Intern. J. Fuzzy Mathematical Archive
Vol. 23, No. 1, 2025, 41-53
ISSN: 2320 –3242 (P), 2320 –3250 (online)
Published on 20 July 2025
www.researchmathsci.org
DOI: http://dx.doi.org/10.22457/ijfma.v23n1a04250

International Journal of Fuzzy Mathematical Archive

Fuzzy Quantum-Inspired MCDM for Smart City Renewable Hub Selection

Nivetha Martin[1*] **and *R. Priya***[2]

[1]Department of Mathematics, Arul Anandar College (Autonomous), Karumathur, Madurai, India
Email: Nivetha.martin710@gmail.com
[2]Department of Mathematics, Sethu Institute of Technology, Madurai, India
email: iampriyaravi@gmail.com
*Corresponding author

Received 12 May 2025; accepted 12 July 2025

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 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.

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 ∈ X }, where $\mu_A(x): X \to [0,1]$ is the membership grade of x ∈ 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) $^{\alpha}B$ is a closed interval

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

3.4. Triangular fuzzy number

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

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

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):**

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

- **Division(if 0∉ $\tilde{B}$):**

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

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 $A_1, A_2, \ldots, A_m$ with respect to n criteria $C_1, C_2, \ldots, C_n$. 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
- $\alpha_i \epsilon C$: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=$\{A_1, A_2, \ldots, A_n\}$ be the set of alternatives
- C=$\{C_1, C_2, \ldots, C_m\}$ be the set of criteria
- W=$\{w_1, w_2, \ldots, w_m\}$ 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.

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

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

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

For cost criteria

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

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:

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

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

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

Step 6: Ranking of the Alternatives
The alternatives $A_1, A_2, \ldots, A_n$ 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.

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)

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 $|\alpha_{ij}|^2$= 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) → α^2 = $\frac{0.111+0.143+0.1673}{3}$ = 0.140
- C2: (0.4, 0.5, 0.6) → 0.500
- C3: (0.017, 0.020, 0.025) → 0.021
- C4: (0.1, 0.3, 0.5) → 0.300
- C5: (0.4, 0.5, 0.6) → 0.500

So A's quantum preferences $|\alpha ij|^2$ = [0.140, 0.500, 0.021, 0.300, 0.500]
The aggregate Quantum Preference Qi is determined using step 5.

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

For each of the alternate,

- **A**: Q_A=0.2(0.140+0.500+0.021+0.300+0.500)=0.2×1.461=0.292
- **B**: Q_B=0.2(0.206+0.733+0.051+0.500+0.733)=0.2×2.223=0.445
- **C**: Q_C=0.2(0.108+0.500+0.014+0.933+0.933)=0.2×2.488=0.498
- **D**: Q_D=0.2(0.511+0.933+0.683+0.733+0.500)=0.2×3.360=0.672
- **E**: Q_E=0.2(0.206+0.300+0.021+0.500+0.300)=0.2×1.327=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	**Qi**	**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 $A_1, A_2, \ldots, A_n$ and criteria $C_1, C_2, \ldots, C_m$. Assign weights $w_1, w_2, \ldots, w_m$ such that $\sum w_j = 1$	Same as SAW: Define alternatives, criteria, and fuzzy weights $\widetilde{w}_j$(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: $v_{ij} = w_j . x_{ij}'$	Multiply normalized fuzzy values by fuzzy weights: $\tilde{v}_{ij} = \widetilde{w}_j \otimes \tilde{r}_{ij}$
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})

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.

Acknowledgement. The authors sincerely thank the esteemed referees for their insightful comments and constructive suggestions, which have greatly enhanced the clarity, depth, and overall quality of the paper.

Conflicts of Interest. The authors declare that there is no conflict of interest regarding the publication of this paper.

Author's Contributions. All research activities, including conceptualization, data analysis, and manuscript writing, were collaboratively and solely conducted by the authors, without any external assistance.

REFERENCES

1. L.A.Zadeh, The role of fuzzy logic in the management of uncertainty in expert systems. *Fuzzy Sets and Systems,* 11(1-3) (1983) 199-227.
2. S.Rezvanjou, M.Amini and M. Bigham. Renewable Energy Location in Disruption Situation by MCDM Method and Machine Learning. *International Journal of Industrial Engineering and Operational Research,* 5(4) (2023) 75-89.
3. M.A.Rahman, T. Ahmed, M. M. Rana, B.Hossain, M. R. Bhuiyan, and M. J. Alam. A comparative analysis of MCDM methods for selecting the optimal renewable energy source for Rajshahi, Bangladesh. In *2024 International Conference on Recent Progresses in Science, Engineering and Technology (ICRPSET)*, pp. 1-5. IEEE, 2024.
4. P.A.Adedeji, . *Hybrid renewable energy-based facility location: a Geographical Information System (GIS) integrated multi-criteria decision-making (MCDM) approach*. University of Johannesburg (South Africa), 2020.
5. S.Narayanamoorthy, T. N Parthasarathy, S. Pragathi, P. Shanmugam, D. Baleanu, A.Ahmadian, and D. Kang. The novel augmented Fermatean MCDM perspectives for

identifying the optimal renewable energy power plant location. *Sustainable Energy Technologies and Assessments,* 53 (2022) 102488.

