.3.1 The reciprocal pairwise comparison matrix in terms of criterion time for multiple alternatives	24
Table 3.3.2 The maximal eigenvectors for 11 CWPs from individual reciprocal comparison matrix of criterion time.....	25
Table 3.3.3 The normalized maximal eigenvectors for 11 CWPs from individual reciprocal comparison matrix of criterion time	25
Table 3.3.4 The maximal eigenvalues in terms of criterion time for multiple expert.....	26
Table 3.3.5 The CI in terms of criterion time for multiple experts.....	26
Table 4.2.1 The weighted preferences for multiple CWPs and experts in terms of criterion time	32
Table 4.2.2 The ranked group decision making for $[[CWP]]_1$ and experts in terms of criterion time..	32
Table 4.2.3 The ranked group decision making for $CWP1$ for its corresponding CI in terms of criterion time	33
Table 5.1.1 The ranked partial information granule for $CWP1$ in terms of criterion time	36
Table 5.2.1 The lower bound $ei -$, weighted median $ei *$, and upper bound $ei +$ for information granule for multiple CWPs in terms of criterion time.....	39
Table 5.2.2 The lower bound $ei -$, weighted median $ei *$, and upper bound $ei +$ for information granule for multiple CWPs in terms of criterion cost	39
Table 5.2.3 The lower bound $ei -$, weighted median $ei *$, and upper bound $ei +$ for information granule for multiple CWPs in terms of criterion safety	40
Table 5.2.4 The lower bound $ei -$, weighted median $ei *$, and upper bound $ei +$ for information granule for multiple CWPs in terms of criterion quality.....	40
Table 5.2.5 The ranked information granule for criterion time	40

Table 5.3.1 Ranking of CWPs of Wind Farm Project based on their contribution to project risks or uncertainties	43
Table 6.3.1 The PSO generation for elements in reciprocal pairwise comparison matrix 1000 iterations for criterion time.....	53
Table 6.3.2 The scale of the parameter γ for objective function in PSO	57
Table 6.3.3 The IT2FS from PSO generation when $\gamma = 0.2$ for criterion time	57
Table 6.3.4 The percentage of the preferences of experts for all criteria with different parameter γ	62
Table 6.3.5 The IT2F of the preferences of experts for criterion time and cost with different parameter $\gamma = 0.2$	63
Table 6.3.6 The IT2F of the preferences of experts for criterion quality and safety with different parameter $\gamma = 0.1$	63
Table 6.3.7 The PSO generated the final ranking of CWPs with appropriate parameter γ	64

List of Figureures

Figure 2.1.1. Work breakdown structure (WBS) for wind farm projects	5
Figure 2.2.1 The AHP for Leadership.....	9
Figure 2.5.1 Triangular and trapezoidal membership function.....	16
Figure 2.5.2 Standard triangular IT2FS	18
Figure 2.5.3 Standard trapezoid IT2FS.....	19
Figure 3.1.1 The AHP structure of Wind Farm Project.....	22
Figure 5.3.1 The IT2FS on a three-dimensional coordinate system	42
Figure 6.1.1 Modification for a four-dimensional reciprocal pairwise comparison matrix	47
Figure 6.1.2 The UD for randomization	48
Figure 6.2.1 The summation of HD for different ϵ for 1000 iteration of criterion time.....	50
Figure 6.2.2 The summation of specificity multiply coverage for different ϵ for 1000 iteration of criterion time	50
Figure 6.3.1 Coverage changing trend for criterion time for iteration in PSO	53
Figure 6.3.2 HD changing trend for criterion time for iteration in PSO.....	54
Figure 6.3.3 Specificity changing trend for criterion time for iteration in PSO	54
Figure 6.3.4 The convergence of the objective function when $\gamma = 0.1$ for criterion time in terms of CWP's	55
Figure 6.3.5 The summation of the total specificity in terms of different γ in PSO	56
Figure 6.3.6 The summation of the total coverage in terms of different γ in PSO	56
Figure 6.3.7 The summation of the total HD in terms of different γ in PSO.....	57
Figure 6.3.8 The summation of the total coverage in terms of different γ from 0.1 to 0.3 in PSO.....	58
Figure 6.3.9 The summation of the total specificity in terms of different γ from 0.1 to 0.3 in PSO	59
Figure 6.3.10 The summation of the total HD in terms of different γ from 0.1 to 0.3 in PSO	59
Figure 6.3.11 The summation of HD for four criteria with different γ	60

Figure 6.3.12 The summation of specificity for four criteria with different..... 60

Figure 6.3.13 The summation of coverage for four criteria with different τ 61

List of Symbols

A	reciprocal pairwise comparison matrix
x_n	n -th decision-makers
λ	eigenvalues from reciprocal pairwise comparison matrix
r_{ij}	elements of reciprocal pairwise comparison between the alternatives i and j
λ_{max}	maximum eigenvalue from reciprocal pairwise comparison matrix
I	identity matrix
e	eigenvectors from reciprocal pairwise comparison matrix
V^+	upper bounds for the principle of justifiable granularity
V^-	lower bounds for the principle of justifiable granularity
U	the universe of discourse for fuzzy set
D	The size of the swarm of particles
μ	triangular or trapezoidal membership function
$\mu(x)$	membership degree of fuzzy set
$A(x)$	interval type-2 fuzzy set

$A(x)^+$ upper bounds for interval type-2 fuzzy set

$A(x)^-$ lower bounds for interval type-2 fuzzy set

E_i The weighted preference for single alternative i

cov coverage

sp specificity

Gr granularity

γ parameter for PSO

Obj objective function for PSO

Exp preference of experts

List of Abbreviations

AHP	Analytic Hierarchy Process
WBS	Work Breakdown Structure
MCGDM	Multiple Criteria Group Decision-making
IT2FS	Interval Type-2 Fuzzy Set
PSO	Particle Swarm Optimization
CI	Consistency Index
CR	Consistency Ratio
RI	Random Consistency Index
FOU	Footprint Of Uncertainty
CWP	Construction Working Package
GM	Geometric Mean
UD	Uniform Distribution
HD	Hamming Distance

Chapter 1 Introduction

Considering that artificial intelligence can replace humans in some aspects of predictive, classification, and decision making, it is widely expected to find more efficient and less expensive methods for decision making in projects. There is the Human-Centric System that incorporates the system of the human perspective, which is proposed for better decision-making. While facing a decision-making problem with insufficient, rare, or low-quality data or even without data, this Human-Centric System, with its expressed preferences and judgments from invited experts, is vital[1].

Promoting performance on infrastructure projects is an essential topic in numerous fields. Exploring the appropriate balance between safety, efficiency, and construction and maintenance costs is necessary and beneficial for improving the performance of the infrastructure of a Wind Farm Project. To be more specific, the assessment of numerous risks addressed through their life cycles on a Wind Farm infrastructure project is a significant component of the promotion of cost and construction. Renewable energy projects that can harness energy from renewable resources, such as solar panels and wind farms, have attracted much concentration from academia recently.[2] However, insufficient and low-quality data contributes to the challenge of infrastructure risk assessment. Allocating the evaluation assignment to authoritative specialists will reduce the difficulties of assessment and provide accurate and high-quality data. Therefore, comprehensive multiple risk assessments for Wind Farm Project can be treated as group decision-making problems. There are four criteria that should be assessed in order to evaluate the comprehensive risks of the project: cost, time, quality, and safety. Thus, the risk assessment for Wind Farm infrastructure projects can be treated and tackled using multi-criteria group decision-making (MCGDM) techniques.

Saaty developed the analytic hierarchy process (AHP) for multi-criteria decision-making (MCDM), which depends on the pairwise comparison of decision alternatives and criteria. [3] This technic is widely applied and can obtain a successful outcome in decision-making problems.[4] However, there are defects in terms of consensus-building for this mechanism, and it is challenging to utilize this mechanism in group decision-making. In order to collect an appropriate consensus outcome from group decision-making, the resolution of consensus should be supported by the majority of decision-makers, rather than including and being impacted by a few radical decision-makers. Then, the methodology can be developed for consensus-building for the aggregation of the preference of experts by listening to multiple experts for each decision alternative while applying the AHP technique. This article is to develop a new mechanism for MCGDM as an extension of AHP technology, and this new mechanism aggregates the consequences produced by interval-based fuzzy sets of preferences from the AHP model. These interval-based fuzzy sets represent the consensus between the decision-makers, which have been developed by using the principle of justifiable granularity. The principle maximizes the coverage and their specificity, indicating where the intervals occur, which include the majority of the individual preference indices and the lowest level of uncertainty.

Besides, the assessed risks of infrastructure in terms of multiple alternatives are evaluated by the new MCGDM technique to rank construction work packages (CWPs). The overall risk ranking is based on the contribution of the uncertainty in achieving the criteria in terms of cost, time, quality, and safety.

Furthermore, the flexibility of the Human-Centric System can be assessed by undertaking different data and still offering appropriate results. Acceptance of different dimensions of alternatives and random pairwise comparison preferences can testify to the adaption of our model. On the other hand, because of insufficient data and excluded preferences from the principle of justifiable

granularity, the promotion technique is proposed to reduce excluded preference from the group decision-making using the AHP model. This optimization technique is applied for the modification of original pairwise comparison matrices to elevate consensus. In order to limit the time complexity and calculation cost, the Particle Swarm Optimization (PSO) should slightly modify the preferences of experts through AHP to include more preferences in the principle of justifiable granularity. The PSO generates multiple random variables from Uniform Distribution(UD) for whole alternatives for the revision of pairwise comparison preferences. The constraints to maintain suitable granularity and different preferences are introduced in the following content.

The thesis is structured as follows. A brief background and methodology are offered in Chapter 2. An introduction of the AHP technique and the description of challenges for group decision-making using the AHP technique is in Chapter 3. Then, the MCGDM technique and principle of justifiable granularity are described in Chapter 4 and Chapter 5. Chapter 6 introduces the ranking mechanism and the result of infrastructure risks. The exploration and the optimization mechanism and experimental result analysis are listed in Chapter 6. And the conclusions and further studies are presented in Chapter 7.

Chapter 2 Background

This chapter describes the background for the Wind Farm Project and the methodology of the model we used to accomplish the risk assessment task. There is a basic background introduction of the Wind Farm Project in Section 2.1. The AHP algorithm is the assessment mechanism for linguistic conflicts from the preferences of experts in Section 2.2. In Section 2.3 and Section 2.4, the background information for MCGDM and the concept of the principle of justifiable granularity are illustrated, respectively. The description of the interval type-2 fuzzy set and the aggregation methodology for fuzzy sets are listed in Section 2.5. Finally, the background surrounding PSO is elaborated in Section 2.6.

2.1 The Wind Farm Project

The proposed Wind Farm Project is to be situated in the Township of West Lincoln, in the Niagara Region of Ontario. The wind turbines would be erected for the purpose of capturing energy from the wind, a renewable resource, and converting it into clean, useable electricity. The proposed Wind Farm Project undertaking includes three phases, construction, maintenance, and decommissioning of the facility and its associated infrastructure. This electricity will be transported to consumers via interconnection facilities, including transformers and distribution lines. 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.

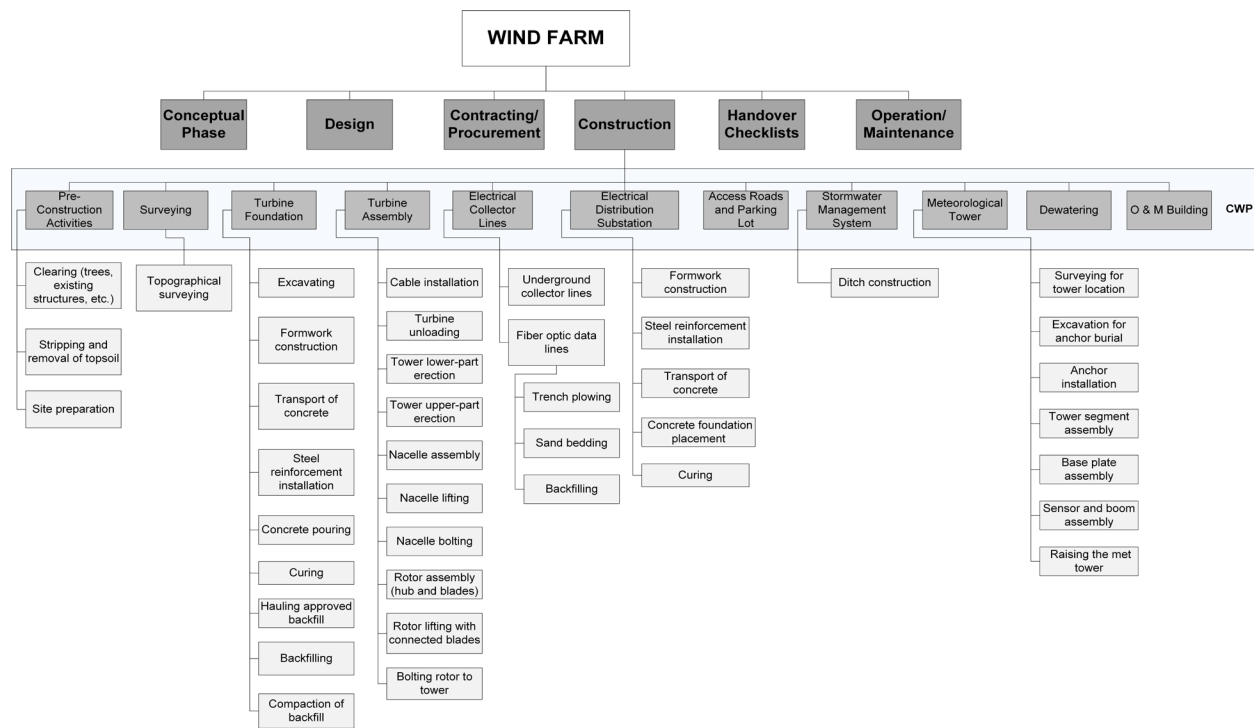


Figure 2.1.1. Work breakdown structure (WBS) for wind farm projects

The 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 context-specific WBS for wind farm projects, as shown in Figure. 2.1.1 represents CWPs at the third level; for example, 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.).

The risk factors are defined and evaluated depending on the WBS; for example, if the concrete delivery was damaged during transportation, the cost will be extremely high while maintaining the infrastructures. Besides, the expensive cost, low power generation efficiency, and infrastructure damage would occur if the existing trees were not cleaned in pre-construction. In other words, the WBS representative risk factors and the CWPs are the combinations and summation of the risk factors. Experts are required to consider the risk severity for CWPs in terms of four criteria in the questionnaires and express the weighted preferences of the pairwise of CWPs. The questionnaire is illustrated in the appendix to clarify how the experts express their risk assessments (preferences) in terms of CWPs.

However, it is challenging to assess risks on these projects because data is often either scarce or of low quality. The situation at this location needs to be considered as an independent project rather than relying on simulated data. The environment situation needs to be analyzed from field trips in order to obtain convincing data for construction. Then, due to concerns about the need for real data, the preference of local experts must be collected. And then, to ensure the accuracy of decision-making, multiple experts are assigned to evaluate the infrastructure risks for the

construction of the Wind Farm Project so that the impact of having too few experts who may hold extreme opinions can be avoided, and the risk assessment problem is treated as a MCGDM problem. On the other hand, the linguistic ambiguities and conflicts between alternatives and criteria raised because of the preferences are basically differences in verbal language from experts. Verbal ambiguities and conflicts will be dealt with using the Analytic Hierarchy Process (AHP) methodology developed by Saaty[3].

2.2 The Analytic Hierarchy Process

The AHP is a significant method for decision-making, especially on some extraordinarily complex and vague problems, and it is especially suitable for those problems that are difficult to analyze completely quantitatively. It is a straightforward, flexible and practical multi-criteria decision-making method proposed by American operations researcher Professor T. L. Saaty in the early 1970s. In the systematic analysis of social, economic, and scientific management issues, people are often faced with a complex system composed of many factors which are interrelated and mutually constrained and often lack quantitative data.

AHP provides a modern, concise, and practical modeling method for decision-making and ranking of such problems. Usually, the AHP is often utilized in multi-objective, multi-criteria, multi-element, multi-level unstructured complex decision-making problems[2]. Decomposing the elements related to such problems into goals, criteria, alternatives, and other levels and performing qualitative and quantitative analysis on the basis can better solve the evaluation of complex systems with multiple factors interrelated and mutually constrained, which often lack quantitative data. In practical work, the analytic hierarchy process is often combined with the Delphi method and the percent weight method to determine the weight of evaluation indicators. Relying on the basic concept of AHP, with the first step being decomposition followed by synthesis, the elements

to be analyzed are first layered and stepped to form a multi-level analysis and evaluation model. Finally, the weight of each level of indicator order will be determined.

AHP expresses a complex problem as an orderly hierarchical structure and gives the order (or weight) of alternatives through supervisor judgments and scientific calculations. In short, AHP, as its name implies, must first construct a reasonable level, and secondly, analyze the pros and cons of each factor within the level.

For interpretation of the concept mentioned above, the hierarchy structure is constructed based on a simple problem. For example, let us assume the goal is to choose a leader based on their experience, age, educational background, and charisma, where those factors are treated as the criteria. Then three alternatives are listed as the name of the person. The final aggregation of the weights through criteria are ranked to explain the consequence of the leader in Figure 2.2.1.

Furthermore, the linguistic preferences from decision-makers can be measured mathematically through the construction of pairwise comparison matrices for each layer. Thus, the elements in pairwise comparison matrices are reciprocal through comparison, and their background measures the importance in terms of criteria. In this paper, the collection of n alternatives, which x_1, x_2, \dots, x_n are utilized for decision-making with the AHP technique.

