

Fuzzy Quantum-Inspired MCDM for Smart City Renewable Hub Selection

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Abstract. Smart cities are transitioning towards sustainable energy infrastructure. This transformation requires robust decision-making systems to handle the intricacies of imprecision, uncertainty, ambiguity and conflicting criteria. This research proposes a fuzzy quantum-based multi-criteria decision-making (MCDM) approach for optimal location selection of renewable energy hubs. The developed model is the intersection of fuzzy logic, quantum decision theory and MCDM. The key criteria considered in this study include costs, energy efficacy, environmental impact, scalability and compatibility. The results obtained through this integrated method are more reliable and consistent. The rankings of the alternatives are compared with the existing traditional approaches to demonstrate the competency of the proposed method. Sensitivity analysis exhibits the increased efficiency of the fuzzy quantum-based MCDM approach.

Keywords: Quantum theory, Fuzzy Logic, MCDM, Smart cities, Renewable hub location

AMS Mathematics Subject Classification (2010): 94D05

1. Introduction

Industrialisation and urbanisation have caused an increase in the demand for sustainable energy in modern cities. Renewable energy systems are eco-friendly and play a crucial role in the smart city framework. The installation of renewable energy hubs fulfils the energy requirements of the urban populace. However, as the city ecosystems are increasingly technology-driven, selecting a viable location for renewable energy hubs becomes more complex. Furthermore, criteria such as costs, energy efficiency, environmental impact, scalability, and compatibility are generally considered in this decision-making problem. Moreover, these criteria are highly conflicting, multidimensional and interdependent. To handle this complex circumstance, the multi-criteria decision-making (MCDM) methods are generally preferred. The approach of any MCDM method is to select the optimal alternative that satisfies the criteria considered for the study. The criteria are usually classified as beneficial and non-beneficial based on their influence over the selection of the alternatives. In this case, the criteria such as cost and

environmental impact are non-beneficial, and the other criteria are beneficial. The decision makers intend to maximize the benefit criteria and to minimize the cost criteria.

The classical MCDM techniques are well-suited for handling a deterministic-based decision-making environment. The MCDM methods are generally used to determine criterion weights and rank alternatives. However, these models fall short of addressing human cognition, decision uncertainty, non-linearity and interdependent criteria. This has led to the development of quantum-based decision-making, guided by the principles of superposition, entanglement, and interference. Unlike classical MCDM, quantum-based approaches facilitate the decision-makers in considering multiple preferences simultaneously, interdependencies between criteria and non-rational human behaviour such as indecisiveness and preference reversals. However, if the environment is uncertain and ambiguous, quantum models must be integrated with fuzzy logic to evolve a more comprehensive and dynamic decision-making model. Zadeh [1] introduced fuzzy sets to handle uncertain and vague environments. Since the decision-making situations are constrained and hindered by subjective judgements of the experts, imprecise data, fuzzy logic-based models are proven to be more effective in deriving optimal solutions to the problems.

In alignment with it, this research work proposes a fuzzy integrated quantum decision-making model and demonstrates the application in the location selection of renewable energy hubs. As the decision-making environment involves human reasoning, there are chances for inconsistency and non-rationality, leading to conflicting preferences. Quantum models, based on the principles of superposition and interference, are effective in handling multiple preferences and contextual changes, respectively. Also, the subjective opinions of the experts are handled by fuzzy sets. Thus, integrating the principles of quantum and fuzzy logic leads to the development of a hybrid decision model. The comparison of the characteristics of the models based on traditional MCDM, quantum, and fuzzy quantum is presented in Table 1.

Table 1: Comparison of Traditional MCDM, Quantum and Fuzzy Quantum

Problem Characteristics	Traditional MCDM	Quantum	Fuzzy Quantum
Vagueness	×	×	✓
Indeterminacy	×	✓	✓
Non-linear Interactions	×	✓	✓
Human Cognition	×	✓	✓
Dynamic & Contextual Reasoning	×	✓	✓
Real-world Complexity	Partial	✓	✓

The above table clearly picturizes the efficiency of the proposed fuzzy quantum-based decision-making model. The integration of fuzzy logic outperforms existing models, and

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this synergy contributes to the development of a more adaptable and compatible model suitable for selecting a location for a renewable energy hub.