6. C.N.Wang, , Y.F. Huang, Y.C. Chai, and V. T. Nguyen. A multi-criteria decision making (MCDM) for renewable energy plants location selection in Vietnam under a fuzzy environment. *Applied Sciences*, 8(11) (2018) 2069.
7. G.M.Magableh, and N. K. Bazel. Exploring Future Renewable Energy Technologies Using a Developed Model and a Variety of MCDM Approaches. *Sustainability,* 17(7) (2025) 3057.
8. S.S.Goswami, T. Tapankumar, N. Channa Keshava Naik, J. Gowrishankar, Nilesh Bhosle, Amrita Singh, G. Sanyasi Raju, D. Nagesh, and A. Johnson Santhosh. Multi-model MCDM framework for sustainable renewable energy selection in India: integrating CRITIC-EDAS-CODAS-CoCoSo. *Discover Sustainability,* 6(1) (2025) 500.
9. P.Kut, and K. Pietrucha-Urbanik. Integration of Artificial Intelligence and MCDM Methods in the Evaluation of Renewable Energy Systems in a Hybrid and Critical Perspective. *Green Dimensions: Fundamental, Applied, and Industrial Aspects», June 5− 7, 2025 [Electronic resource], Mykolaiv: PMBSNU, 2025,* 100 (2025) 48.
10. S.K.Saraswat, A. K. Digalwar, and V. Vijay. Analysis of multi-renewable energy potential sites in India using spatial characteristics: a GIS and Hybrid MCDM approach. *Process Integration and Optimization for Sustainability,* 8(5) (2024) 1493-1526.
11. A. Soltani, M.A. Imani, Overcoming implementation barriers to renewable energy in developing nations: A case study of Iran using MCDM techniques and Monte Carlo simulation, *Results in Engineering*, 24 (2024) 103213.
12. T. Li, H. Wang, Y. Lin, Selection of renewable energy development path for sustainable development using a fuzzy MCDM based on cumulative prospect theory: The case of Malaysia, *Scientific Reports,* 14 (1) (2024) 15082.
13. N. Ajabnoor, A new approach of tree soft set with MCDM technique for leadership in international climate policy: Measuring renewable energy sources and policies, *Neutrosophic Sets and Systems,* 70 (1) (2024) 6.
14. S.K. Sahoo, B.B. Choudhury, P.R. Dhal, M.S. Hanspal, A comprehensive review of multi-criteria decision-making (MCDM) toward sustainable renewable energy development, *Spectrum of Operational Research*, 2 (1) (2025) 268–284.
15. N. Hashunao, B.A. Shimray, H. Kashung, A review survey on MCDM technique for usage in site selection of renewable energy, *Proc. 2024 IEEE 1st Int. Conf. on Green Industrial Electronics and Sustainable Technologies (GIEST), IEEE,* (2024) 1–6.
16. S. Hosouli, N. Gaikwad, S.H. Qamar, J. Gomes, Optimizing photovoltaic thermal (PVT) collector selection: A multi-criteria decision-making (MCDM) approach for renewable energy systems, *Heliyon*, 10 (6) (2024).
17. R. Akpahou, L.D. Mensah, D.A. Quansah, F. Kemausuor, Long-term energy demand modeling and optimal evaluation of solutions to renewable energy deployment barriers in Benin: A LEAP-MCDM approach, *Energy Reports,* 12 (2024) 1888–1904.
18. G.M. Magableh, M.Z. Mistarihi, *S.A. Dalu*, Innovative hybrid fuzzy MCDM techniques for adopting the appropriate renewable energy strategy, *Resources, Environment and Sustainability*, 21 (2025) 100234.

19. A. Gaurav, A. Tyagi, S.K. Jha, B. Kumar, Assessment using MCDM approach of renewable hybrid energy system with hydrogen production capability, *International Journal of Hydrogen Energy*, 137 (2025) 448–460.
20. N. Ersoy, Assessing renewable energy impact in Nordic-Baltic region: Sensitivity analysis and MCDM approach, *Renewable Energy Research and Applications*, 6 (1) (2025) 47–60.
21. P.S. Manoharan, K. Chidambarathanu, J. Vishnupriyan, Optimization of self-sufficient hybrid renewable energy source fed BWRO desalting plant through Fuzzy AHP and VIKOR MCDM techniques, *Desalination and Water Treatment,* (2025) 101215.
22. S. Liu, A quantum-inspired MADM method and the application in e-commerce recommendation, *Technological and Economic Development of Economy*, 24(5) (2018) 1941–1954.
23. G. Mukherjee, A. Mukherjee, S. Sinha, S. Bhadra, M. Halder, S. Haidar, A. Chakraborty, Quantum-enhanced solar site selection: A novel MCDM approach, *Journal of Electrical Systems*, 20 (2024) 1664–1678.
24. P. Mandal, L. Mrsic, A. Kalampakas, T. Allahviranloo and S. Samanta, Pythagorean linguistic information-based green supplier selection using quantum-based group decision-making methodology and the MULTIMOORA approach, *Artificial Intelligence Review, 58 (7) (2025) 199.*
25. Q. Wu, X. Liu, L. Zhou, Z. Tao, J. Qin, A quantum framework for modeling interference effects in linguistic distribution multiple criteria group decision making, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 52(6) (2021) 3492–3507.
26. S. Yan, Y. Zeng and N. Zhang, Multi-attribute quantum group decision-making method considering decision-makers' risk attitude, *Soft Computing,* 28 (6) (2024) 5339–5357.