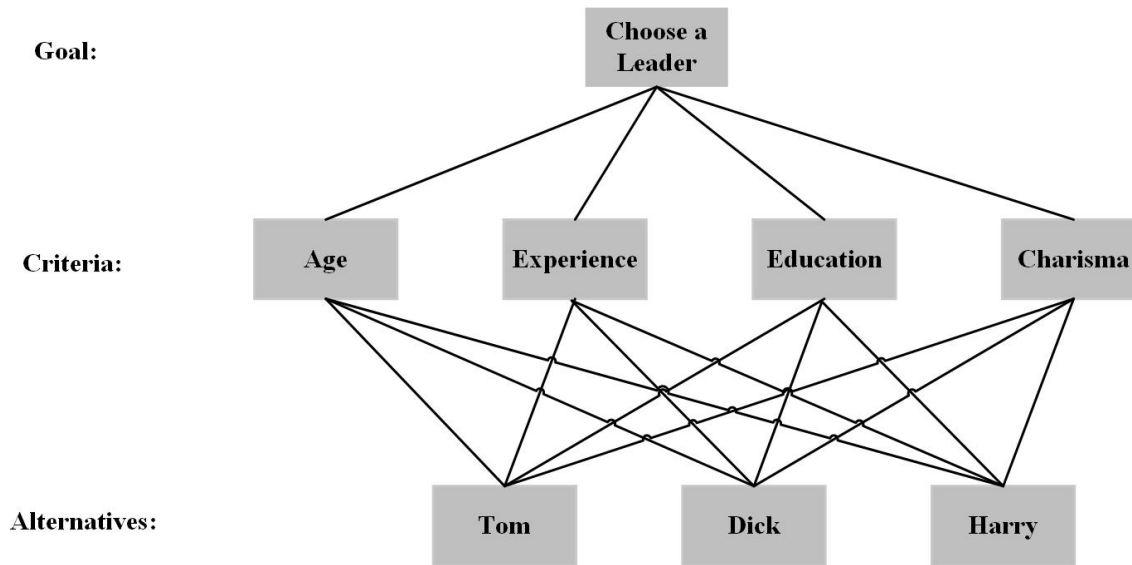


Figure 2.2.1 The AHP for Leadership

Then, 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 as the function below:

$$A = [r_{ij}], \quad r_{ij} = \frac{1}{r_{ji}}, \quad i, j = 1, 2, \dots, n \quad (1)$$

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. On the other hand, other essential constraints in AHP is the appropriate scale of the reciprocal pairwise comparison matrix. An inappropriate scale for capturing verbal preferences results in a low consistency index (CI) and will affect the relationship between alternatives and criteria. If too small of a scale, the result may be too weighted, but if too great of a scale, the result may be too dissimilar from the comparison. The most popular scale for the multiple criteria decision-making problem is listed below:

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

Table 2.2.1 The Linguistic scale of the AHP technique

After completing the construction of the reciprocal pairwise comparison matrix based on the judgment of experts, it is necessary to order the hierarchy and check consistency for individual alternatives and criteria. The reciprocal matrix A that developed above is the maximal eigenvalue λ_{max} . Moreover, its corresponding eigenvector is determined using equation 2 and 3:

$$\det(A - \lambda I) = 0 \quad (2)$$

$$(A - \lambda_{max}I) e = 0 \quad (3)$$

where A is the reciprocal matrix, λ and λ_{max} stands for all eigenvalues and 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. And e represents the corresponding eigenvectors collected from the maximal eigenvalue λ_{max} . Accordingly, the consistency index (CI) of the reciprocal matrix is determined by comparing the maximum eigenvalue among all eigenvalues and the dimensions of reciprocal pairwise comparison matrix, as presented below.

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (4)$$

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. According to the development from Saaty[5], the Consistency Ratio (CR) of the 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:

$$CR = CI/RI \quad (5)$$

The threshold for the maximum acceptable consistency ratio (CR) is specified to rule out any inconsistent reciprocal matrices. Considering the dimension of the reciprocal matrix, for Random Consistency Index (RI) listed below:

n	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Table 2.2.2 The Random Consistency Index for Different Dimension of Reciprocal Pairwise comparison Matrix

Where the n represents the dimension of the reciprocal matrix, in this paper, the threshold for the maximum acceptable consistency ratio is less than 10% [3], [4], [6]. Any reciprocal matrix with a consistency ratio of 10% or higher are 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 [7]. 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.

Finally, considering the individual who is involved in the final decision-making, the aggregation of the weight (order) for the whole criteria in terms of alternatives determined the ranking of goals. (i.e., the final ranking from high to low weight for people in leadership problem is determined though the summation of all separate weight in considerable layers.)

However, the result from AHP demonstrated there is a defect in the extreme preferences of the decision-maker. Depending on different educational backgrounds, experiments, and the impact of the environment, the preferences and the final weights could be different or extreme. Thus, in order to overcome this defect in the AHP technique, the MCGDM mechanism based on multi-expert decision-making is proposed for the Wind Farm Project.

2.3 The Multiple Criteria Group Decision-Making

The AHP technique suggested above assists us in dealing with multiple criteria decision-making problems through the pure control of personal decision-makers[8]. However, the results illustrate shortcomings in group decision-making. The individual decision-makers have a short-sighted

defect, and the concept of group decision-making should be brought forward for dealing with these multiple criteria decision-making problems.

Decision-making has been developed throughout various historical stages to reflect the characteristics of the times. Decision-making has increasingly shown some new characteristics with changes in the environment, economy, and society[9]. Especially, the most typical of which is that group decision-making has been valued and developed rapidly. As for complex decision-making problems, the multiplicity of goals, the dynamics of the time, and the uncertainty of the state are usually involved, which is beyond the control of pure personal ability. For this reason, group decision-making has been recognized by more and more decision-makers and is increasingly valued because of its unique benefits.

Decision-making problems become much more difficult with the complexity of multiple criteria decision-making problems. Some multiple criteria decision-making problems do not have an absolute single solution. A variety of decision-making consequences can be derived from different decision-makers who possess unrelated educational backgrounds, experiments, and subjective judgments.

Initially, the internal and external environment facing decision-makers is becoming increasingly complex and changeable, and all the while, the complexity of many issues continues to increase. Correspondingly, it requires a combination of expertise in many fields to deal with the problems which arise. This cross-domain knowledge, which is required, often exceeds the limits of one individual.

Moreover, the personal values, attitudes, beliefs, and backgrounds of decision-makers have certain limitations[10]. In addition, these factors will have an impact on the types of problems, ideas, and methods needed for solving them. For example, if decision-makers concentrate on economic value,

they will tend to make decisions about substantive situations, including marketing, production, and profit issues. If they pay special attention to the natural environment, they will consider the issue from an ecological point of view. Thus, individual decision-makers cannot be good at handling all types of problems and making every single type of decision.

Finally, the interconnected criteria and alternative of decision-making objectively require experts from different fields to participate, provide relevant information, and recognize problems from different angles. Diversely, the members in group decision-making undertake hazards together rather than one individual decision-maker undertaking something by himself. In this way, the majority of the experts support the final consensus from group decision-making and this eliminates the possibility of having some extreme opinions only a few experts[11].

Disadvantages of group decision-making are also particular and evident—which mainly are slow speed and efficiency to come to a group decision by building-consensus. Experts from different backgrounds will fall into blind discussions and can be inconvincible to reach a consensus. Instead of developing consensus in the real-world group, the simulation method for consensus establishment initiates the concept of the principle of justifiable granularity.

2.4 The Principle of Justifiable Granularity

This section describes the background of the methodology for building consensus between a group of decision-makers whose decisions are presented as the preferences matrices that are developed using the AHP technique. The concept of the principle of justifiable granularity offers the mechanism to form the information granules in the field of Granular Computing. The information granule includes as much data with the appropriate linguistic explanation. For example, there is an interval defined by the verbal explanation, and any which belongs in the interval is in this granule.

The measurement for the above definition of information granule can be achieved through two factors, e.g., coverage and specificity. Those two factors are necessary to be maximized simultaneously. The coverage is usually increasing in the number of data points contained in the interval. Meanwhile, the specificity is treated as a decreasing function of the interval length. Increasing coverage leads to decreasing specificity and makes two contradictory equations. Then, the appropriate information granule is transferred to multiple objective optimization problems.

According to previous research [12], the optimization problem has been transferred to the product of two equations (coverage and specificity). The interval is divided into two parts and processed and optimized separately. Assuming we have a series of a one-dimensional data set defined as C , which is the optimization problem, as well as the interval, it can also be divided into two assignments.

$$\begin{aligned} \max_b V^+ &= f_1(\text{card}\{x_k | \text{median} < x_k \leq b\}) * f_2(|\text{median} - b|) \\ \text{s.t. } b &\in [\text{median}, x_{\max}] \end{aligned} \quad (6)$$

$$\begin{aligned} \max_a V^- &= f_1(\text{card}\{x_k | a \leq x_k < \text{median}\}) * f_2(|\text{median} - a|) \\ \text{s.t. } a &\in [x_{\min}, \text{median}] \end{aligned} \quad (7)$$

Those two equations are quoted from [13], where the f_1 and f_2 are coverage and specificity respectively denoted as $f_1(u) = u$ and $f_2(u) = 1 - u$ for simply. In order to maximize the product of coverage and specificity, the left and right boundaries of the interval presented as a and b should be ensured in the objective function V^+ and V^- . Then, x_{\min} , x_{\max} , and the median represented the minimum, maximum, and median value of the data set, respectively.

2.5 The Fuzzy Logic and Type-2 Fuzzy Set

High precision along with high complexity is incompatible when dealing with decision-making and the Human-Centric System in natural language processing. When this happens, linguistic variables are proposed to overcome the complexity by sacrificing precision, and the values of linguistic variables used are words or sentences instead of numbers. Moreover, the collection of linguistic variables is from the natural or artificial language which is generally less specific than numerical ones[14]. For example, the value of young in terms of age is represented as a linguistic variable rather than being expressed by a specific number, such as 30. This linguistic variable plays the same role as the specific value, though with less precision and less information. Also, in the fuzzy set of the age, the different labels can also be defined as extremely young, not young, etc.

The general fuzzy set is defined as a pair (U, m) where U is a set and $m: U \rightarrow [0,1]$ a membership function. The reference set U is called the universe of discourse, and for each $x \in U$, the value $\mu(x)$ is denoted as the membership degree of x in (U, m) . The function $\mu = \mu_A$ is called the membership function of the fuzzy set $A = (U, m)$.

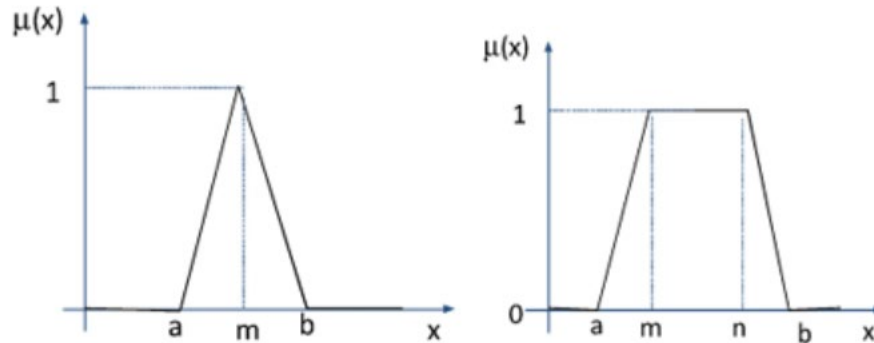


Figure 2.5.1 Triangular and trapezoidal membership function

An illustration of the triangular and trapezoidal membership function is displayed in the above Figure. The following equations respectively represent the definition of the triangular and trapezoidal membership function:

$$\mu(x) = \begin{cases} 0 & \text{if } x \leq a \\ \frac{x-a}{m-a} & \text{if } x \in [a, m] \\ \frac{b-x}{b-m} & \text{if } x \in [m, b] \\ 0 & \text{if } x \geq b \end{cases} \quad (8) \quad \mu(x) = \begin{cases} 0 & \text{if } x < a \\ \frac{x-a}{m-a} & \text{if } x \in [a, m) \\ 1 & \text{if } x \in [m, n] \\ \frac{b-x}{b-n} & \text{if } x \in [n, b] \\ 0 & \text{if } x > b \end{cases} \quad (9)$$

Where the a and b are the boundaries for membership degree, in both boundaries, the membership degree increases or decreases, the above general fuzzy set was treated as Type-1 Fuzzy Set according to the thesis[15]. On the other hand, the operations on the fuzzy set offer the aggregation for criteria and alternatives, and the ranking result for the final fuzzy set is measured by the Geometric Mean(GM).

The operations are the generalization of crisp set operations, and the most widely utilized operations are called standard fuzzy set operations, such as fuzzy complements, fuzzy intersection, and fuzzy unions. In general, standard fuzzy set operations are named De Morgan's Laws and include a complement, intersection(t-norm), and union(t-conorm).

Standard Complement

$$\mu_{\neg A}(u) = 1 - \mu_A(u) \quad (10)$$

Standard Intersection

$$\mu_{A \cap B}(u) = \min\{\mu_A(u), \mu_B(u)\} \quad (11)$$

Standard Union

$$\mu_{A \cup B}(u) = \max\{\mu_A(u), \mu_B(u)\} \quad (12)$$

The type-1 fuzzy set is the general fuzzy set that was quoted previously and the uncertainty of the type-1 fuzzy set is captured by the type-2 fuzzy set[16]. The essence of the type-2 fuzzy set is the

implementation that the interval is to describe the footprint of uncertainty (FOU) rather than the numeric value. Thus, the elements x in the universe of discourse X represents the interval instead of the membership degree. The interval type-2 fuzzy set (IT2FS) [16], as a particular case of type-2 fuzzy sets, has attracted attention due to their reduced computational cost. Let us define the IT2FS by $A(x)$, whose FOU is bounded by $A^+(x)$ and $A^-(x)$ defined by the following equations as examples of standard triangular and trapezoid IT2FS, respectively. The illustration of the IT2FS is shown in Figure 2.5.2 and 2.5.3. As it has been noted, an IT2FS can be uniquely specified by the vector of parameters $t = (t_1, \dots, t_n, h)^T$.

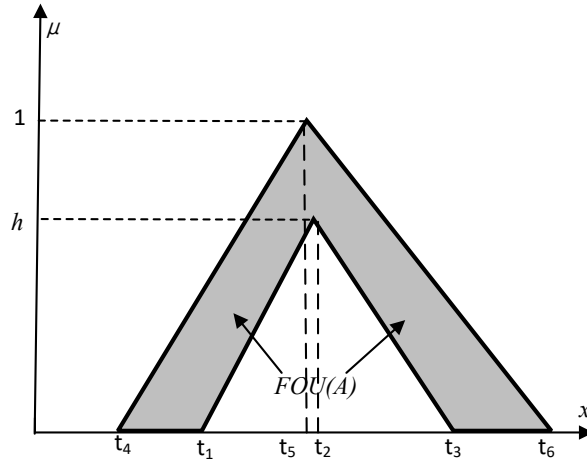


Figure 2.5.2 Standard triangular IT2FS

$$A^+(x) = \begin{cases} (x - t_4)/(t_5 - t_4), & t_4 \leq x < t_5 \\ 1, & x = t_5 \\ (t_6 - x)/(t_6 - t_5), & t_5 \leq x < t_6 \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

$$A^-(x) = \begin{cases} h(x - t_1)/(t_2 - t_1), & t_1 \leq x < t_2 \\ h, & x = t_2 \\ h(t_3 - x)/(t_3 - t_2), & t_2 \leq x < t_3 \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

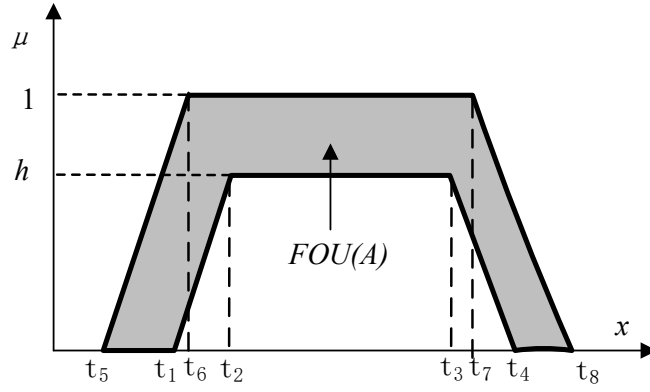


Figure 2.5.3 Standard trapezoid IT2FS

$$A^+(x) = \begin{cases} (x - t_5)/(t_6 - t_5), & t_5 \leq x < t_6 \\ 1, & t_6 \leq x < t_7 \\ (t_8 - x)/(t_8 - t_7), & t_7 \leq x < t_8 \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

$$A^-(x) = \begin{cases} h(x - t_1)/(t_2 - t_1), & t_1 \leq x < t_2 \\ h, & t_2 \leq x < t_3 \\ h(t_4 - x)/(t_4 - t_3), & t_3 \leq x < t_4 \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

2.6 The Particle Swarm Optimization

The Particle Swarm Optimization (PSO) [17] initially stimulates and provides imaging of the unpredictable feeding behavior of a bird's brood. Sharing the position of food to the brood offers motivation and direction for the whole brood to approach the location of the food. To be more specific, the PSO applies to simulate social behavior. In the algorithm, the individuals of a whole brood are treated as particles and "evolved" by cooperation and competition among the individuals themselves through generations. Each particle adjusts its flying according to its own flying experience and its companions' flying experience[18]. On the other hand, PSO always applied to

the complex objective function, which is non-differentiable or non-continuous. PSO has been widely utilized to handle global optimization problems due to some benefits such as simplicity of implementation, fewer parameters, and higher convergence rate. The following equations introduce the main concepts of PSO. Assume that the size D is the swarm of particles exploring the search space, and every particle has its own velocity and position information. The objective function describes the goodness of the position of the particle. Then, the j th ($j = 1, 2, \dots, D$) particle is represented as

$$Y_j^{(k+1)} = Y_j^k + V_j^k \quad (17)$$

$$V_j^{(k+1)} = wV_j^k + c_1r_j^k(pb_{best}^k - V_j^k) + c_2t_j^k(g_{best}^k - V_j^k) \quad (18)$$

Where $w \in [0,1]$ is the inertia constant, c_1 and c_2 represent the cognitive constant and social constant, and usually, the default value is 2. r_j and t_1 are the random vectors that allocated in the interval $[0,1]$ from the UD. The pb_{best} explains the particle experienced the best position so far, and the g_{best} represents the best positions for whole particles in swarm. On the other hand, the Y_j^k and V_j^k describe the position and velocity of the j th particle. Moreover, $k+1$ is the next position and velocity of this particle. The PSO is applied for the final exploration and elevation for consensus in the MCGDM problem for Wind Farm Project.

2.7 Conclusion

The concept of all methodologies utilized for the Wind Farm Project is meant to capture the uncertainty of the real preferences of experts by AHP and will be explained in the next chapter. The MCGDM for the Wind Farm Project and Principle of Justifiable Granularity is introduced in chapter 4. The IT2FS, aggregation method and ranking method are given in chapter 5. Then, the

PSO exploration and elevation for consensus will be studied in chapter 6. The following chapter will include real data along with its corresponding analysis.

Chapter 3 The Uncertainty Captured by AHP

The structure of AHP, the methodology of the uncertainty of the linguistic variables, and the pairwise comparison matrices in terms of criteria are introduced in this chapter. In addition, the weights of the experts and the preference from each expert are collected from their linguistic variable through establishing the AHP with its corresponding matrices.

3.1 The Structure of AHP

According to the basic concept of AHP in chapter 2.2 and Figure 2.2.1 as an example, the final goal, the alternative layer, and the criteria layer have to be ensured before comparing each risk factor. The final goal, which is quite apparent in chapter 2.1, is to choose the best way to construct the Wind Farm Project. As required by the Wind Farm Project, the CWPs must be selected through ordering the priority means of the construction for the Wind Farm infrastructures in terms of risk assessment. Thus, the alternatives layer is defined to include all the CWPs, and the multiple risk factors are in the criteria layer.