The other contents of the work are presented as follows: the literature review is discussed in section 2. The basic definitions related to this work are stated in Section 3. The methodology for the proposed fuzzy quantum decision-making is described in Section 4. The application of the developed approach to location selection for a renewable energy hub is discussed in Section 5. The results of the model are discussed and compared with the existing models in Section 6. The last section concludes the work.

2. Literature review

This section presents a review of works related to the applications of quantum decision-making models and other decision models in renewable energy systems. The research gaps are identified and the novel contributions of this work are also discussed in this section.

Rezvanjou et al., Rahman et al., Adedeji [2-4] applied crisp MCDM methods of Simple Additive Weight (SAW), Analytical Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) in renewable site selection. The crisp based MCDM lack competency to handle uncertainty. To deal with vagueness and linguistic representations, researchers developed fuzzy based MCDM. Narayanamoorthy et al., Wang et al., and Magableh et al. [5-7] integrated fuzzy logic and Fermatean sets with MCDM. Fuzzy representations are used to handle uncertainty and subjective experts' judgement. Goswami et al [8] developed hybrid frameworks such as CRITIC-EDAS-CODAS-CoCoSo. Kut and Pietrucha-Urbanik [9] developed AI-based decision models to enhance adaptability and robustness. Saraswat et al., [10] Adedeji integrated GIS tools with decision-making. Soltani and Imani [11] integrated simulation tools such as Monte Carlo in making spatial and probabilistic evaluations of renewable energy. The evaluation of regional planning and policy modelling is also performed by MCDM. Li et al and Ajabnoor [12-13] explored the strategies and climate policy subjected to renewable energy. The review of MCDM applications in renewable energy contexts are studied by Sahoo et al[14]. and Hashunao et al [15]. For better understanding the aforementioned works are tabulated in Table 2.

Table 2: MCDM Applications in Renewable Energy Systems

Author and Year	MCDM Type	Application Domain
Wang et al. (2018) [6]	Fuzzy MCDM	Renewable plant location in Vietnam
Adedeji (2020) [4]	Crisp MCDM + GIS	Hybrid renewable facility location
Narayanamoorthy et al. (2022) [5]	Fermatean Fuzzy MCDM	Optimal renewable energy plant location
Rezvanjou et al. (2023) [2]	Crisp MCDM + ML	Renewable energy location under disruption
Li et al. (2024) [12]	Fuzzy MCDM + Cumulative Prospect Theory	Renewable energy path selection in Malaysia
Soltani & Imani (2024) [11]	Crisp MCDM + Monte Carlo	Overcoming barriers to renewable energy in Iran

Rahman et al. (2024) [3]	Crisp MCDM	Selecting optimal energy source for Bangladesh
Hashunao et al. (2024) [15]	Crisp MCDM (Review)	Survey on site selection techniques
Hosouli et al. (2024) [16]	MCDM	Photovoltaic thermal (PVT) collector selection
Saraswat et al. (2024) [10]	GIS + Hybrid MCDM	Site analysis of multi-renewable energy in India
Akpahou et al. (2024) [17]	LEAP + MCDM	Energy planning and barrier evaluation in Benin
Ajabnoor (2024) [13]	Tree Soft Set + MCDM	Climate leadership and energy policy evaluation
Magableh & Bazel (2025) [7]	Multiple MCDM	Future renewable energy technology planning
Magableh et al. (2025) [18]	Hybrid Fuzzy MCDM	Adopting renewable energy strategy
Gaurav et al. (2025) [19]	MCDM	Assessment of hybrid energy with hydrogen production
Ersoy (2025) [20]	MCDM + Sensitivity Analysis	Impact assessment in Nordic-Baltic region
Goswami et al. (2025) [8]	Hybrid MCDM (CRITIC-EDAS-CODAS-CoCoSo)	Renewable selection framework in India
Manoharan et al. (2025) [21]	Fuzzy AHP + VIKOR	Optimization of renewable-fed desalination plant
Kut & Pietrucha-Urbanik (2025) [9]	AI + MCDM	Hybrid evaluation of renewable systems

The aforementioned MCDM methods discussed both under crisp and fuzzy fall short of handling the complexity caused by human-based reasoning and conflicting criteria. This led to the development of quantum decision methods. In addition to MCDM methods, researchers have applied the quantum decision-making approach. Li [22] applied quantum inspired in making recommendations on E-commerce. Mukerjee [23] employed in solar site selection. Madal et al, Wu et al , and Yang et al [24-26] have also applied the quantum decision-making approach in handling superposition states and conflicting criteria. However, these models do not address uncertainty, and this has led to the development of fuzzy logic integrated quantum models.