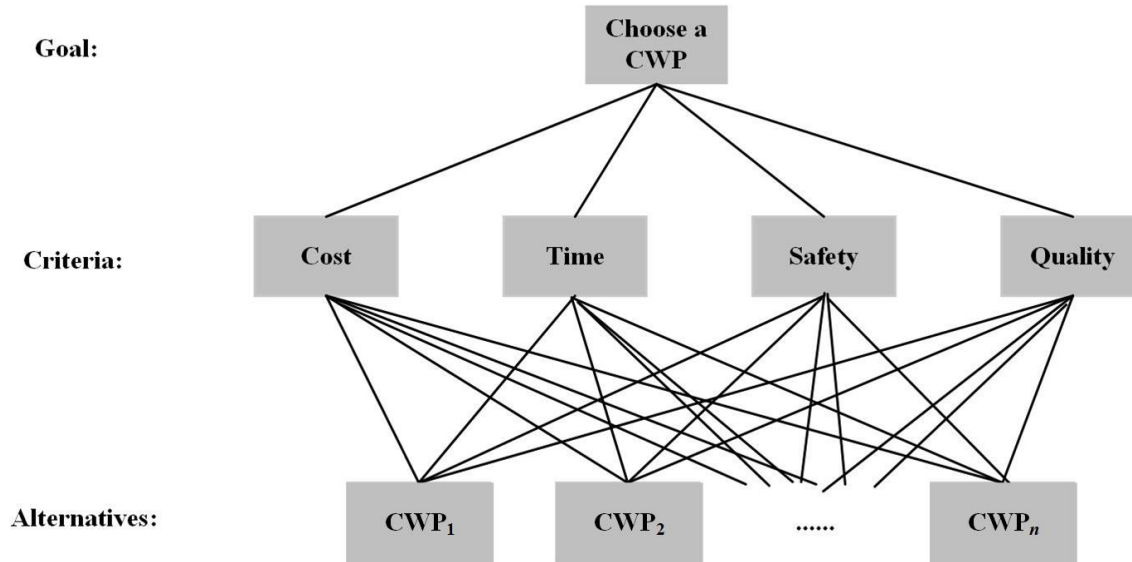


Figure 3.1.1 The AHP structure of Wind Farm Project

The CWPs were obtained through the taxonomy of massively detailed factors to specific classes such as Surveying, Turbine Foundation, Turbine Assembly, etc. Then, all CWPs depend on the combination of the weights of multiple risk factors in terms of cost, time, safety, and quality in the criteria layer.

3.2 The Uncertainty of the Linguistic Variables Captured by AHP

The questionnaires are created based on the preferences of the CWPs and the multiple criteria risk factors. As for multiple alternatives, we defined all alternatives as *CWP* and obtained as CWP_i , where $i = 1, 2, \dots, n$. Instead of expressing the specific number of the preferences of the CWPs, the invited experts were merely required to order and rank all the CWPs as linguistic variables with ambiguous assessment information for Wind Farm Project. For example, the preferences can be defined as $Cost = Time = Safety = Quality = 0.25$ and $CWP_1 > CWP_3 = CWP_2 > \dots > CWP_n$, where the CWPs are clear to be ranked by experts in questionnaires as Surveying, Turbine Foundation, Turbine Assembly, etc. On the other hand, the experts also have to be required

to describe the similarity and different degrees of the CWPs in questionnaires for preference establishment.

Once the multiple criteria linguistic variables from experts have all been collected, the transformation of the linguistic variables to the pairwise comparison matrix is an essential step for preference establishment. The number of the alternatives (CWPs) is 11 after the classification, and the introduced most popular scale in Table 1.1 for AHP linguistic variables is utilized to capture the uncertainty and the conflicts among alternatives. According to previous experience[19-21], the lower scale 1-7 is not specific enough to measure 11 CWPs, and no matter how much we change the elements in the pairwise comparison matrix, another target CR always can never be satisfied. On the other hand, if assuming the scale is 1-11, the last three CWPs are always close enough to be the same. For example, elements such as $\frac{1}{9}, \frac{1}{10}, \frac{1}{11}$ are almost the same in the pairwise comparison matrix. The complexity of the calculation for preferences is elevated. However, the difference is not described as specific enough as required. The final preferences are almost the same among the three elements by using this scale. Thus, the appropriate grade from 1 to 9 can be comprehensive enough to describe 11 CWPs, because some of the experts expressed that the weight of the preferences is the same among CWPs.

3.3 The Establishment of the Reciprocal Pairwise Comparison Matrix

1	3	5	7	5	5	3	5	5	5	3
1/3	1	3	5	3	1	1	3	3	1	1
1/5	1/3	1	1/3	1/5	1/5	5	3	3	3	3
1/7	1/5	3	1	1/3	1/3	1/3	1/3	1/3	1/3	1/3
1/5	1/3	5	3	1	1	1/3	1	1	1	1

1/5	1	5	3	1	1	1/3	1	1	1	3
1/3	1	1/5	3	3	3	1	3	5	3	1
1/5	1/3	1/3	3	1	1	1/3	1	1	3	1
1/5	1/3	1/3	3	1	1	1/5	1	1	1	1
1/5	1	1/3	3	1	1	1/3	1/3	1	1	1
1/3	1	1/3	3	1	1/3	1	1	1	1	1

Table 3.3.1 The reciprocal pairwise comparison matrix in terms of criterion time for multiple alternatives

The pairwise comparison matrix is utilizing the scale 1-9 and the rule of the reciprocal matrix in chapter 2.2, where we reuse the definition of the reciprocal pairwise comparison matrix as $A = [r_{ij}]$, $r_{ij} = \frac{1}{r_{ji}}$, $i, j = 1, 2, \dots, n$. The reciprocal pairwise comparison matrix of the individual expert-created on above Table 3.2.1, and each row and column are following the order from CWP_1 to CWP_{11} . Every element obtained with its corresponding comparison value represents the importance of itself and others while comparing itself on the diagonal of the matrix, where the value is 1.

Applying equations (2) and (3) and the corresponding concept of AHP in chapter 2.2, the maximum eigenvalues and its corresponding eigenvectors are calculated. In this paper, the result of taxonomy for CWPs offers 11 alternatives that trigger the Identity Matrix I with the same 11 dimensions in equations (2) and (3). In order to simplify visualization of results in this chapter, the example merely displays the preferences of the individual expert in terms of criterion time, such as the maximum eigenvalue with its corresponding eigenvectors and the CI value. The calculated maximal eigenvalue from the example in Table 3.2.1, the defined $\lambda_{max} = 14.002$, and then the corresponding eigenvectors are showing in Table 3.2.2.

$e_1 \sim e_{11}$										
0.7062	0.3137	0.2855	0.1142	0.2283	0.2657	0.3170	0.1533	0.1302	0.1408	0.1573

Table 3.3.2 The maximal eigenvectors for 11 CWP_s from individual reciprocal comparison matrix of criterion time

Denoting the maximal eigenvectors as e for every CI as the same notation in equation (4), where $e_i, i = 1, 2, \dots, n$. Table 3.2.2 interprets the importance and the preferences among all our CWP_s from left to right. Moreover, the difference between each alternative is quite apparent. However, the difference between CWP_{10} and CWP_{11} is ambiguous in Table 3.2.2 as e_{10} and e_{11} . Then, in order to specify the difference more distinct, normalizing all eigenvectors by maximal values is the better option. The difference among eigenvectors is transferred to the weights of the maximal eigenvectors.

$$e'_i = \frac{e_i}{e_{max}} \quad (19)$$

Where the e_{max} and e'_i represents the maximal eigenvectors in the preferences of experts and the normalized eigenvectors, respectively.

$e'_1 \sim e'_{11}$										
1	0.4442	0.4043	0.1617	0.3233	0.3763	0.4488	0.2171	0.1843	0.1994	0.2227

Table 3.3.3 The normalized maximal eigenvectors for 11 CWP_s from individual reciprocal comparison matrix of criterion time

On the other hand, the CI could be obtained by the maximal eigenvalues by equation (4) with $n = 11$ because of 11 dimensions for reciprocal pairwise comparison matrix, the CI for the reciprocal comparison matrix in Table 3.2.1 obtained as 0.6998. In this paper, the CI represents the weights of experts as an essential factor while complying with the principle of justifiable granularity to

elevate the consensus of MCGDM. However, the CI test refers to the logical consistency of the reciprocal pairwise comparison matrix. For example, CWP_1 is weighted more important than CWP_2 , and CWP_2 is weighted more significant than CWP_3 , then apparently the CWP_1 must be weighted heavier than CWP_3 . If the CR is greater than 0.1, the reciprocal comparison matrix suggested being adjusted for lower CR because the value of CR means there are some logical conflicts among pairwise comparison elements.

The CI was divided by the 11th RI random consistency ratio 1.51, $CR = 0.4634$. The preferences of the individual expert include conflicts in his judgment of the infrastructure risks. Traditionally, the judgment logic of the reciprocal pairwise comparison matrix is suggested to be revised for appropriate logic. However, the preference is real data mapping from experts, and their weights are still valuable for the MCGDM problem in the next chapter. The elevation of CI will be introduced in the PSO chapter.

Gathering experimental data for multiple alternatives and experts provides sufficient inputs for MCGDM, and the combination of preferences of multiple experts for each alternative (CWPs) is taken out separately to obtain a fuzzy set as consensus.

λ_{max}^i							
14.0020	13.4159	14.0020	13.7646	13.6901	14.8905	16.0414	15.0582
14.4010	14.7841	13.6111	15.6185	14.8835	13.8527	15.5341	

Table 3.3.4 The maximal eigenvalues in terms of criterion time for multiple expert

CI_i							
0.6998	0.7584	0.6998	0.7235	0.7310	0.6109	0.4959	0.5942
0.6599	0.6216	0.7389	0.5381	0.6117	0.7147	0.5466	

Table 3.3.5 The CI in terms of criterion time for multiple experts

The CI and the normalized eigenvectors for multiple experts in terms of criterion time could be obtained based on their maximal eigenvalues in Table 3.2.4. As for multiple experts, we capture and visualize the λ_{max}^i and CI_i in Table 3.2.4 and Table 3.2.5, where $i = 1, 2, \dots, n$. In this paper, questionnaires were sent to 15 experts for data collection.

3.4 Conclusion

In this chapter, the uncertainty and conflicts of the preferences of experts for the Wind Farm Project are captured by the AHP structure and reciprocal pairwise comparison matrix. The example merely illustrates the results of individual criterion time, but the preferences of all criteria are collected in the whole experiment process. The final ranking result of CWP depends on the aggregation of all criteria, and the aggregation methodology will be introduced in the further chapters.

Execution of the integral AHP provides complete CI and its corresponding normalized eigenvectors in terms of time, cost, safety, and quality, which are the significant inputs for consensus building for the MCGDM problem in the next chapter. On the other hand, the CR value is not good enough for the consistency judgment of the reciprocal pairwise comparison matrix. The generation of the PSO in chapter 6 elevates the CI and the CR values as compensation.

Chapter 4 The Consensus Building for MCGDM Problem

Tackling the MCGDM problem, especially the weighted preferences from a variety of experts and the traditional methodology for consensus-building of the MCGDM problem is illustrated in this chapter.

4.1 The Traditional Methodologies in MCGDM Problem

Traditionally, the methodologies for the MCGDM can be constrained in a few ways, such as Consensus decision-making, Voting-based methods, the Delphi method, and Dotmocracy. The Voting-based method requires the voters to score one or more alternatives, which satisfy the needs of the Wind Farm Project in this paper. However, choosing the highest average or the majority of the voters (more than 50% for MCGDM) offers “losers” groups[22]. When those experts have an equal percentage of the largest block and fall short of a majority, it is hard to find results for this type of MCGDM problem.

The Dotmocracy method relies on the use of forms called “dotmocracy sheets” to allow large groups to brainstorm and recognize their thoughts to obtain consensus. Nevertheless, having too many preferences and opinions could be overwhelming while taking action. Some experts review or criticize their preferences before filling the dotmocracy sheet, and the results can be a mix of confusion, extreme views, and false preferences.

The Delphi method is the most popular way to solve a MCGDM problem. This structured technique system relies on the communication of experts. The action and prediction rely on the group of experts through the interactive and forecasting method[23]. The accuracy of the structured rule-based and organization for prediction is much higher than a chaotic prediction. Moreover, each expert is required to make anonymous predictions, and the experts of the knowledge group must have sufficient background knowledge of the decision problem filed[24]. Furthermore, the Delphi Method allows participants to comment anonymously and to revise their forecasts and preferences. Although the Delphi method is widely utilized to forecast, the track record of this method is mixed and produced poor results when facing multiple cases.

One of the main disadvantages of the Delphi method is making sophisticated forecasts with multiple factors. Then, the visible weakness of this method is that the prediction is not always predicted correctly by the consensus of experts because some of the experts are holding extreme preferences due to their own subjective judgment. As expected, the degree of uncertainty is too tremendous for prediction to be correct.

4.2 Consensus Collection for MCGDM problem

Compared with the above three methodologies, the traditional Consensus decision-making methodology is still acceptable for the Wind Farm Project. It tries to avoid “winners” and “losers.” This methodology still relies on the majority approval from the given group of experts. In other words, if the minority is against the action, then objectionable features are hard to be eliminated or modified. Traditionally, the majority approval is still required to explore, and the consensus does not emphasize the goal of full agreement.

The adversarial debate and the formation of competing factions can appear through collecting consensus. Dynamic collecting harms the relationships among decision members and undermines the cooperation of the execution of the contentious decision. Three decision-making models are the most popular strategies to collect consensus. Initially, the consensus voting demands at least three referees to decide the majority consensus or criticize any extreme preferences, even including the debate proceeds and comments. The list of options will represent the consensus if the debate fails to bring about a verbal consensus[25]. Then, the referees decide the option or composite, which leads to the outcome of the consensus. If the consensus level surpasses the minimum consensus coefficient, the consensus could be accepted by referees and result in an output consensus[26]. This methodology is still constrained by the extremely subjective opinion, the background knowledge of MCGDM, and conflicts between decision-makers.

Once the discussion has been set up for the primary goal, alternatives, and preferences in the Blocking methodology can be identified[27]. Experts must agree to the meeting proposal procedure for collecting consensus. Each member of the group should express their preferences, whether to agree or consent, to stand aside or object by utilizing hand gestures or by actively raising a colored card. Then, comparing with the consent threshold, if satisfied, the consensus and the action for MCGDM could be taken after any potential harms have been addressed[28]. On the other hand, if not satisfied, the discussion of the proposal goal or the objections must be reevaluated

to vote until satisfied with the consent threshold[29]. The disadvantage of this methodology is apparent in that cycling for re-voting and modifying goals will cost much time. Some experts may still be holding extreme preferences against the consensus, even when criticized by the majority of the supporting voters.

The Quaker-based model involves active listening and sharing information among the whole decision-making group. The MCGDM problem has a facilitator who identifies areas of agreement, goals, and disagreements. The facilitator demands to recognize if experts are uniting with the decision for selfish interests. All objection perspectives are classified and summarized in the outcome part.[30][31] Whether to “Stand aside” or “Stop” for consensus and action must be decided by the facilitator. The essential component of Quaker-based consensus is unity, where the facilitator is serving the group rather than individual selfish interests[32][33]. In other words, the Quaker model allows the participants to discuss, support, and compromise for each other's preferences.

Collecting consensus while identifying, avoiding, and modifying objections is always the main research goal. Then, the methodology named the “ Principle of Justifiable Granularity for Consensus Collection” will be introduced in the following chapters. The modifying objections for consensus rely on the PSO chapter.

$CWP_1 \sim CWP_6$						
Exp_1	1.0000	0.4442	0.4043	0.1617	0.3233	0.3763
	0.1396	0.0885	1.0000	0.5064	0.3746	0.2085
Exp_6	1.0000	0.4442	0.4043	0.1617	0.3233	0.3763
	0.7467	0.7554	0.3955	1.0000	0.4367	0.3728
	0.1000	0.1332	0.7471	1.0000	0.5177	0.3855

	0.4880	0.4659	0.6783	0.5505	0.5449	0.7626
--	--------	--------	--------	--------	--------	--------

Table 4.2.1 The weighted preferences for multiple CWPs and experts in terms of criterion time

Sufficient data must support the MCGDM problem. Thus, the whole team of experts has expressed their preferences for all alternatives and criteria. Defining the number of experts as Exp , then we have Exp_k , where $k = 1, 2, \dots, n$. The partial weighted preferences for multiple CWPs and experts in terms of criterion time are illustrated in Table 4.2.1. The partial data in Table 4.2.1 reveals the varieties of background and knowledge of experts, and there is a tremendous gap in the assessment and the perception of the same alternative.

The AHP structure supplies the preferences in terms of all criteria and alternatives, respectively. Then, the consensus collection is still following the rule of “divide and conquer,” where each alternative possesses its consensus in a MCGDM problem for the Wind Farm Project. The AHP structure completely generates the preferences of all experts in terms of all criteria and alternatives before collecting consensus. Finally, the result of a single alternative is ranked and picked up for consensus collection.

CWP_1							
0.1000	0.1396	0.2077	0.2447	0.3456	0.3524	0.3603	0.4382
0.4385	0.4846	0.4880	0.7467	1.0000	1.0000	1.0000	

Table 4.2.2 The ranked group decision making for $[CWP]_1$ and experts in terms of criterion time

The normalized eigenvectors rename as the weighted preferences for the individual alternative CWP_1 . The consensus is temporarily defined as all weighted preferences above in Table 4.2.2. The extreme preferences are low weighted and high weighted, such as $e'_1 = 0.1$ and $e'_{15} = 1.0$. Depending on the rough consideration and observation through Table 4.2.2, the majority for

consensus MCGDM should be from $e'_5 = 0.3456$ to $e'_{11} = 0.4880$. On the other hand, the ranking depends on the weighted preferences; if these experts are expressing the same maximal preference for the single alternative, the ranking also relies on the second factor and third factor, whereas its corresponding CI and the non-normalized eigenvectors, for example, the weighted preferences from e'_{13} to e'_{15} are equal to 1.0. The ranking initially depends on the corresponding CI , and then the normalized eigenvectors.

CI for CWP_1							
0.7310	0.7584	0.7147	0.6117	0.6599	0.5381	0.6216	0.5466
0.7389	0.5942	0.6109	0.7235	0.4959	0.6998	0.6998	

Table 4.2.3 The ranked group decision making for CWP_1 for its corresponding CI in terms of criterion time

The last three weighted preferences from e'_{13} to e'_{15} are ranked utilizing the CI as the second factor. CI_{14} and CI_{15} are still holding the same value. Comparing with the third factor the non-normalized eigenvectors between $e'_{14} = 0.4833$ and $e'_{15} = 0.7062$ and the ranking result are apparent.

4.3 Conclusion

In this chapter, the traditional methodologies of MCGDM have been introduced. Also, the advantages, disadvantages, and the main research direction have been illustrated. Then, collecting consensus relies on the maximal eigenvalues, eigenvectors, and CI . The weighted preferences are gathered from the result of the AHP structure. The temporary consensus includes some extreme preferences, and this will be described in the next chapter.

Chapter 5 The Principle of Justifiable Granularity and Aggregation for Preferences

This chapter describes the methodology for consensus establishment from the temporary consensus in the last chapter between a group of decision-makers whose decisions are presented as weighted preference. In order to build the consensus, the preference matrices, the weighted preferences, and the weight of experts are developed by the AHP structure. The principle of justifiable granularity establishes and elevates the majority of consensus; meanwhile, extreme preferences are excluded.

5.1 The Information Granule for the Principle of Justifiable Granularity

The principle of justifiable granularity dwells upon the concept of granular computing, and information granules are used to establish blocks that represent problems, models, and decision-making.[13] The granular computing concentrates on processing information granules and develops the discipline of the existing technologies and formalizes of sets, such as shadowed sets, fuzzy sets, and rough sets. In other words, granular computing can be realized as a system to express the integral concept or special semantics of an information granule, where this collection of partial data reflects the nature of the property of the experimental evidence. Then, the optimization problem is proposed to express the well-defined linguistic information collection, and the optimization results can be represented by interval or fuzzy sets.