The existence of a more comprehensive model to address uncertainty, conflicting environment and human-based cognition is very limited. This has motivated the authors to develop a more adaptable decision method suitable for dynamic decision-making environments.

3. Preliminaries

This section presents the basic definitions related to this work.

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3.1. Fuzzy set

Let X be a universe of discourse. A fuzzy set $\tilde{A}$ is defined to be a set of ordered pairs of the form $\{ (x, \mu_A(x)), x \in X \}$, where $\mu_A(x): X \rightarrow [0,1]$ is the membership grade of $x \in X$.

3.2. Linguistic Variable

A variable assuming linguistic values is called as linguistic variable. For example, to describe the performance of an equipment, linguistic variables such as ‘low’, ‘medium’ and ‘high’ shall be used to describe the working competence of the equipment.

3.3 Fuzzy number

A fuzzy number B is a special kind of fuzzy set on R satisfying the following properties,

- (i) B is a normal fuzzy set
- (ii) Support is bounded
- (iii) “ B is a closed interval

here $\mu_B(x): R \rightarrow [0,1]$.

3.4. Triangular fuzzy number

Triangular fuzzy number $\tilde{T}$ is of the form (l,m,n) , where

$$\mu_T(x) = \begin{cases} 0 & x < l \\ \frac{x-l}{m-l} & l \leq x \leq m \\ \frac{m-x}{n-m} & m \leq x \leq n \\ 0 & x > n \end{cases}$$

3.5 Arithmetic Properties of Triangular Fuzzy Number

Let $\tilde{A} = (l_1, m_1, n_1)$ and $\tilde{B} = (l_2, m_2, n_2)$

- **Addition:**

$$\tilde{A} + \tilde{B} = (l_1 + l_2, m_1 + m_2, u_1 + u_2)$$

- **Subtraction:**

$$\tilde{A} - \tilde{B} = (l_1 - u_2, m_1 - m_2, u_1 - l_2)$$

- **Multiplication(approximate):**

$$\tilde{A} + \tilde{B} = (l_1 \cdot l_2, m_1 \cdot m_2, u_1 \cdot u_2)$$

- **Division(if $0 \notin \tilde{B}$):**

$$\tilde{A}/\tilde{B} = (l_1/u_2, m_1/m_2, u_1/l_2)$$

3.6. Defuzzification

A triangular fuzzy number of the form $\tilde{T} = (l, m, n)$ is converted to its crisp form using centroid method.

$$T = \frac{l + m + n}{3}$$

3.7. Decision matrix

A matrix representing the performance of m alternatives $A_1, A_2, \dots, A_m$ with respect to n criteria $C_1, C_2, \dots, C_n$. The decision matrix D is generally represented of the form $D = [x_{ij}]_{m \times n}$

3.8. Superposition state

The preference of the decision maker to an alternative can be represented as a quantum superposition.

$$|\psi_{ij}\rangle = \sum_{i=1}^n \alpha_{ij} |1\rangle$$

where:

- $|A_i\rangle$: quantum state corresponding to alternative A_i
- $\alpha_i \in C$: complex probability amplitude
- $\sum_{i=1}^n |\alpha_i|^2 = 1$

4. Methodology of fuzzy quantum decision making

This section presents the steps involved in the decision-making approach of Fuzzy Quantum.

Step 1: Define Alternatives and Criteria of the problem of study

Let

- $A = \{A_1, A_2, \dots, A_n\}$ be the set of alternatives
- $C = \{C_1, C_2, \dots, C_m\}$ be the set of criteria
- $W = \{w_1, w_2, \dots, w_m\}$ be the weight vector of the criteria such that $\sum w_j = 1$

Step 2: Construction of Fuzzy Decision Matrix with linguistic values

The decision-making matrix considering linguistic values is initially constructed, where each value of the matrix represents the performance of the alternatives with respect to the criteria. The linguistic values are represented using triangular fuzzy numbers of the form $\tilde{r}_{ij} = (l_{ij}, m_{ij}, u_{ij})$. Thus, the linguistic matrix is modified into a triangular fuzzy matrix.

$$\tilde{R} = \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \dots & \tilde{r}_{1m} \\ \tilde{r}_{21} & \tilde{r}_{22} & \dots & \tilde{r}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{r}_{n1} & \tilde{r}_{n2} & \dots & \tilde{r}_{nm} \end{bmatrix}$$

Step 3: Normalization of the Triangular Fuzzy Decision Matrix

The matrix obtained in Step 2 is normalized using the (1) and (2)

For benefit criteria

$$\tilde{r}_{ij}^N = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+} \right) \text{ where } u_j^+ = \max_i u_{ij} \quad (1)$$

For cost criteria

$$\tilde{r}_{ij}^N = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}} \right) \text{ where } l_j^- = \min_i l_{ij} \quad (2)$$

Step 4: Quantum Representation of Fuzzy preferences

The fuzzy normalized values obtained in Step 4 are modelled as quantum states. For each alternative-criterion pair $\tilde{r}_{ij}^N = (a, b, c)$, define a quantum preference amplitude:

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$\psi_{ij} = \alpha_{ij}|1\rangle + \beta_{ij}|0\rangle$ such that $|\alpha_{ij}|^2 + |\beta_{ij}|^2 = 1$

Let

$|\alpha_{ij}|^2 = \text{Defuzzified value of } \tilde{r}_{ij}^N$.

The centroid method of defuzzification is used.

Then $|\beta_{ij}|^2 = 1 - |\alpha_{ij}|^2$. This represents the superposition of both agreeing and disagreeing decision states.

Step 5: Aggregate Quantum Preferences Across Criteria

The quantum -weighted preference for each alternative is computed using (3)

$$Q_i = \sum_{j=1}^m w_j \cdot |\alpha_{ij}|^2 \quad (3)$$

The value Q_i is the aggregate quantum preference across all criteria.

Step 6: Ranking of the Alternatives

The alternatives $A_1, A_2, \dots, A_n$ are ranked based on aggregate score values obtained in Step 5. The alternatives with higher values of Q_i are given priorities.

5. Illustration of fuzzy quantum decision making

In this section, the fuzzy-based quantum approach is applied in the location selection of a renewable energy hub in smart cities. Let us consider the decision-making problem considering five location sites of the energy hub, say A, B, C, D and E. The criteria considered for location selection are Cost (C1), Energy Efficiency (C2), Environmental Impact (C3), Scalability (C4) and Compatibility (C5). The brief description of the criteria considered is presented in Table 3.

Table 3: Description of criteria

Criteria	Description	Nature
Cost (C1)	Investments and Operational expenses	Non-Benefit
Energy Efficiency (C2)	The ratio of output to input	Benefit
Environmental Impact (C3)	The impacts on ecosystem in terms of emissions and land use	Non-Benefit
Scalability (C4)	The potential for capacity expansion	Benefit
Compatibility (C5)	The flexibility in integrating with urban systems	Benefit

Let us construct a hypothetical decision-making matrix with linguistic values.

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Alternatives	C1	C2	C3	C4	C5
A	H	M	M	L	M
B	M	H	L	M	H
C	VH	M	H	VH	VH
D	L	VH	VL	H	M
E	M	L	M	M	L

The description of the linguistic values is presented in Table 4.

Table 4: Numerical values of linguistic term

Linguistic Term	Meaning	Triangular Fuzzy Representation	Defuzzified Values
Very Low (VL)	Extremely unsatisfactory	(0.0, 0.0, 0.2)	0.067
Low (L)	Below average	(0.1, 0.3, 0.5)	0.300
Medium (M)	Average/satisfactory	(0.4, 0.5, 0.6)	0.500
High (H)	Above average	(0.6, 0.7, 0.9)	0.733
Very High (VH)	Excellent	(0.8, 1.0, 1.0)	0.933

The modified matrix is obtained using the respective triangular fuzzy number values represented in Table 5