The construction of an information granule has to meet two compelling requirements. The numeric evidence accumulated in the space or range must be as high as possible. The expectation of the existence of an information granule can be proved and reflect the existing experimental data. For instance, if the collection of the information (set) is an interval as an information granule, the more data contained within the boundary makes the set becomes more reasonable. On the other hand, if the set is represented as a fuzzy set, the higher the sum of membership degrees of the data, the higher the justifiability of the fuzzy set. Besides, the information granule should be as linguistically specific as possible while at the same time keeping numeric evidence. The information granule keeps enough that is semantically meaningful while also keeping the information granule highly detailed. Then, the aggregation of the preference (temporary consensus) index for each decision alternatives i is determined by $E_i = [e'_1, e'_2, \dots, e'_p]$, where e'_j represents the normalized preference index determined by decision maker j and p stands for the number of decision makers. In the second step, the consistency of each reciprocal matrix j is calculated as CI_j in order to weight the preference indices determined by the decision maker j . Thus, the information granule including the aggregation of preference indices for decision alternative i is determined by $E_i =$

$[(C_1, e'_1), (C_2, e'_2), \dots, (C_p, e'_p)]$, where CI_j stands for the consistency of the reciprocal matrix developed by decision maker j .

CWP_1								
CI_j	0.7310	0.7584	0.7147	0.6117	0.6599	0.5381	0.6216	0.5466
e'_j	0.1000	0.1396	0.2077	0.2447	0.3456	0.3524	0.3603	0.4382

Table 5.1.1 The ranked partial information granule for CWP_1 in terms of criterion time

Table 5.1.1 merely illustrates the partial description of the information granule for alternative CWP_1 in terms of criterion time and full information. The ranking of data in the information granule depends on the weighted preferences. While applying for the principle of justifiable granularity, the CI is utilized as weights of experts to consensus selection and boundaries assessment.

5.2 The Principle of Justifiable Granularity Determine the Interval Type-2 Fuzzy Set for Consensus

The information granule for such consensus is developed and aggregated in the last session. The elements are where the ranked combination of CI and weighted preferences, are represented as type-2 fuzzy sets, and where the preference matrix is represented 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. Thus, utilizing interval-valued fuzzy sets is preferable in this case since it provides more information than using the type-1 fuzzy sets.

No matter the interval, the type-2 fuzzy set is triangular or trapezoid, the interval $[0.1, 1]$ is obtained from the weighted preferences in Table 4.2.2 for CWP_1 in terms of criterion time. Then, the upper and lower boundaries for the principle of justifiable granularity depends on the clear semantic meaning with sufficient experimental evidence. The coverage and specificity are proposed to represent the experimental evidence and the semantic meaning, respectively[34]. The semantic meaning and the experimental evidence must be guaranteed at the same time, where for the above boundaries e^- and e^+ for consensus, selection depends on the calculation of the two main constraints. In this step, the principle of justifiable granularity is utilized 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 (20).

$$e_i^* = \operatorname{argmin} \sum_{j=1}^p C_{I_j} |e_{j,i} - e_i^*| \quad (20)$$

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 . Considering the lower and upper bounds e^- and e^+ 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[35]. Thus, the lower e^- and the upper e^+ bounds of the interval-valued preference index of the alternative i are determined using (21) and (22), respectively.

$$e_i^- = \operatorname{argmax} \operatorname{Cov}(e_i^-) \cdot \operatorname{Sp}(e_i^-) \quad (21)$$

$$e_i^+ = \operatorname{argmax} \operatorname{Cov}(e_i^+) \cdot \operatorname{Sp}(e_i^+) \quad (22)$$

where $\operatorname{Cov}(e_i^-)$ stands for the coverage of the lower bound of the interval-valued preference index of alternative i and $\operatorname{Sp}(e_i^-)$ stands for the specificity of the lower bound of the interval-valued preference index of alternative i . $\operatorname{Cov}(e_i^+)$ and $\operatorname{Sp}(e_i^+)$ 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 (23) and (24), respectively [35], [36], [37].

$$\operatorname{Cov}(e_i^-) = \sum_{j=1}^p CI_j \quad \text{when } e^- < e_p < e^* \quad (23)$$

$$\operatorname{Cov}(e_i^+) = \sum_{j=1}^p CI_j \quad \text{when } e^* < e_p < e^+ \quad (24)$$

The specificity of the lower and upper bounds of the interval-valued preference index of alternative i are calculated in the following form [35], [36], [37].

$$\operatorname{Sp}(e_i^-) = 1 - \frac{|e^- - e^*|}{|e_{\min} - e^*|} \quad (25)$$

$$\operatorname{Sp}(e_i^+) = 1 - \frac{|e^+ - e^*|}{|e_{\max} - e^*|} \quad (26)$$

For each alternative in terms of CWPs, the principle of justifiable granularity elevates and selects the consensus of the MCGDM problem for the Wind Farm Project. Any biases from the preferences of experts and extreme preferences are excluded from the consensus, and the majority

of experts constructs and support the consensus, in the event the principle of justifiable granularity meets the requirement of consensus decision-making.

$CWP_1 \sim CWP_{11}$											
e_i^-	0.3456	0.3460	0.5614	0.4848	0.5176	0.3727	0.2774	0.3508	0.6326	0.1993	0.2910
e_i^*	0.4382	0.4442	0.6541	0.5687	0.5449	0.4760	0.4457	0.3990	0.6872	0.2574	0.3700
e_i^+	0.4880	0.4659	0.6541	0.6802	0.7393	0.4759	0.4967	0.5112	0.6873	0.2574	0.5201

Table 5.2.1 The lower bound e_i^- , weighted median e_i^* , and upper bound e_i^+ for information granule for multiple CWPs in terms of criterion time

For each CWP, the type-2 fuzzy set represents an interval $[e_i^-, e_i^*, e_i^+]$, for example, the CWP_1 has its interval as $[0.3456, 0.4382, 0.4880]$. On the other hand, the interval for multiple alternatives in terms of the other criteria of cost, quality, and safety are also constrained by the principle of justifiable granularity.

$CWP_1 \sim CWP_{11}$											
e_i^-	0.2528	0.1716	0.7854	0.7626	0.4389	0.4322	0.1652	0.2468	0.5027	0.2362	0.4430
e_i^*	0.3003	0.2505	0.8970	0.7626	0.5597	0.6521	0.2227	0.3481	0.6797	0.2617	0.5737
e_i^+	0.4410	0.5187	0.8970	0.8394	0.6976	0.7771	0.3192	0.4078	0.6821	0.4516	0.6634

Table 5.2.2 The lower bound e_i^- , weighted median e_i^* , and upper bound e_i^+ for information granule for multiple CWPs in terms of criterion cost

$CWP_1 \sim CWP_{11}$											
e_i^-	0.1239	0.2281	0.5803	0.4429	0.4367	0.3727	0.3337	0.3510	0.6041	0.1993	0.3699
e_i^*	0.1464	0.3888	0.9178	0.5467	0.5177	0.4039	0.4488	0.3718	0.8613	0.3899	0.4899
e_i^+	0.2393	0.4443	0.9187	0.6333	0.6257	0.5755	0.6380	0.5075	0.9053	0.4122	0.5861

Table 5.2.3 The lower bound e_i^- , weighted median e_i^* , and upper bound e_i^+ for information granule for multiple CWP_s in terms of criterion safety

$CWP_1 \sim CWP_{11}$											
e_i^-	0.1395	0.2279	0.9999	0.4050	0.4059	0.3727	0.2220	0.2170	0.3925	0.1749	0.2910
e_i^*	0.1477	0.2672	0.9999	0.5899	0.4367	0.3855	0.2775	0.2748	0.5609	0.2189	0.4148
e_i^+	0.5017	0.4536	0.9999	0.7959	0.4864	0.5289	0.3209	0.4430	0.6910	0.2189	0.4197

Table 5.2.4 The lower bound e_i^- , weighted median e_i^* , and upper bound e_i^+ for information granule for multiple CWP_s in terms of criterion quality

The consensus for multiple criteria and alternatives in group decision-making is elevated and selected by the principle of justifiable granularity. The IT2FS provides the membership degree for the preferences of experts belonging to this. The percentage of the data utilization of the preferences of experts illustrates the majority support of the consensus.

CWP_1			
CI_j	e'_j	CI_j	e'_j
0.7310	0.1000	0.7389	0.4385
0.7584	0.1396	0.5942	0.4846
0.7147	0.2077	0.6109	0.4880
0.6117	0.2447	0.7235	0.7467
0.6599	0.3456	0.4959	1.0000
0.5381	0.3524	0.6998	1.0000
0.6216	0.3603	0.6998	1.0000
0.5466	0.4382		

Table 5.2.5 The ranked information granule for criterion time

In chapter 5.1, the CWP_1 is represented by the information granule $[(CI_1, e'_1), (CI_2, e'_2), \dots, (CI_p, e'_p)]$, the IT2FS offers the interval $[e_1^-, e_1^*, e_1^+]$ as $[0.3456, 0.4382, 0.4880]$, and the preference of experts within the interval constructs the consensus which supported the majority of experts. Because 46.66% of the preference of experts is selected as the consensus, that means the other preferences are much further apart, whether much lower or higher. The discrete preferences cannot be combined and supported as the consensus; however, the excluded preferences also have an impact on the measurement of lower and upper bounds of IT2FS.

5.3 The Aggregation and Ranking for Consensus

Traditionally, experts are also required to evaluate and rank the criteria to aggregate the final interval for each alternative, and the final weights and sequence of alternatives could be obtained for the final decision-making problem. For example, the Wind Farm Project demands a ranking strategy for CWPs, where the CWPs contain a variety of strategies for infrastructure establishment. The combination of the IT2FS could solve the MCGDM problem as a decision-making action.

However, the experts refuse to share the preference for criteria, and the weights for criteria are treated weighted equally. The aggregation depends on the fuzzy set operation introduced in chapter 2.5. Furthermore, after aggregation for each criterion and alternative, the methodology named GM is proposed to tackle the ranking of the triangular fuzzy set. Based on the concept of IT2FS[13], the IT2FS is represented as the index of alternatives on the x-axis and the interval on the y-axis on the rectangular coordinate system. On the other hand, the third dimension of the IT2FS is treated as the fuzzy set, the membership on the second dimension (y-axis) is less than the lower bound or higher than the lower bound is 0 membership degree in the third dimension. Usually, the highest membership degree is defined as 1 when meeting the weighted median. In this paper, the fuzzy set

in the third dimension can be treated as the triangular fuzzy set in Figure 5.3.1, where M represents the weighted median.

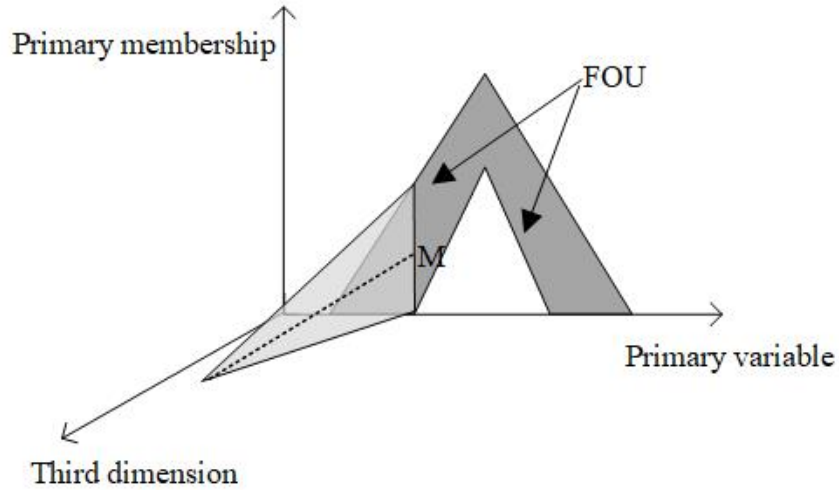


Figure 5.3.1 The IT2FS on a three-dimensional coordinate system

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

Table 5.3.1 Ranking of CWPs of Wind Farm Project based on their contribution to project risks or uncertainties

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 the 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.

5.4 Conclusion

The results of the analysis presented in Table 5.3.1. reveals the problem of data loss since the data from multiple individual experts are excluded from the final IT2FS in each case. The reality is that the public infrastructure risks assessment data is rare and insufficient, which makes the loss unaffordable. As an example, according to Table 5.3.1, the remarkable data loss for CWP1 is 53.3%, indicating that more than half of the expert knowledge is not considered for determining

the risks associated with this CWP. Moreover, as for all criteria, cost, time, safety, and quality, 61.4% of the expert data is excluded from the IT2FS.

Thus, the optimization mechanism for reducing data loss needs to be developed, in which the original IT2FS ought to be extended wider to include more of the preferences of experts when the preference is changing. Then, the achievement of the optimization mechanism is that of moving expert data to eventually add more expert knowledge in each IT2FS. On the other hand, the feedback from the company is good enough for decision-making for the construction of the infrastructure in the Wind Farm Project.

Chapter 6 Exploration and Elevation of Consensus by Particle Swarm Optimization

In order to reduce data loss, provide ever-fluctuating advice for experts to modify the extreme preference, and elevate the consensus, this chapter initially describes exploration for optimization of consensus because the existence of optimized or elevated consensus must be proved. Furthermore, the robustness of the model should testify for various data: for example, a different dimension of the reciprocal pairwise comparison matrix and the different scale of preferences of the experts to obtain the information granule for consensus—finally, the elevated consensus and the advice for excluded for each alternative and criterion.

6.1 Constraints for the Exploration of Optimized Consensus through Particle Swarm Optimization

Before applying for the exploration of consensus elevation and reducing the data loss, there are some measurements that constraints. Initially, the granularity of the information granule must be proposed to keep the specific semantic meaning with enough experimental evidence.[38] In other words, widening the IT2FS to include more preferences from experts in regards to specificity, and maintaining the weights of experts as coverage to keep enough experimental evidence, must be done simultaneously. According to the analysis of data loss, aiming at exploring optimal professionals' data captures the principle of justifiable granularity differently. The previous conference paper offers the essential constraints of granularity, which is coverage and specificity for the elevation of MCGDM.

For simplification, analyzing mathematics and modifying elements in pairwise comparison matrices from experts' preferences triggers the modification of coverage and specificity for the information granule. However, it is risky to revise the preferences of experts. Editing only slightly from the first preference keeps the accuracy and authenticity of data. When modifying the elements in the reciprocal pairwise comparison matrix, the corresponding *CI* also will be transformed. Thus, the editing for elements also impacts the consideration of coverage and the specificity in IT2FS.

The *CI* and non-extreme preferences from experts are precise factors when optimizing the expert data, and inappropriate modification triggers improper coverage and specificity. For instance, including too many preferences of experts will lose too much specificity in IT2FS when modifying the elements to cover the extreme points.

So as to capture appropriate IT2FS to minimize the modifications to the original reciprocal matrices developed by the experts, the concept of Hamming Distance (HD) is proposed to measure and minimize the difference between original and revised matrices.

While revising the elements in the reciprocal pairwise comparison matrices, we must ensure that the granularity is maximized while the HD between the original and modified data is minimized. Thus, depending on the previous result and concept for Granularity (Gr), the mechanism is quoted below:

$$Gr = \frac{\sum_{j=1}^p \sum_{i=1}^p Cov(e_i)}{\sum_{j=1}^p \sum_{i=1}^p (e_i^+ - e_i^-)} \quad \text{when } e^- < e_i < e^+ \quad (27)$$

Where for every CWP, i illustrates the index of experts of CI in the information granule that e_i in $[e^-, e^+]$ and the length of the specificity are parameters to measure the granularity.

As for the HD for original and revised reciprocal pairwise comparison matrices, the measurement of each alternative i is the distance between original and revised eigenvectors, rather than the massive calculation of the distance between reciprocal pairwise comparison matrices.

$$HD = \sum_{j=1}^p \sum_{i=1}^p ||e_i - e'_i|| \quad (28)$$

Where e'_i stands for the revised normalized value of the preference index for each CWP, and i illustrates the index of experts. 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.

Fortunately, the opinion of experts is described by the reciprocal pairwise comparison matrix, where $A = [r_{ij}]$, $r_{ij} = \frac{1}{r_{ji}}$, $i, j = 1, 2, \dots, n$, and r_{ij} represents the result of the pairwise comparison between the alternatives i and j . Less than half of the elements of the matrix need to be amended in the pairwise comparison matrix from every expert. For instance, there is an example of the four dimensions pairwise comparison matrix:

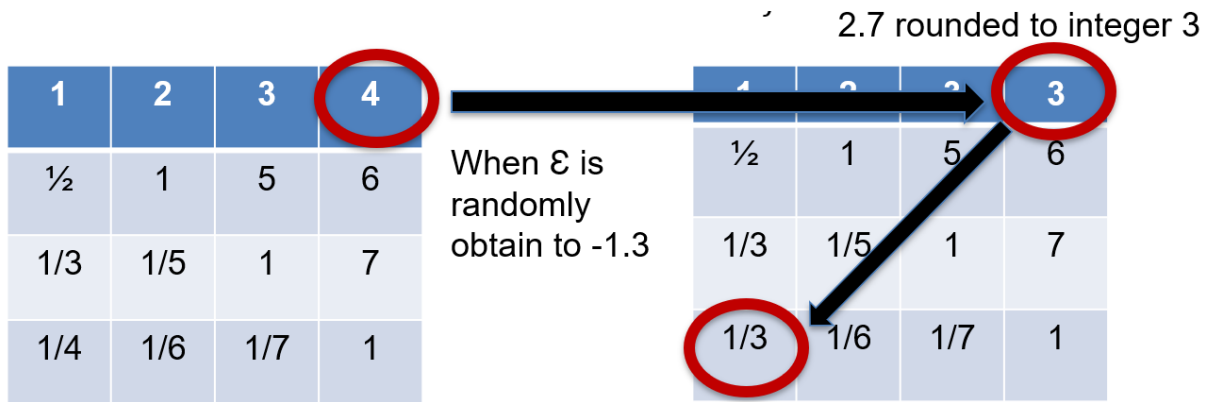


Figure 6.1.1 Modification for a four-dimensional reciprocal pairwise comparison matrix

The amending variables are above the diagonal and are all compared by themselves and equal to 1. Figure 6.1.1 displays the random number ϵ is increased to be added up to the original variable, and the revised variable is adjusted to an integer. Finally, the reciprocal element modification is the last step. To obtain the number randomly and keep the fair occurrence probability, the UD is raised to meet this requirement. In this paper, the UD of the randomization mechanism provides equal probabilities of each random component.

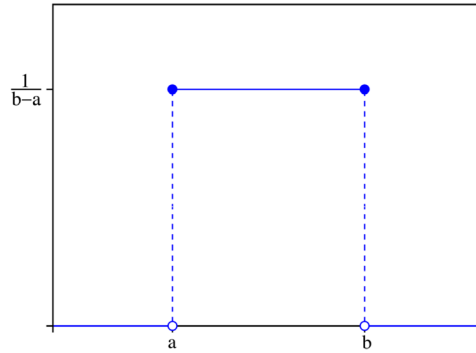


Figure 6.1.2 The UD for randomization

The scale of the UD for the PSO model is $[-9, 9]$, which fits the original size of the reciprocal pairwise comparison matrices. The mechanism revises half of the elements and rounds them to total integer in the whole matrix with its corresponding diagonal element.