Table 5: Modified Matrix with Triangular fuzzy numbers

Alt.	C1	C2	C3	C4	C5
A	(0.6, 0.7, 0.9)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)	(0.1, 0.3, 0.5)	(0.4, 0.5, 0.6)
B	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.9)	(0.1, 0.3, 0.5)	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.9)
C	(0.8, 1.0, 1.0)	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.9)	(0.8, 1.0, 1.0)	(0.8, 1.0, 1.0)
D	(0.1, 0.3, 0.5)	(0.8, 1.0, 1.0)	(0.0, 0.0, 0.2)	(0.6, 0.7, 0.9)	(0.4, 0.5, 0.6)
E	(0.4, 0.5, 0.6)	(0.1, 0.3, 0.5)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)	(0.1, 0.3, 0.5)

Identify max and min values:

- For **benefit criteria** (C2, C4, C5):
 $u_j^+ = \max (u_{ij})$ for all the criteria = 1.0
- For **cost criteria** (C1, C3):
 $l_j^- = \min (l_{ij})$
 - C1: min = 0.1
 - C3: min = 0.0, but assumed to be 0.01 for computations.

The normalized matrix $\tilde{r}_{ij}^N$ is determined using Step 3.

Alt.	C1 (↓)	C2 (↑)	C3 (↓)	C4 (↑)	C5 (↑)
A	(0.111, 0.143, 0.167)	(0.400, 0.500, 0.600)	(0.017, 0.020, 0.025)	(0.100, 0.300, 0.500)	(0.400, 0.500, 0.600)
B	(0.167, 0.200, 0.250)	(0.600, 0.700, 0.900)	(0.020, 0.033, 0.100)	(0.400, 0.500, 0.600)	(0.600, 0.700, 0.900)

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C	(0.100, 0.100, 0.125)	(0.400, 0.500, 0.600)	(0.011, 0.014, 0.017)	(0.800, 1.000, 1.000)	(0.800, 1.000, 1.000)
D	(0.200, 0.333, 1.000)	(0.800, 1.000, 1.000)	(0.050, 1.000, 1.000)	(0.600, 0.700, 0.900)	(0.400, 0.500, 0.600)
E	(0.167, 0.200, 0.250)	(0.100, 0.300, 0.500)	(0.017, 0.020, 0.025)	(0.400, 0.500, 0.600)	(0.100, 0.300, 0.500)

Let us calculate $|\alpha_{ij}|^2 = \text{Defuzzified value of } \tilde{r}_{ij}^N$ and $|\beta_{ij}|^2 = 1 - |\alpha_{ij}|^2$. These values represent the superposition of both agreeing and disagreeing decision states.

For Alternative A

- C1: (0.111, 0.143, 0.167) $\rightarrow \alpha^2 = \frac{0.111+0.143+0.167}{3} = 0.140$
- C2: (0.4, 0.5, 0.6) $\rightarrow 0.500$
- C3: (0.017, 0.020, 0.025) $\rightarrow 0.021$
- C4: (0.1, 0.3, 0.5) $\rightarrow 0.300$
- C5: (0.4, 0.5, 0.6) $\rightarrow 0.500$

So A's quantum preferences $|\alpha_{ij}|^2 = [0.140, 0.500, 0.021, 0.300, 0.500]$

The aggregate Quantum Preference Q_i is determined using step 5.

$$Q_i = \sum_{j=1}^5 w_j \cdot |\alpha_{ij}|^2, w_j = 0.2 \forall Ci$$

For each of the alternate,

- **A:** $Q_A = 0.2(0.140+0.500+0.021+0.300+0.500) = 0.2 \times 1.461 = 0.292$
- **B:** $Q_B = 0.2(0.206+0.733+0.051+0.500+0.733) = 0.2 \times 2.223 = 0.445$
- **C:** $Q_C = 0.2(0.108+0.500+0.014+0.933+0.933) = 0.2 \times 2.488 = 0.498$
- **D:** $Q_D = 0.2(0.511+0.933+0.683+0.733+0.500) = 0.2 \times 3.360 = 0.672$
- **E:** $Q_E = 0.2(0.206+0.300+0.021+0.500+0.300) = 0.2 \times 1.327 = 0.265$

Based on the above computations, the rankings of the alternatives is presented in Table 6.