Then, the decision space is in the interval $(0,9]$, while the original elements add a negative random number from UD up to negative or zero, the modified elements are rounded to an integer 1. Because according to the concept of reciprocal pairwise comparison matrix, two CWPs can be treated as the same through comparison. Thus, depending on linear transformation and previous research, the revised eigenvectors are compared with the original in the Objective Function (*Obj*) for measurements through HD.

On the other hand, the essential parameters in PSO generation, such as velocity = 0.5, iterations = 1000, the number of variables (nvars) is 825, two boundaries are the UD boundaries $[-9,9]$, and part of those parameters are settled to default in the program.

6.2 Exploration for Flexibility and Optimized Consensus

The varieties of dimensions of the pairwise comparison matrix are tried as from 3 dimensional to 11 dimensional. As the three dimensional is concerned, utilizing the scale as 1 to 9 on a 3-dimensional reciprocal pairwise comparison matrix is meaningless. Traditionally, the appropriate scale must be utilized on the appropriate number of alternatives, and the number of alternatives and criteria are always different. Usually, the experts express their preferences for alternatives and criteria at the same time, and the adaptive scale is also needed for the different number of criteria and alternative; for example, as for the Wind Farm Project in this paper, the experts can also provide their preferences to rank the four criteria in terms of cost, time, safety, and quality. Then the final combination weights for multiple criteria can be obtained depending on the above methodologies for MCGDM and IT2FS.

The primary exploration depends on the maximum granularity because collecting the maximal coverage and specificity proves the flexible interval to explore the appropriate granularity. On the other hand, the flexibility of the IT2FS model could be proven to adapt to random preference. The different revising scales for random numbers from UD in Figure 6.1.1 are to be increased to keep the equal probability of occurrence. The integer changing scale is increased from 1 to 13 as ϵ . Then, the PSO iterates 1000 times for each ϵ , and the summation of the granularity and HD for each alternative are collected for analysis.

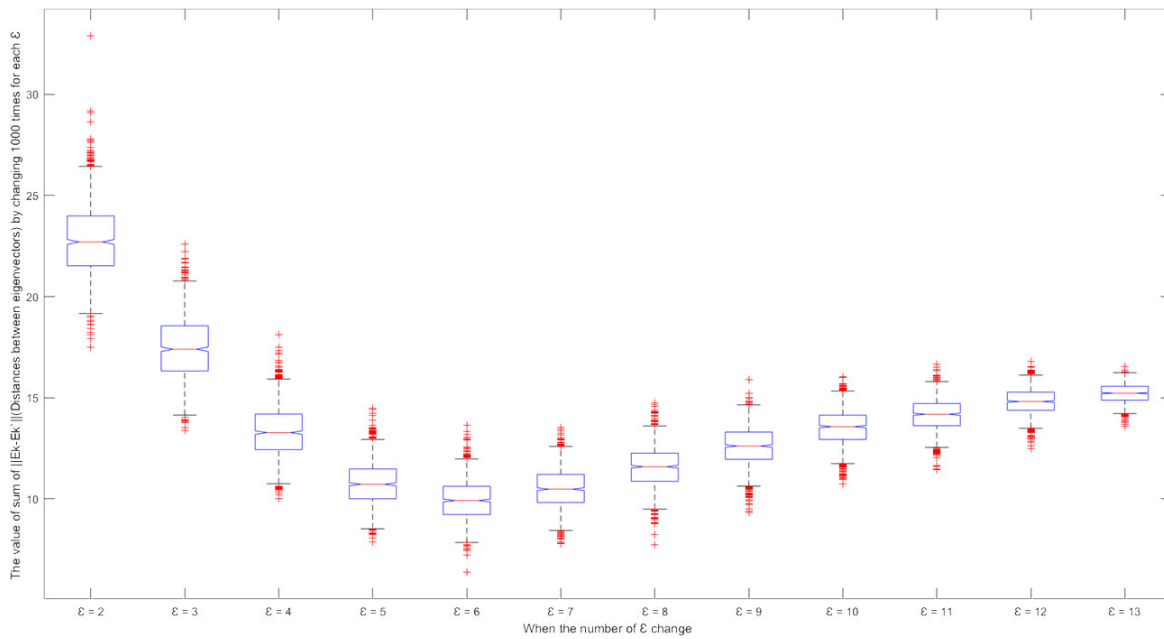


Figure 6.2.1 The summation of HD for different ϵ for 1000 iteration of criterion time

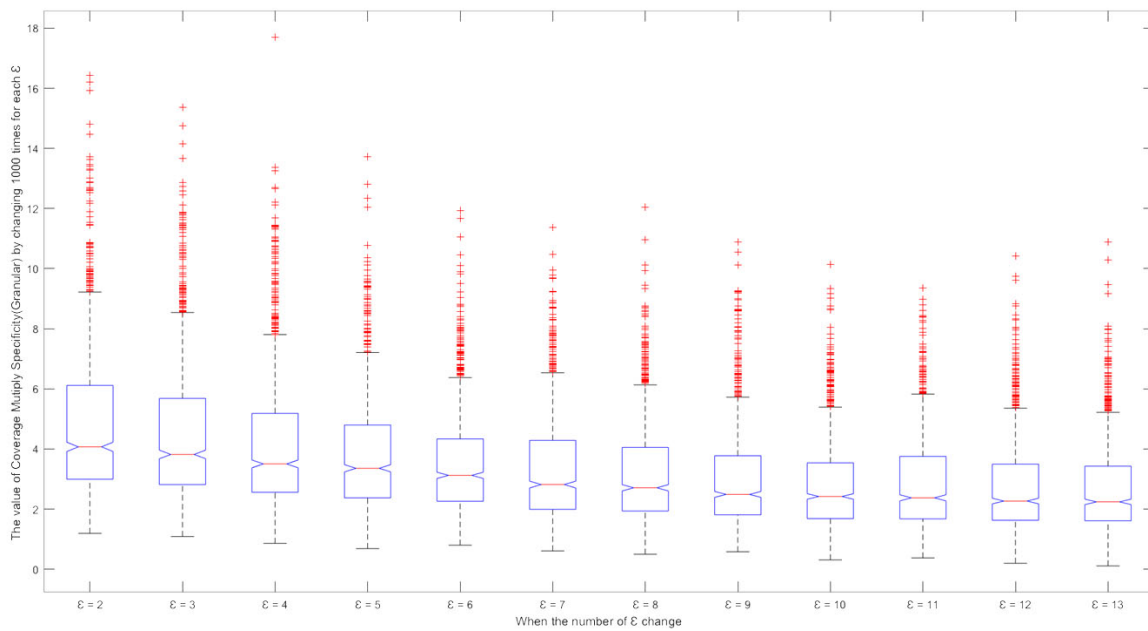


Figure 6.2.2 The summation of specificity multiply coverage for different ϵ for 1000 iteration of criterion time

In Figure 6.2.2, the objective function is following the coverage as the included experts' preferences multiplies the specificity as $e_i^+ - e_i^-$, then divide by the HD distance in the formula

(28). The requirement for the PSO objective function is to keep the HD the lowest because the revised reciprocal pairwise comparison matrix must be kept closet to the original preferences of the experts. And constraints in (21) and (22) should also be applied in (29) to maintain the principle of justifiable granularity for each iteration.

$$Obj = Max \frac{\sum_{j=1}^p \sum_{i=1}^p Cov(e_i)(e_i^+ - e_i^-)}{\sum_{j=1}^p \sum_{i=1}^p \|e_i - e_i'\|} \quad \text{when } e^- < e_i < e^+ \quad (29)$$

Where the j represents the number of the alternative to calculate its corresponding summation, the main data distribution of the HD is illustrated in Figure 6.2.1. The data distribution of HD can be described as a curve that witnesses a fluctuation when the lowest distances are $\varepsilon=6$. For 1000 times iteration, the data distribution is showing like when ε is equal to 6, which means the interval is $[-6,6]$. The distances are getting the lowest around about ten, which means eigenvectors are closest to the original eigenvectors when the ε is equal to 6. The distance is getting closer to about 15 when the number is more significant than 6. In Figure 6.2.1, by trying for 1000 times for each ε , we can see the best value should be 1 and 2, because 15 matrices made from random consistency values are the best. The probability of getting a consistency value is greater than the others.

The Figure 6.2.1 and 6.2.2 also offer information for the model, that no matter how the random number is picked for UD, the model will always respond with a different information granule, which means there is always consensus for even different random preferences of experts. In other words, not limited to the Wind Farm Project, the model possesses enough flexibility for different dimensions and preferences for any decision-making project. It only requires that preferences are provided by experts.

6.3 Elevation of Consensus for MCGDM Problem

The essential methodology for the elevation of consensus is keeping appropriate semantic meaning, where the specific must be specific enough to be smaller than the whole interval from the temporary information granule, including the whole set of preferences from experts. On the other hand, experimental evidence (coverage) is required to include more preferences from experts in the consensus. Once those essential factors are ensured, the summation of the HD should be as close as possible to the original preference. The needs of suitable granularity and the smallest HD between the original and modified data transform the problem into a multi-objective optimization problem. Because of the appropriate modification of pairwise comparison, matrices increase coverage results without losing too much specificity. PSO reduces difficulties and complexity when generating constraints and random mechanisms. The PSO objective function (Obj') for PSO optimization is presented below:

$$Obj' = Max \frac{Gr}{HD} = Max \frac{\sum_{j=1}^p \sum_{i=1}^p Cov(e_i)}{\sum_{j=1}^p \sum_{i=1}^p (e_i^+ - e_i^-) ||e_i - e_i'||} \quad when \quad e^- < e_i < e^+ \quad (30)$$

Based on the formula (20), (21), and (22), the summation of the granularity is terms of multiple CWPs and in terms of single criterion time obtained, where j is the index of CWPs. Thus, the Gr is the coverage whose corresponding preference is in specificity, the length of specificity ($e_i^+ - e_i^-$). The HD between preferences construct the above objective function (30), where each CWP owns its HD, followed by a summation of all CWPs. Furthermore, i is the index of decision-makers. Logically, the PSO generates the optimized result for all CWPs in terms of single criterion time. This generation costs some time to compile and succeed in obtaining the effective optimal result, and the GM aggregation for all criteria can also be displayed and calculated through spending lots of time.

After PSO generation and the comparison of Table 5.2.1 and Table 6.3.1, the granularity for just a few of the Coverage of CWPs is wider without losing as much specificity as we expected.

According to Figure 6.3.1, the Coverage of the CW1 in terms of criterion time is elevated to be higher, which means the CI , the weights of experts, increases along with iterations. Moreover, Figure 6.3.2 illustrates the changing trend with iterations in terms of HD, where the difference between the experts' preferences is kept similar to the original. Finally, Figure 6.3.3 explains a slight and ambiguous decrease in specificity. However, analyzing the result of the comparison of Table 5.2.1 and Table 6.3.1, there is a decrease in specificity that excludes more experts' preferences.

$CWP_1 \sim CWP_{11}$ for criterion time											
e^-	0.9430	0.6607	0.6308	0.5495	0.4262	0.3458	0.4135	0.3025	0.2339	0.1743	0.2214
e^+	1.0000	0.6609	0.6516	0.7395	0.4436	0.3756	0.4382	0.3419	0.3348	0.1843	0.2673

Table 6.3.1 The PSO generation for elements in reciprocal pairwise comparison matrix 1000 iterations for criterion time

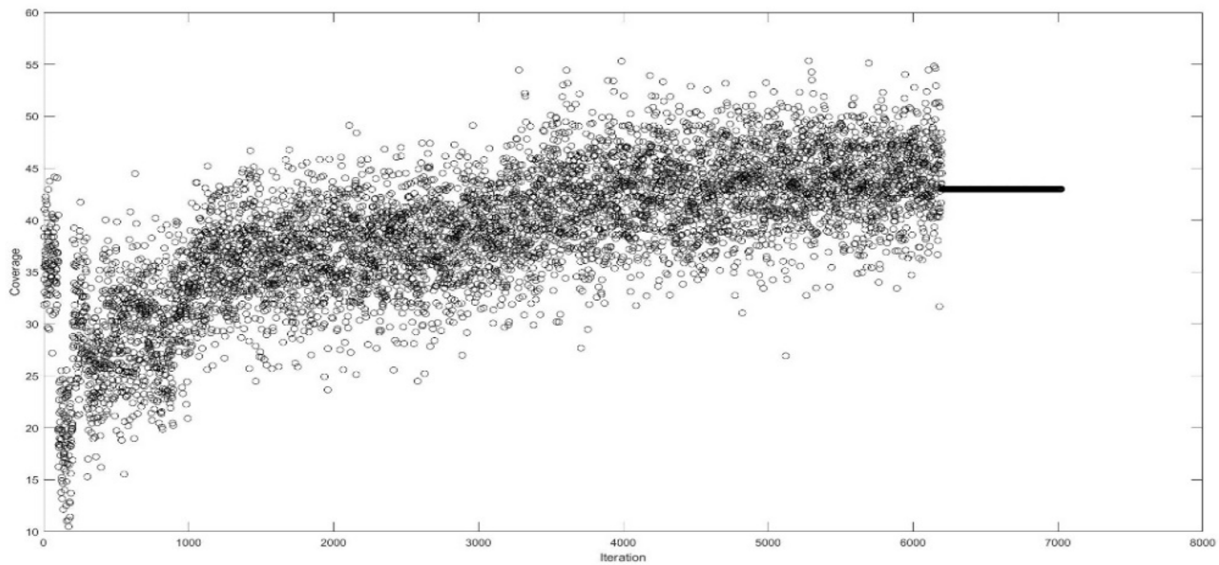


Figure 6.3.1 Coverage changing trend for criterion time for iteration in PSO

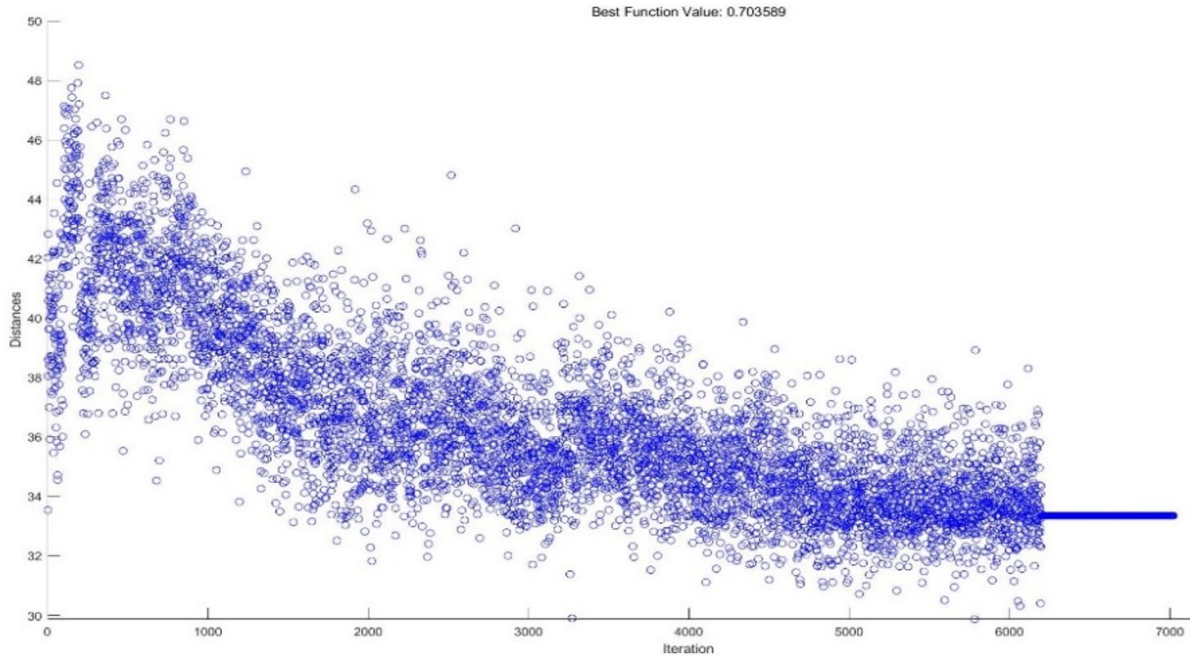


Figure 6.3.2 HD changing trend for criterion time for iteration in PSO

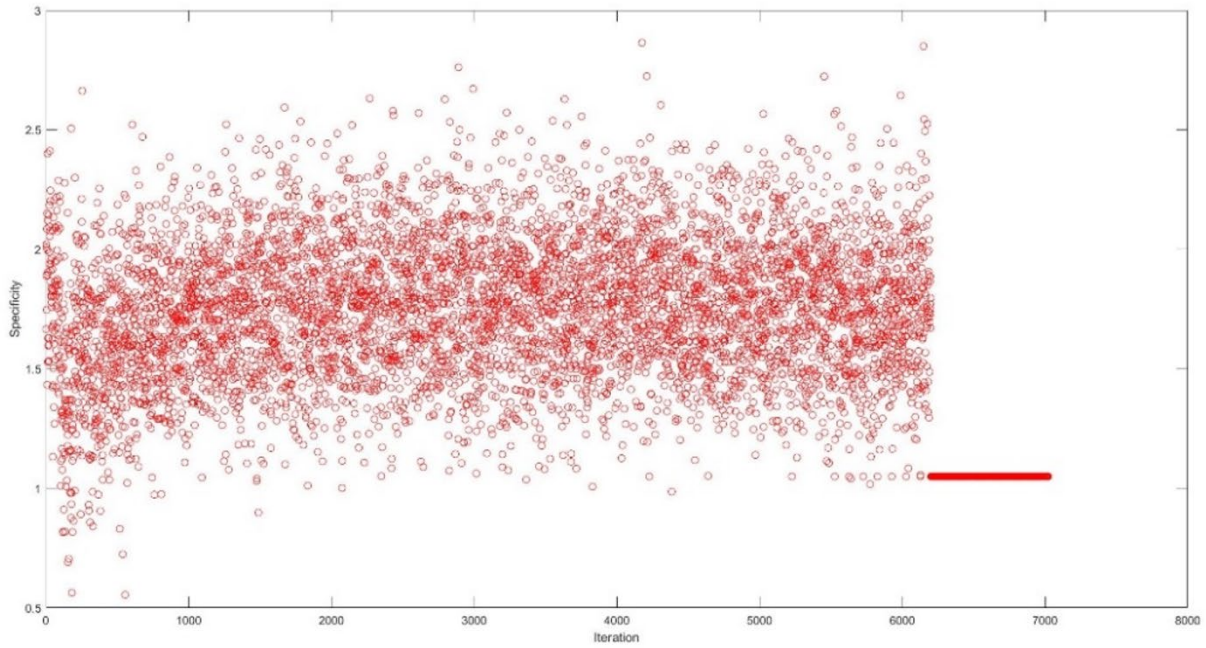


Figure 6.3.3 Specificity changing trend for criterion time for iteration in PSO

Then, the coverage for each alternative should be elevated while also at the same time the appropriate specificity to include more preferences should be kept and enlarged. The changing

trend above illustrated the constraints for the specificity is necessary to be as described. Adding the power of the length of specificity in the objective function based on (29) displays below.

$$Obj'' = Max \frac{Gr}{HD} = Max \frac{\sum_{j=1}^p \sum_{i=1}^p Cov(e_i)}{\sum_{j=1}^p \sum_{i=1}^p (e_i^+ - e_i^-)^\varkappa ||e_i - e_i'||} \quad \text{when } e^- < e_i < e^+ \quad (30)$$

Where the parameter \varkappa for the power of the specificity into the objective function in PSO, then there are varieties of \varkappa to be trained to explore the appropriate specificity. On the other hand, the other parameters are the same as the equation (29). Then, depending on the PSO algorithm, we also need to keep the trend of the objective function to be convergence. So the plot for the value of the objective function is illustrated below.

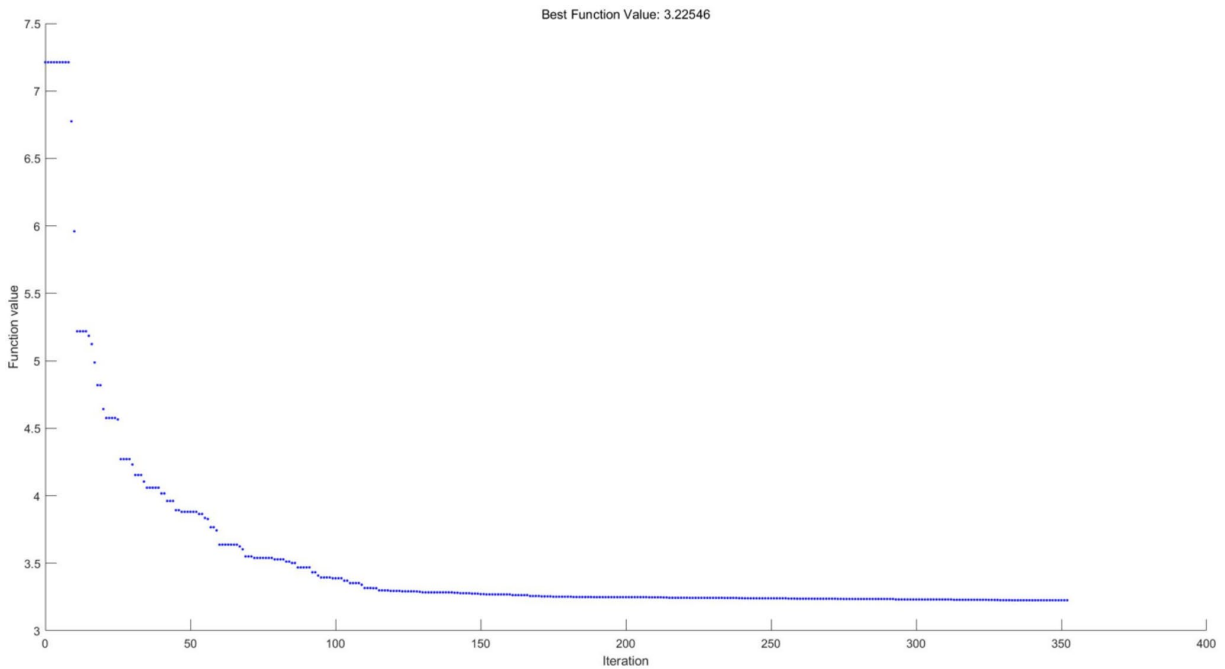


Figure 6.3.4 The convergence of the objective function when $\varkappa = 0.1$ for criterion time in terms of CWPs

Figure 6.3.4 displays the value of the objective function is resulting in convergence after 150 iterations. When the trend of the objective function keeps steady, the iteration of the PSO will stop, and the generation of the variables for the pairwise comparison matrix is finally successful. There

are 825 variables generated finally for original multiple matrices from decision-makers, and the final pairwise comparison matrices are gained from adding variables to the original matrices. As far as each criterion is concerned, a different value of γ must be trained for time, cost, safety, and quality for the Wind Farm Project.

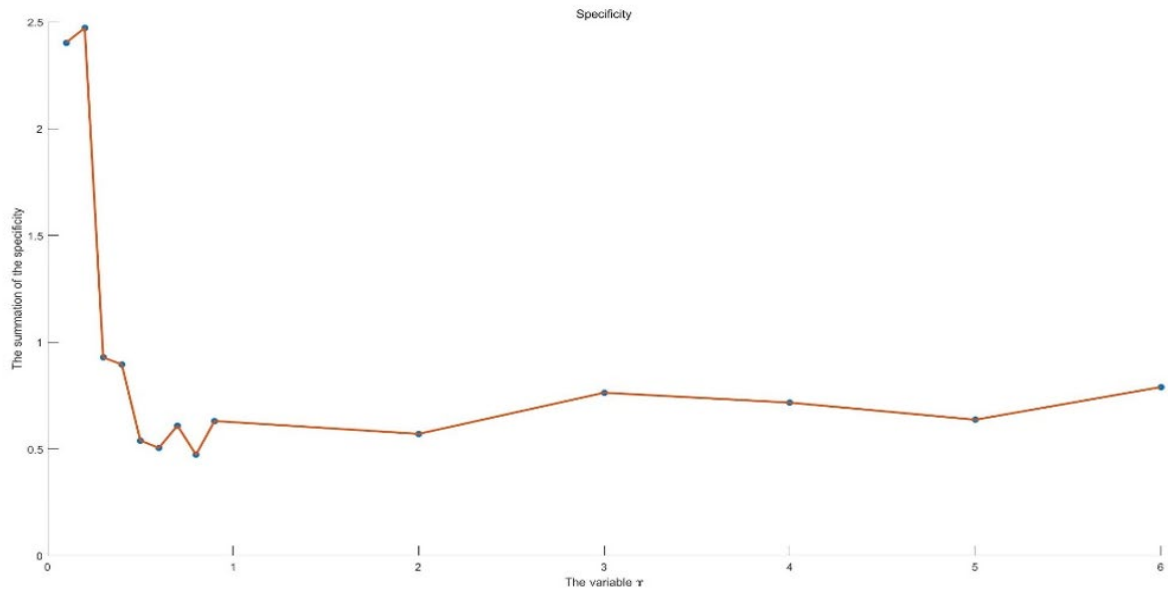


Figure 6.3.5 The summation of the total specificity in terms of different γ in PSO

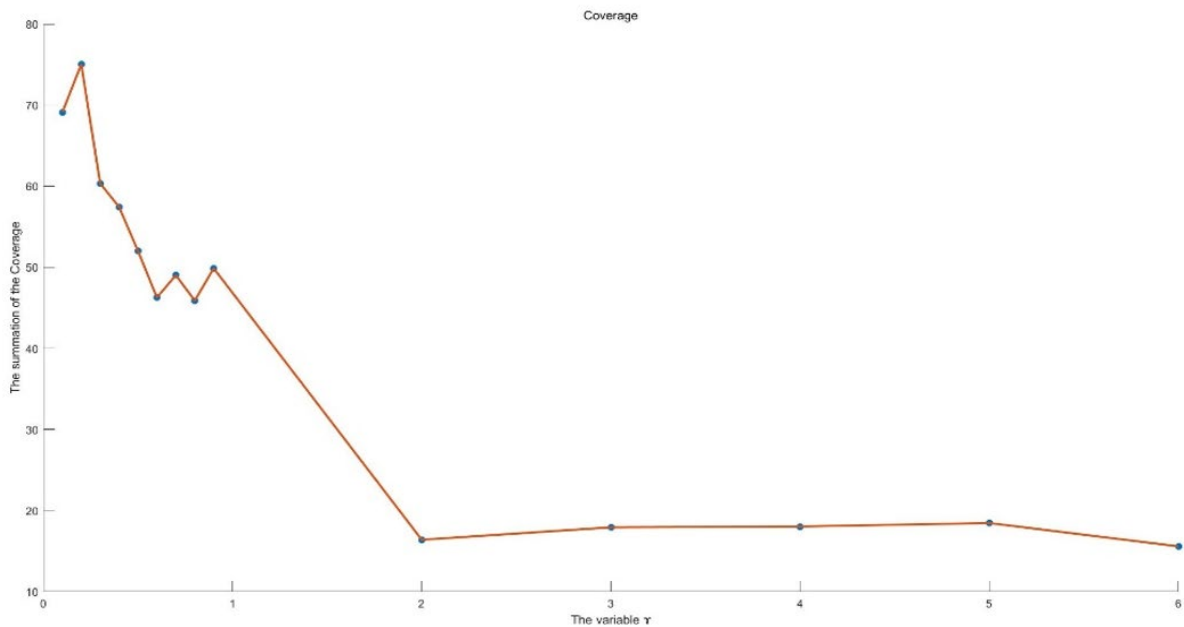


Figure 6.3.6 The summation of the total coverage in terms of different γ in PSO

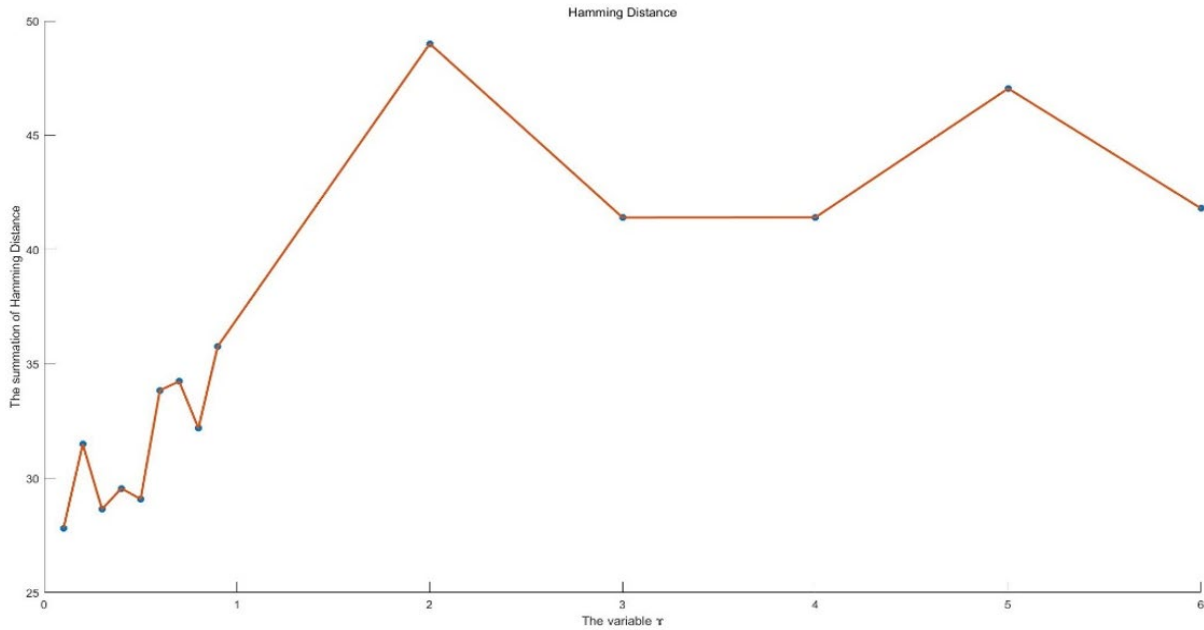


Figure 6.3.7 The summation of the total HD in terms of different τ in PSO

τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	2	3	4	5	6
--------	-----	-----	-----	-----	-----	-----	-----	-----	-----	---	---	---	---	---

Table 6.3.2 The scale of the parameter τ for objective function in PSO

The power variable τ is trained as diverse as the following scale in Table 6.3.2. The above Figures, 6.3.5, 6.3.6, and 6.3.7, explain the trend of specificity, coverage, and HD through different τ . It is evident that the coverage and specificity witnessed severe decline while the parameter $\tau > 1$; meanwhile, the HD increases pretty much. The appropriate parameter τ should be less than 1. The remarkable $\tau = 0.2$ is the best variable, while the coverage and specificity are the maximum, and the corresponding HD is appropriately close to the original preference of experts.

$CWP_1 \sim CWP_{11}$ for criterion time											
e^-	0.6415	0.5065	0.5174	0.3748	0.3456	0.3568	0.2370	0.2188	0.2169	0.1970	0.1298
e^+	0.7390	0.8202	0.7693	0.7614	0.6873	0.4782	0.3704	0.4215	0.5501	0.2772	0.2825

Table 6.3.3 The IT2FS from PSO generation when $\tau = 0.2$ for criterion time

By calculating the optimal result of the individual criterion time, due to the highest specificity and coverage and the least distance, we can ensure the best parameter $\gamma = 0.2$ is temporarily the best for the PSO temporary. Then, as for the more accurate parameter of γ , the more decimal places should also be explored, for example, the interval $[0.1,0.3]$ with the step size 0.02.

The three following Figure 6.3.8 to 6.3.10 explain the trend of the different parameter γ , and the primary coverage experienced an oscillation, when $\gamma = 0.2$, the coverage gets the second maximum. On the other hand, the specificity obtains the maximum simultaneously with the appropriate HD. In conclusion, the best parameter is still 0.2, with the normal step size = 0.1. The curve changing trend is also similar to Figure 6.3.5 to 6.3.7. The appropriate decimal point should be 1, and the value of the parameter γ should be less than 1. The approximation of the global best for the PSO algorithm in terms of each iteration triggers that there is some difference, even using the same value of the parameter $\gamma = 0.2$ or 0.3.

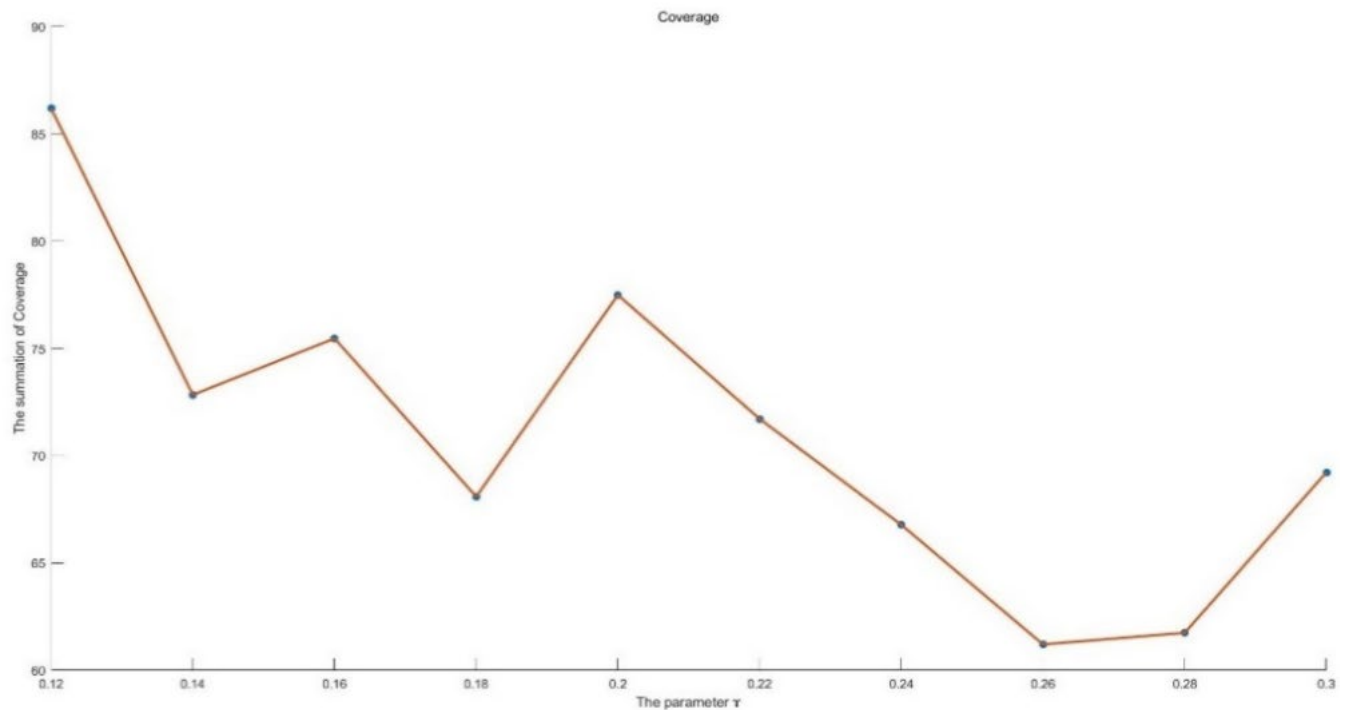


Figure 6.3.8 The summation of the total coverage in terms of different γ from 0.1 to 0.3 in PSO

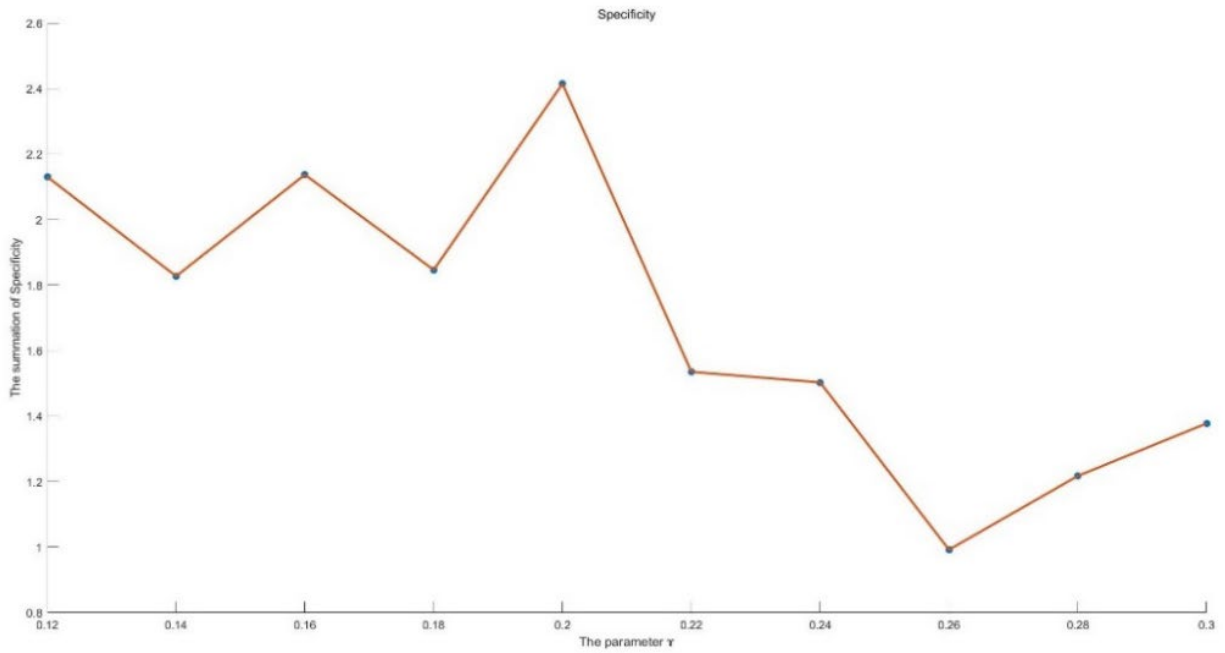


Figure 6.3.9 The summation of the total specificity in terms of different γ from 0.1 to 0.3 in PSO