Table 6: The final ranking of the alternatives

Alternative	Q_i	Rank
D	0.672	1
C	0.498	2
B	0.445	3
A	0.292	4
E	0.265	5

6. Results and discussions

From the ranking results in Table 6, it is observed that the alternative D occupies first position, and it seems to be a more suitable location for a renewable energy hub. To demonstrate the consistency of the results obtained using fuzzy quantum, the same problem is handled using crisp and fuzzy MCDM. The crisp MCDM method of Simple Additive Weighting and Fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is applied, and the results obtained are presented in Table 7.

Table 7: Fuzzy SAW, Fuzzy TOPSIS and Fuzzy Quantum values

Alt	SAW (Crisp)	Fuzzy TOPSIS	Fuzzy Quantum
A	0.415	0.426	0.292
B	0.609	0.637	0.445
C	0.606	0.675	0.498
D	0.867	0.870	0.672
E	0.404	0.404	0.265

From Table 7, it is found that alternative D occupies the first position in all three different methods. However, the fuzzy quantum approach quantifies the strong preference for alternative D using quantum amplitudes $\alpha^2 = 0.672$, providing more decision confidence. The reliability of the results is also observed. Alternatives B and C have close scores in crisp and fuzzy MCDM methods; however, the fuzzy quantum scores show finer differentiation. This facilitates decision-making free from conflicts. The proposed fuzzy quantum method shows decision stability. The method of fuzzy quantum serves as a validator and it strengthens the decision results. The below table 8 elucidate the SAW vs Fuzzy TOPSIS procedures.

Table 8: Methodology of SAW vs Fuzzy TOPSIS

Step	SAW (Simple Additive Weighting)	Fuzzy TOPSIS
Definition of Alternatives and Criteria	Define alternatives $A_1, A_2, \dots, A_n$ and criteria $C_1, C_2, \dots, C_m$. Assign weights $w_1, w_2, \dots, w_m$ such that $\sum w_j = 1$	Same as SAW: Define alternatives, criteria, and fuzzy weights $\tilde{w}_j$ (can be crisp or fuzzy).
Construction of Decision Matrix	Build a crisp decision matrix $X = [x_{ij}]$, where x_{ij} is the score of alternative A_i under criterion C_j .	Construct a fuzzy decision matrix using triangular fuzzy numbers $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$
Normalization of the Decision Matrix	Benefit $x_{ij}' = \frac{x_{ij}}{\max x_{ij}}$ Cost $x_{ij}' = \frac{\min x_{ij}}{x_{ij}}$	Normalize fuzzy numbers: Benefit: $\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j}, \frac{m_{ij}}{u_j}, \frac{u_{ij}}{u_j} \right)$ Cost: $\tilde{r}_{ij} = \left(\frac{l_j}{u_{ij}}, \frac{l_j}{m_{ij}}, \frac{l_j}{l_{ij}} \right)$
Determining the normalized weighted matrix	Compute weighted normalized scores: $v_{ij} = w_j \cdot x_{ij}'$	Multiply normalized fuzzy values by fuzzy weights: $\tilde{v}_{ij} = \tilde{w}_j \otimes \tilde{r}_{ij}$
Computation of Total Score	$S_i = \sum_{j=1}^m v_{ij}$ (large S_i is better)	Calculate distances from: - FPIS (Ideal): $\tilde{A}^+ = \max(u_{ij})$ FNIS (Negative Ideal): $\tilde{A}^- = \min(l_{ij})$

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Computation of Closeness Coefficient (CC)	Not applicable – final score is S_i	Compute distances: D_i^+ =distance from FPIS D_i^- =distance from FNIS $CC_i = \frac{D_i^+}{D_i^+ + D_i^-}$
Ranking of the Alternatives	Rank alternatives based on the highest S_i	Rank alternatives based on highest CC_i

7. Conclusion

This research work proposes a fuzzy-based quantum decision-making method. The efficiency of the newly developed approach is demonstrated by applying it to the problem of selecting a location for a renewable energy hub in smart cities. The hybrid method integrates fuzzy logic with a quantum approach to increase the efficiency of ranking the alternatives. The comparison of the results with the crisp and fuzzy MCDM methods falls short off handling the non-linearity of the alternatives and multiple preferences. The robust nature of fuzzy quantum decision making is well exhibited in this work, and this shall be applied to a real-time data set.

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