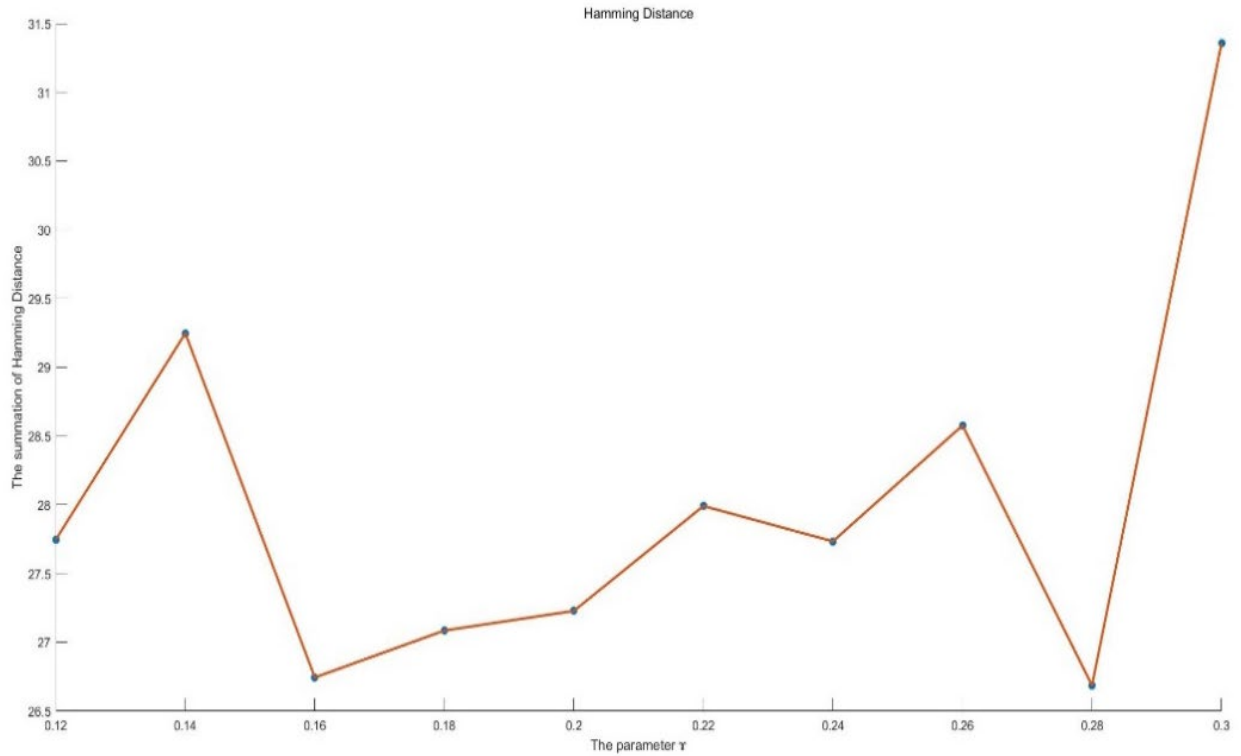


Figure 6.3.10 The summation of the total HD in terms of different γ from 0.1 to 0.3 in PSO

After ensuring the appropriate parameter γ for individual criterion time of the PSO, the data loss from the included number of experts should be checked to see if it is worth it. Meanwhile, the best parameter γ for all criteria in terms of time, cost, quality, and safety became the essential experiment to elevate the consensus for the whole data set.

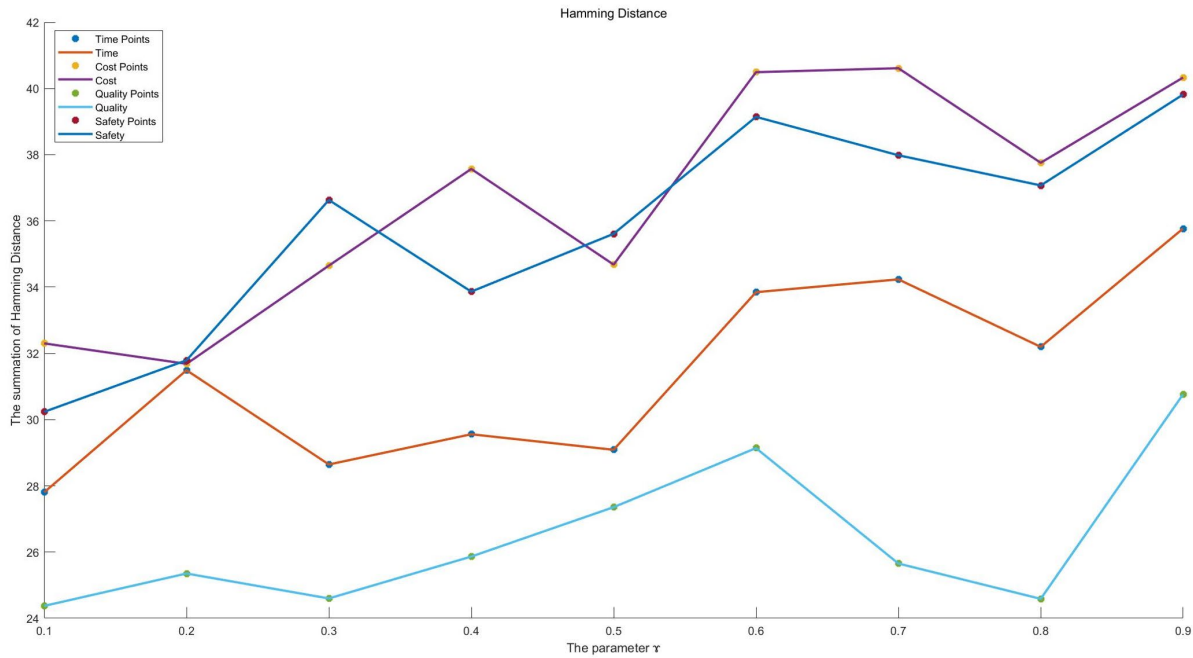


Figure 6.3.11 The summation of HD for four criteria with different γ

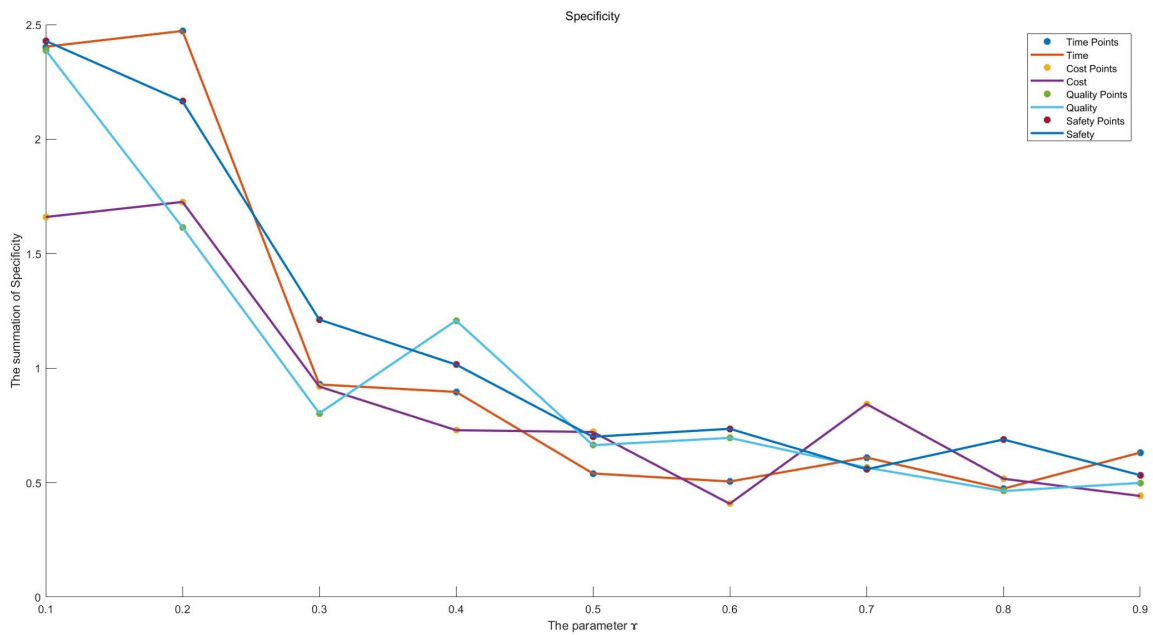


Figure 6.3.12 The summation of specificity for four criteria with different

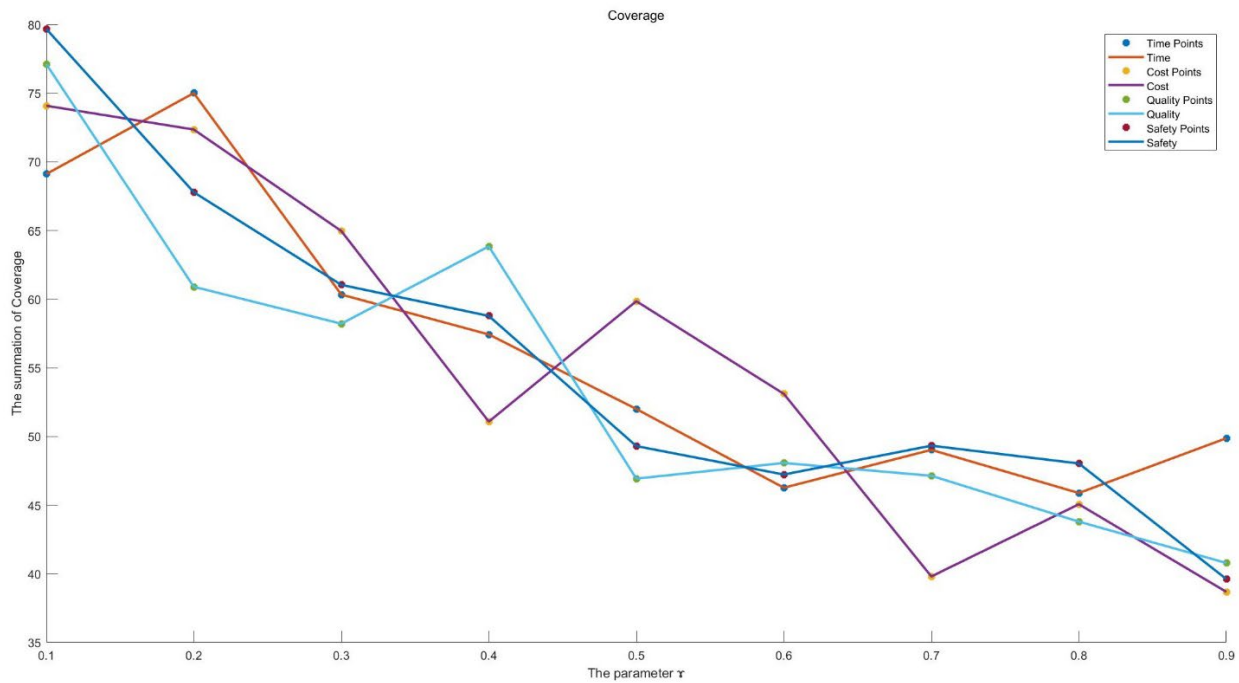


Figure 6.3.13 The summation of coverage for four criteria with different γ

Analyzing Figures 6.3.10. to 6.3.13, the appropriate parameter γ for each criterion is $\gamma = 0.2, 0.2, 0.1, 0.1$ for time, cost, quality, and safety, respectively. With this parameter, all those consensus for Wind Farm Project are optimized and elevated to higher enough coverage and specificity with keeping close to the original preference of preference. Then, the number of experts that are included in the consensus can be calculated through the optimized IT2FS, and Table 6.3.2 illustrates the result.

Time	Cost	Quality	Safety	Parameter γ .
0.678788	0.690909	0.690909	0.727273	0.1
0.757576	0.678788	0.6	0.624242	0.2
0.6	0.563636	0.557576	0.515152	0.3
0.436364	0.472727	0.563636	0.460606	0.4

0.315152	0.551515	0.436364	0.442424	0.5
0.369697	0.430303	0.509091	0.393939	0.6
0.424242	0.424242	0.424242	0.345455	0.7
0.266667	0.369697	0.393939	0.393939	0.8
0.387879	0.339394	0.345455	0.375758	0.9
0.454545	0.593939	0.509091	0.575758	1

Table 6.3.4 The percentage of the preferences of experts for all criteria with different parameter α

In Table 6.3.4, the maximum percentage of included experts in consensus for each criterion also evidenced the appropriate parameter α for each criterion, which is $\alpha = 0.2, 0.2, 0.1, 0.1$ for time, cost, quality, and safety, respectively. In terms of the criterion cost, the reason parameter is 0.2 is dropping 2% (1 or 2 preferences) data in exchange for higher specificity. The parameters that give the percentage higher than 50% are all could be explained as the majority supported consensus in MCGDM. Comparing with the original percentage of 61.4% of data utilization, the PSO with four parameters $\alpha = 0.2, 0.2, 0.1, 0.1$ give us 71.36% of data utilization, which is much higher than the expected 50% for every single criterion. Finally, the combination of all consensus of criteria provides the final IT2FS for multiple alternatives. The final ranking by applying GM for optimized IT2FS for each criterion is displayed in the tables below.

Time					Cost			
Original		PSO			Original		PSO	
Lower	Upper	Lower	Upper		Lower	Upper	Lower	Upper
0.345555	0.488043	0.641508	0.738979		0.252792	0.441036	0.535132	0.892752
0.345984	0.46595	0.506549	0.820231		0.171638	0.518736	0.455684	0.480183
0.561419	0.654086	0.517418	0.769292		0.785392	0.896956	0.863346	0.90469
0.484845	0.680206	0.374794	0.761361		0.762554	0.839403	0.490167	0.658013

0.517613	0.739292	0.345643	0.687349		0.438885	0.697609	0.471243	0.668063
0.372729	0.475899	0.356763	0.478242		0.432187	0.777097	0.379373	0.639714
0.277446	0.496681	0.23696	0.370356		0.165232	0.319249	0.231312	0.35774
0.350834	0.511207	0.218753	0.421502		0.246768	0.407848	0.231376	0.356518
0.632566	0.687291	0.216898	0.550077		0.502719	0.682072	0.181252	0.428106
0.19933	0.257363	0.196989	0.277216		0.236242	0.451607	0.178854	0.301426
0.290999	0.520086	0.129756	0.282517		0.442976	0.663391	0.18158	0.237823

Table 6.3.5 The IT2F of the preferences of experts for criterion time and cost with different parameter $\tau = 0.2$

Quality					Safety			
Original		PSO			Original		PSO	
Lower	Upper	Lower	Upper		Lower	Upper	Lower	Upper
0.139526	0.501737	0.391719	0.822199		0.123867	0.239344	0.484582	0.633946
0.227936	0.45358	0.363302	0.603787		0.228093	0.444256	0.426736	0.653323
0.999929	0.999929	0.740793	0.895235		0.580289	0.918715	0.549088	0.908854
0.40499	0.795916	0.336225	0.703561		0.442872	0.633324	0.451577	0.63372
0.405899	0.486405	0.367657	0.570709		0.436667	0.625715	0.356316	0.625145
0.372728	0.528862	0.215269	0.525874		0.372706	0.575538	0.300036	0.526452
0.222014	0.320897	0.218594	0.332029		0.33373	0.638032	0.203488	0.605518
0.216992	0.442983	0.192671	0.231639		0.350969	0.507466	0.24622	0.330783
0.392535	0.690985	0.170526	0.397035		0.604117	0.905314	0.226378	0.39312
0.174857	0.218872	0.111703	0.261651		0.19933	0.412165	0.186387	0.38227

Table 6.3.6 The IT2F of the preferences of experts for criterion quality and safety with different parameter $\tau = 0.1$

Analyzing tables 6.3.5 and 6.3.6, when compared with the original IT2FS, the specificity results from PSO are much broader and offer higher coverage. The final consensus is much broader and better than the original. On the other hand, comparing Table 6.3.7 with Table 5.3.1, the final

ranking result is completely different from the original, in that for the second alternative in terms of criterion time, the weighted median, and ranking are totally different. The final interval is wider than the original and the higher percentage of data utilization illustrates more preferences of experts are included in the IT2FS.

CWP	Interval-Valued Preference Index			Rank
	Lower Limit	Upper Limit	GM	
Turbine foundation	0.6677	0.8695	0.7686	1
Pre-construction activities	0.5132	0.7720	0.6426	2
Turbine Assembly	0.4132	0.6892	0.5512	3
Surveying works	0.4381	0.6394	0.5387	4
Electrical collector lines	0.3852	0.6378	0.5115	5
Electrical distribution substation	0.3129	0.5426	0.4277	6
Meteorological tower	0.1988	0.4421	0.3204	7
Storm water management system	0.2226	0.4164	0.3195	8
Meteorological tower	0.2223	0.3351	0.2787	9
Dewatering	0.1685	0.3056	0.2371	10
O & M Building	0.1562	0.2884	0.2223	11

Table 6.3.7 The PSO generated the final ranking of CWPs with appropriate parameter α

6.4 Conclusion

The flexibility of the model is proven to adapt to a variety of preferences for different MCGDM problems only if enough preferences from experts have been gathered. Then, the consensus is elevated by adding the extra parameter for *Obj* in PSO, the IT2FS for all alternatives are enlarged to include more preferences. Although some of the preferences of experts are revised, the

requirement of the higher consensus of MCGDM is achieved. On the other hand, the revised reciprocal pairwise comparison matrix is kept closest to the original. The model can offer a better consensus than the consensus in chapter 5.

Chapter 7 Summary and Further Study

7.1 Summary

In this study, the infrastructure risk for the Wind Farm Project must initially be classified into similar groups. After that, the experts express their preferences for alternatives through questionnaires. The uncertainty of the preferences of experts and the conflicts between multiple criteria and alternatives are captured through establishing the AHP structure, and the weighted preferences and the weight of experts are represented by the normalized eigenvectors and the CI, respectively. Then, the temporary consensus collection is allocated to the methodologies of MCGDM; however, the consensus must be supported by the majority of the consensus. Increasing the majority of the consensus is the principal research target. The principle of justifiable granularity is proposed to select and elevate the consensus of the MCGDM problem. The principle of justifiable granularity depends on the mathematical process and always provides the majority of the consensus. The extreme preferences are excluded but also have an impact on the IT2FS for consensus. The result is a necessary one for the real company in Ottawa, and the response is positive for the construction of the infrastructure for the Wind Farm Project.

Depending on the concept of group decision-making, the consensus should include more preferences from experts. The PSO is proposed to elevate the consensus and revise the extreme preferences from experts; the elements in the reciprocal pairwise comparison matrix present the main modification problem in PSO. The parameter constraints are also applied to the objective function, including granularity, the hamming distance for proximity to the original matrices, and the parameter for specificity. Finally, the result of the constrained PSO offers the optimized result, including the higher percentage of preferences needed to reduce the original data loss.

7.2 Further Studies

Further studies concentrate on adding more constraints in PSO to enlarge the granularity based on the original IT2FS results in order to obtain even less data loss and the same ranking as the initial IT2FS results. When comparing the original IT2FS with the revised IT2FS by PSO, the ranking result of the alternatives and the result through GM is absolutely different. Exploring additional parameters for keeping the same ranking is necessary for this Wind Farm Project. Comparing Table 5.2.1 with Table 6.3.1, the original ranking and IT2FS is different from the PSO generated, and further studies should be based on the original IT2FS, rankings, and weighted median for wider IT2FS. The preferences of experts support the majority of the consensus that should not be modified; however, the excluded preferences should be modified to be close to the original IT2FS or included in the consensus without revising the original weighted median and rankings.

On the other hand, the better aggregation methodology for four criteria should be developed rather than using the simple aggregation weight = 0.25, for example, the aggregation methodology for IT2FS or fuzzy sets operations. Finally, the better ranking methodology rather than GM should be developed because the geometric median and mean of the final intervals for CWPs are extremely close to each other.

Bibliography

- [1] S. Zhang *et al*, "Adaptive consensus model with multiplicative linguistic preferences based on fuzzy information granulation," *Applied Soft Computing*, vol. 60, pp. 30-47, 2017. DOI: 10.1016/j.asoc.2017.06.028.
- [2] Y. Hao *et al*, "Consensus building in group decision-making for the risk assessment of Wind Farm Project," in Jun 2019. DOI: 10.1109/FUZZ-IEEE.2019.8858797.
- [3] T. L. Saaty, "A scaling method for priorities in hierarchical structures," *Journal of Mathematical Psychology*, vol. 15, (3), pp. 234-281, 1977. DOI: 10.1016/0022-2496(77)90033-5.
- [4] T. L. Saaty, "Decision making with the analytic hierarchy process," *International Journal of Services Sciences*, vol. 1, (1), pp. 83-98, 2008. DOI: 10.1504/IJSSci.2008.01759.
- [5] T. L. Saaty, "How to make a decision: The analytic hierarchy process," *European Journal of Operational Research*, vol. 48, (1), pp. 9-26, 1990. DOI: 10.1016/0377-2217(90)90057-i.
- [6] T. L. Saaty, "Introduction to a modeling of social decision processes," *Mathematics and Computers in Simulation*, vol. 25, (2), pp. 105-107, 1983. DOI: 10.1016/0378-4754(83)90072-1.
- [7] N. Yaraghi *et al*, "Comparison of AHP and Monte Carlo AHP Under Different Levels of Uncertainty," *Tem*, vol. 62, (1), pp. 122-132, 2015. DOI: 10.1109/tem.2014.2360082.
- [8] W. Pedrycz and Mingli Song, "Analytic Hierarchy Process (AHP) in Group Decision Making and its Optimization With an Allocation of Information Granularity," *Tfuzz*, vol. 19, (3), pp. 527-539, 2011. DOI: 10.1109/TFUZZ.2011.2116029.
- [9] Emrah Koksalmis, Gulsah Hancerliogullari Koksalmis and Ozgur Kabak, "Decision Makers' Weights in Group," . DOI: 10.1007/978-3-030-03317-0_41.
- [10] N. Mironova, "The extension of GDSS architecture by the subsystem of group decision method synthesis," in Sep 2013. DOI: 10.1109/IDAACS.2013.6662674.

- [11] Xiaohong Chen, Zhiyang Chen and Xuanhua Xu, "Research on complex large group decision support system framework in internet or intranet environment," in Jun 2008. DOI: 10.1109/WCICA.2008.4594033.
- [12] Xu Xuan-hua and Chen Xiao-hong, "Study of the group decision making base kit based on complex large group," in Aug 2007. DOI: 10.1109/ICMSE.2007.4421830.
- [13] W. Pedrycz and W. Homenda, "Building the fundamentals of granular computing: A principle of justifiable granularity," *Applied Soft Computing*, vol. 13, (10), pp. 4209-4218, 2013. DOI: 10.1016/j.asoc.2013.06.017.
- [14] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning—I," *Information Sciences*, vol. 8, (3), pp. 199-249, 1975. DOI: 10.1016/0020-0255(75)90036-5.
- [15] P. Acheson and C. Dagli, "Fuzzy Assessor Using Type 1 and Type 2 Fuzzy Sets," *Procedia Computer Science*, vol. 8, pp. 159-164, 2012. DOI: 10.1016/j.procs.2012.01.033.
- [16] N. N. Karnik and J. M. Mendel, "Operations on type-2 fuzzy sets," *Fuzzy Sets and Systems*, vol. 122, (2), pp. 327-348, 2001. DOI: 10.1016/s0165-0114(00)00079-8.
- [17] J. Kennedy and R. Eberhart. Particle swarm optimization. In Proceedings of the IEEE International Conference on Neural Networks, pages 1942–1948, Piscataway, NJ, USA, 1995.
- [18] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in 1998. DOI: 10.1109/ICEC.1998.699146.
- [19] de Gusmão, Ana Paula Henriques *et al*, "Information security risk analysis model using fuzzy decision theory," *International Journal of Information Management*, vol. 36, (1), pp. 25-34, 2016. DOI: 10.1016/j.ijinfomgt.2015.09.003.
- [20] A. M. Aboushady, M. M. Marzouk and M. M. G. Elbarkouky, "Fuzzy consensus qualitative risk analysis framework for building construction projects," in Jun 2013. DOI: 10.1109/IFSA-NAFIPS.2013.6608564.

- [21] K. Vahdat, N. J. Smith and G. G. Amiri, "Fuzzy multicriteria for developing a risk management system in seismically prone areas," *Socio-Economic Planning Sciences*, vol. 48, (4), pp. 235-248, 2014. DOI: 10.1016/j.seps.2014.05.002.
- [22] J. S. Armstrong and A. Graefe, "Predicting elections from biographical information about candidates: A test of the index method," *Journal of Business Research*, vol. 64, (7), pp. 699-706, 2011. DOI: 10.1016/j.jbusres.2010.08.005.
- [23] T. Prokesch, "Integrating prediction market and Delphi methodology into a foresight support system," *Technological Forecasting & Social Change*, vol. 97, pp. 47-64, 2015.
- [24] S. E. Seker, "Computerized Argument Delphi Technique," *Access*, vol. 3, pp. 368-380, 2015. DOI: 10.1109/access.2015.2424703.
- [25] J. Parker and J. Parker, "Peter Emerson, ed., Designing an All-Inclusive Democracy: Consensual Voting Procedures For Use in Parliaments, Councils and Committees," *Public Choice*, vol. 135, (3), pp. 493-496, 2008. DOI: 10.1007/s11127-007-9261-y.
- [26] J. Monguet *et al*, "Vector consensus: Decision making for collaborative innovation communities," in *ENTERprise Information Systems Anonymous 2010*, . DOI: 10.1007/978-3-642-16419-4_22.
- [27] K. Li *et al*, "Proof of vote: A high-performance consensus protocol based on vote mechanism & consortium blockchain," in - *2017 IEEE 19th International Conference on High Performance Computing and Communications; IEEE 15th International Conference on Smart City; IEEE 3rd International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*, 2017, . DOI: 10.1109/HPCC-SmartCity-DSS.2017.61.
- [28] R. K. Shahzad *et al*, "Consensus decision making in random forests," *Revised Selected Papers of the First International Workshop on Machine Learning, Optimization, and Big Data*, pp. 347, 2015.

- [29] J. Ding, Z. Xu and H. Liao, "Consensus-reaching methods for hesitant fuzzy multiple criteria group decision making with hesitant fuzzy decision making matrices," *Frontiers Inf Technol Electronic Eng*, vol. 18, (11), pp. 1679-1692, 2017. DOI: 10.1631/FITEE.1601546.
- [30] D. Ben-Arieh and Z. Chen, "Linguistic group decision-making: opinion aggregation and measures of consensus," *Fuzzy Optim Decis Making*, vol. 5, (4), pp. 371-386, 2006. DOI: 10.1007/s10700-006-0017-9.
- [31] F. J. Cabrerizo *et al*, "Analyzing consensus approaches in fuzzy group decision making: advantages and drawbacks," *Soft Comput*, vol. 14, (5), pp. 451-463, 2009. DOI: 10.1007/s00500-009-0453-x.
- [32] C. Cheng, "Solving a sealed-bid reverse auction problem by multiple-criterion decision-making methods," *Computers and Mathematics with Applications*, vol. 56, (12), pp. 3261-3274, 2008. DOI: 10.1016/j.camwa.2008.09.011.
- [33] Y. Dong, "Consistency measures of linguistic preference relations and its properties in group decision making," in *Fuzzy Systems and Knowledge Discovery Anonymous* 2006. DOI: 10.1007/11881599_58.
- [34] W. Pedrycz and A. Bargiela, "An Optimization of Allocation of Information Granularity in the Interpretation of Data Structures: Toward Granular Fuzzy Clustering," *Tsmcb*, vol. 42, (3), pp. 582-590, 2012. DOI: 10.1109/TSMCB.2011.2170067.
- [35] B. Apolloni, S. Bassis, D. Malchiodi and W. Pedrycz, "Interpolating support information granules," *Neurocomputing*, vol. 71, no. 13, pp. 2433–2445, 2008.
- [36] W. Pedrycz, "Allocation of information granularity in optimization and decision-making models: Towards building the foundations of Granular Computing," *European Journal of Operational Research*, vol. 232, (1), pp. 137-145, 2014. DOI: 10.1016/j.ejor.2012.03.038.
- [37] A. Pedrycz *et al*, "Granular representation and granular computing with fuzzy sets," *Fuzzy Sets and Systems*, vol. 203, pp. 17-32, 2012. DOI: 10.1016/j.fss.2012.03.009.

- [38] F. Liu, Y. Wu and W. Pedrycz, "A Modified Consensus Model in Group Decision Making With an Allocation of Information Granularity," *Tfuzz*, vol. 26, (5), pp. 3182-3187, 2018. DOI: 10.1109/tfuzz.2018.2793885.

Appendix

Questionnaire

Using the analytic hierarchy process (AHP) technique, this study aims to rank the construction work packages (CWPs) of the construction phase of wind farm projects based on their impact on project objectives. The contribution of each CWP to the overall risk or uncertainty involved in achieving project objectives is therefore assessed using pairwise comparisons. The work breakdown structure (WBS) for the construction of wind farm projects has been developed through a literature review and is presented in Figure 1, which shows the eleven CWPs highlighted in blue at the third level of the WBS. The scale used for the pairwise comparisons is illustrated in Table 1 with an example, which is used to compare the contribution of two work packages (i.e., preconstruction activities and surveying works) to the overall risk or uncertainty involved in achieving project objectives. Please complete Tables 2 to 5 to compare each pair of CWPs in terms of their contribution to the overall risk or uncertainty involved in achieving the project objectives, which are cost, time, quality, and safety.

Table 1: Scale used for pairwise comparisons: example of comparing preconstruction activities to surveying works

Scale Value	Meaning
-9	extremely higher contribution of preconstruction activities as compared to surveying works.
-7	much higher contribution of preconstruction activities as compared to surveying works.
-5	higher contribution of preconstruction activities as compared to surveying works.
-3	slightly higher contribution of preconstruction activities as compared to surveying works.
0	equal contribution of preconstruction activities as compared to surveying works.
+3	slightly lower contribution of preconstruction activities as compared to surveying works.

+5 lower contribution of preconstruction activities as compared to surveying works.

+7 much lower contribution of preconstruction activities as compared to surveying works.

+9 extremely lower contribution of preconstruction activities as compared to surveying works.

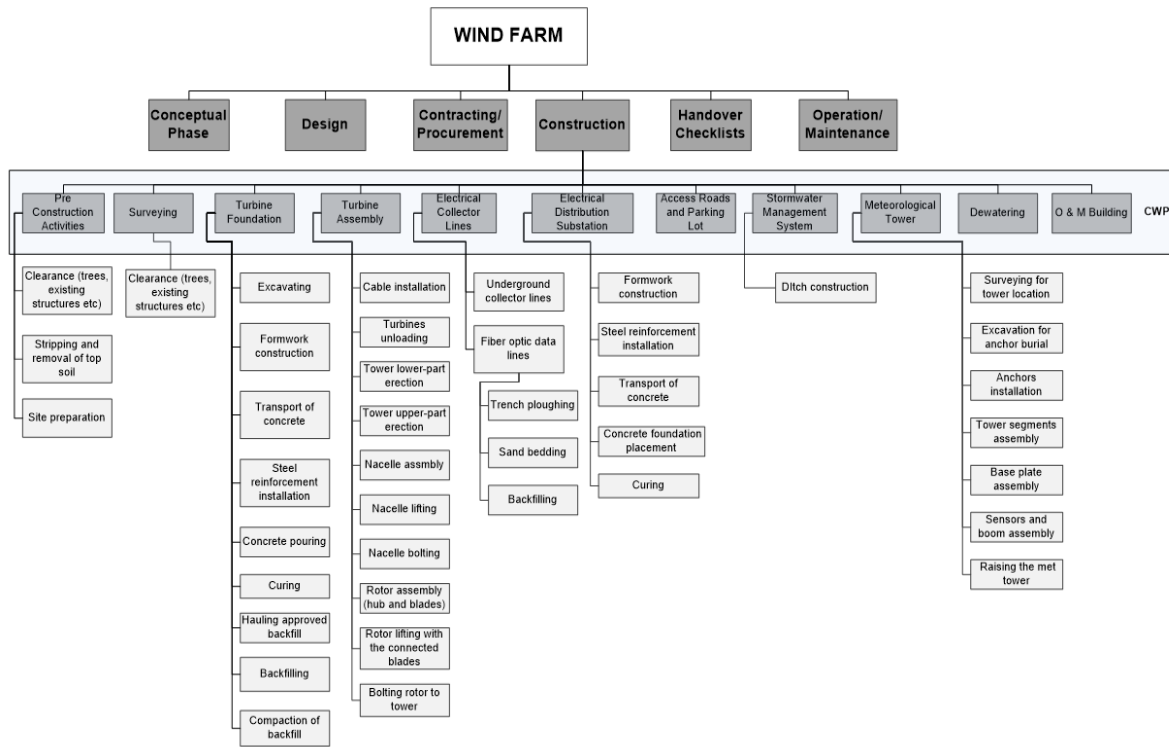


Figure 14. Work breakdown structure of the wind-farm project

Table 2. Pairwise comparison of CWPs of wind farm projects based on contribution to overall **risk or uncertainty** involved in achieving **project cost** objective

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	
										Surveying works

Pre-construction activities										Turbine foundation
										Turbine Assembly
										Electrical collector lines
										Electrical distribution substation
										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O & M Building

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 “**surveying works**” CWP to each of the CWPs listed on the right, using the scale below.

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

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 “**turbine foundation**” CWP to each of the CWPs listed on the right, using the scale below.

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

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 “**turbine assembly**” CWP to each of the CWPs listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Turbine assembly										Electrical collector lines
										Electrical distribution substation
										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

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 “**electrical collector lines**” CWP to each of the CWPs listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Electrical collector lines										Electrical distribution substation
										Access roads

Table 3. Pairwise comparison of CWPs of wind farm projects based on contribution to overall **risk or uncertainty** involved in achieving **project time** objective

<p>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 time objective, compare the “pre-construction activities” CWP to each of the CWPs listed on the right, using the scale below.</p>										
	-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
<p>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 time objective, compare the “surveying works” CWP to each of the CWPs listed on the right, using the scale below.</p>										
	-9	-7	-5	-3	0	+3	+5	+7	+9	
Surveying works										Turbine foundation
										Turbine Assembly
										Electrical collector lines
										Electrical distribution substation
										Access roads
										Storm water management system

											Meteorological tower
											Dewatering
											O & M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project time** objective, compare the “**turbine foundation**” CWP to each of the CWP's listed on the right, using the scale below.

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

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project time** objective, compare the “**turbine assembly**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Turbine assembly										Electrical collector lines
										Electrical distribution substation
										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

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 time** objective, compare the “**electrical collector lines**” CWP to each of the CWPs listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Electrical collector lines										Electrical distribution substation
										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

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 time** objective, compare the “**electrical distribution substation**” CWP to each of the CWPs listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Electrical distribution substation										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

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 time** objective, compare the “**access roads**” CWP to each of the CWPs listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Access roads										Storm water management system
										Meteorological tower
										Dewatering

										O&M Building
--	--	--	--	--	--	--	--	--	--	--------------

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project time** objective, compare the “**storm water management system**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Storm water management system										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project time** objective, compare the “**meteorological tower**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Meteorological tower										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project time** objective, compare the “**dewatering**” CWP to the CWP listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Dewatering										O&M Building

Table 4. Pairwise comparison of CWP's of wind farm projects based on contribution to overall **risk or uncertainty** involved in achieving **project quality** objective

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project quality** objective, compare the “**pre-construction activities**” CWP to each of the CWP's 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

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 quality** objective, compare the “**surveying works**” CWP to each of the CWPs listed on the right, using the scale below.

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

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project quality** objective, compare the “**turbine foundation**” CWP to each of the CWP's listed on the right, using the scale below.

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

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project quality** objective, compare the “**turbine assembly**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Turbine assembly										Electrical collector lines
										Electrical distribution substation
										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project quality** objective, compare the “**electrical collector lines**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Electrical collector lines										Electrical distribution substation
										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project quality** objective, compare the “**electrical distribution substation**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Electrical distribution substation										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project quality** objective, compare the “**access roads**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Access roads										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project quality** objective, compare the “**storm water management system**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Storm water management system										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project quality** objective, compare the “**meteorological tower**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Meteorological tower										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project quality** objective, compare the “**dewatering**” CWP to the CWP listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Dewatering										O&M Building

Table 5. Pairwise comparison of CWP's of wind farm projects based on contribution to overall **risk or uncertainty** involved in achieving **project safety** objective

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

	-9	-7	-5	-3	0	+3	+5	+7	+9	
										Surveying works

Pre-construction activities											Turbine foundation
											Turbine Assembly
											Electrical collector lines
											Electrical distribution substation
											Access roads
											Storm water management system
											Meteorological tower
											Dewatering
											O & M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project safety** objective, compare the “**surveying works**” CWP to each of the CWP's listed on the right, using the scale below.

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

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project safety** objective, compare the “**turbine foundation**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
--	----	----	----	----	---	----	----	----	----	--

Turbine foundation										Turbine Assembly
										Electrical collector lines
										Electrical distribution substation
										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O & M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project safety** objective, compare the “**turbine assembly**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Turbine assembly										Electrical collector lines
										Electrical distribution substation
										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project safety** objective, compare the “**electrical collector lines**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Electrical collector lines										Electrical distribution substation
										Access roads
										Storm water management system

										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project safety** objective, compare the “**electrical distribution substation**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Electrical distribution substation										Access roads
										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project safety** objective, compare the “**access roads**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
Access roads										Storm water management system
										Meteorological tower
										Dewatering
										O&M Building

In order to rank the CWP's presented in Figure 1 in terms of their contribution to the overall risk or uncertainty involved in achieving the **project safety** objective, compare the “**storm water management system**” CWP to each of the CWP's listed on the right, using the scale below.

	-9	-7	-5	-3	0	+3	+5	+7	+9	
										Meteorological tower

Storm water management system										Dewatering
										O&M Building
<p>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 safety objective, compare the “meteorological tower” CWP to each of the CWPs listed on the right, using the scale below.</p>										
	-9	-7	-5	-3	0	+3	+5	+7	+9	
Meteorological tower										Dewatering
										O&M Building
<p>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 safety objective, compare the “dewatering” CWP to the CWP listed on the right, using the scale below.</p>										
	-9	-7	-5	-3	0	+3	+5	+7	+9	
Dewatering										O&M Building