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A Hybrid MCDM Approach Based on Fuzzy MEREC-G and Fuzzy RATMI

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Abstract: Multi-criteria decision-making (MCDM) assists in making judgments on complex problems by evaluating several alternatives based on conflicting criteria. Several MCDM methods have been introduced. However, real-world problems often involve uncertain and ambiguous decision-maker inputs. Therefore, fuzzy MCDM methods have emerged to handle this problem using fuzzy logic. Most recently, the method based on the removal effects of criteria using the geometric mean (MEREC-G) and ranking the alternatives based on the trace to median index (RATMI) were introduced. However, to date, there is no fuzzy extension of the two novel methods. This study introduces a new hybrid fuzzy MCDM approach combining fuzzy MEREC-G and fuzzy RATMI. The fuzzy MEREC-G can accept linguistic input terms from multiple decision-makers and generates consistent fuzzy weights. The fuzzy RATMI can rank alternatives according to their fuzzy performance scores on each criterion. The study provides the algorithms of both fuzzy MEREC-G and fuzzy RATMI and demonstrates their application in adopted real-world problems. Correlation and scenario analyses were performed to check the new approach's validity and sensitivity. The new approach demonstrates high accuracy and consistency and is sufficiently sensitive to changes in the criteria weights, yet not too sensitive to produce inconsistent rankings.

Keywords: fuzzy MEREC-G; fuzzy RATMI; fuzzy logic; hybrid; MCDM

MSC: 03E72; 90B50

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1. Introduction

Multi-criteria decision-making (MCDM), a major subdiscipline of the operations research domain, assists in making judgments in complex real-world challenges. It allows for formulating problems comprising several alternatives in a structured format to find the best ranking or select the best alternative based on multiple conflicting criteria. The criteria are conflicting in the sense of being benefit criteria and non-benefit criteria to reflect their roles in maximizing or minimizing the alternatives, respectively. Moreover, the criteria are weighted to represent the problem better and make the best decision on the alternatives. Several MCDM methods have emerged, with different characteristics and purposes, with broad applications in many disciplines [1,2]. The two primary components of MCDM are weighing the criteria and ranking the alternatives.

The first component of MCDM, weighting the criteria, entails designating importance or preference values to each criterion. Depending on whether the weights are based on quantified qualitative inputs from the decision-maker's judgments using a predefined scale (i.e., subjective data) [3–5], based on quantitative data (i.e., objective data) [6–10], or a combination of both (i.e., a mix of subjective and objective data) [11–13], there are various MCDM methods for weighting criteria. Methods like the analytic hierarchy process (AHP), analytic network process (ANP), and best-worst method (BWM) are examples of subjective methodologies for finding the weights of criteria [4,5]. These pairwise-based methods compare criteria using a scale of preferences to quantify qualitative inputs. Entropy and criteria importance through inter-criteria correlation (CRITIC) are examples of objective methods [14]. These data-based methods use mathematical algorithms to calculate the weights based on the information entropy, the correlation coefficients, or the compromise ranking of the alternatives. However, fuzzy AHP, fuzzy ANP, and fuzzy BWM accept a combination of subjective and objective data for finding the criteria weights. These methods base the calculations of weights in a fuzzy environment to account for uncertainty and ambiguity in decision-makers' inputs [15].

The second component of MCDM, ranking the alternatives, entails the performance scoring of each alternative on each criterion and finding the best ranking or choice accordingly. Various techniques for ranking alternatives based on multiple criteria have been developed. Such methods include outranking algorithms like "élimination et choix traduisant la realité" (ELECTRE), which translates to elimination and choice translating reality, and the preference ranking organization method for enrichment evaluations (PROMETHEE) [16–18], to mention two. These methods compare alternatives pair-wisely using measures of concordance and discordance between them on each criterion.

However, fuzzy MCDM alternative ranking methods have been developed and applied to enable them to handle the uncertainty and ambiguity of decision-makers' subjective scoring inputs. Such methods are the fuzzy BWM [19–26], fuzzy additive ratio assessment (ARAS) [27–29], fuzzy measurement alternatives and ranking according to compromise solution (MARCOS) [30–32], fuzzy technique for order preference by similarity to ideal solution (TOPSIS) [24,33,34], fuzzy multi-attributive border approximation area comparison (MABAC) [35–38], fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [39–42], fuzzy multi-attributive ideal–real comparative analysis (MAIRCA) [43–47], and, most recently, the fuzzy multiple criteria ranking by alternative trace (MCRAT) [48]. Several investigators applied the two components of MCDM in different fields [49–63].

Two of the most recent MCDM methods for weighting the criteria and ranking the alternatives are the method based on the removal effects of criteria (MEREC) [64–66] and ranking the alternatives based on the trace to median index (RATMI) techniques [67]. The MEREC was developed as an objective method for weighting the criteria. In 2023, an updated and enhanced version of the MEREC, labeled as the method for removal effects of criteria with a geometric mean (MEREC-G), was developed to enable it to process objective and subjective data [65]. Also, fuzzy extension and modification of the MEREC method were recently developed, enabling it to process subjective data using linguistic term judgments by decision-makers [68,69]. However, to date, there is no fuzzy extension to the enhanced MEREC-G. Additionally, in 2022, the RATMI was developed as an alternative ranking method. RATMI bases the ranking algorithm on the trace to median index, which combines ranking alternatives based on median similarity (RAMS), and the MCRAT methods, using a majority index and the concept of the VIKOR method [67]. In addition, despite this, the RATMI method is a relatively new alternative ranking method; it has proven its efficacy in real-world applications [70,71]. However, to date, there is no fuzzy extension to the RATMI method.

Therefore, this study aims to first develop a fuzzy MEREC-G as a weighting criteria method and a fuzzy RATMI as an alternative ranking method. Secondly, it proposes a new hybrid MCDM approach based on the developed fuzzy MEREC-G and fuzzy RATMI. The proposed new hybrid MCDM approach will provide advancements in that the fuzzy MEREC-G can accept linguistic input terms from multiple decision-makers, handle their ambiguous judgments on a complex problem, and produce consistent fuzzy weights of the criteria when converted to crisp values. This, in turn, will enable the use of the produced fuzzy weights from the fuzzy MEREC-G in the fuzzy RATMI, which will be able to accept and process fuzzy ranking scores of each alternative for each criterion and rank them accordingly.

The new proposed hybrid MCDM approach is provided in the following section. In the subsequent sections, along with a discussion, a numerical application of the proposed approach is provided to compare its results with other fuzzy MCDM methods to check its validity and sensitivity. Finally, the last section of this paper provides a conclusion to the proposed approach and some future research directions.

2. Preliminaries of Fuzzy Sets

Definition 1 ([69]). *$\tilde{a} = (k,\ l,\ m)$ is a representation of a triangular fuzzy number (TFN). The $\mu_{\tilde{a}}(z)$ membership function of a TEN, $\tilde{a}$, has the definition given by Equation (1).*

$$\mu_{\tilde{a}}(z) = \begin{cases} 0, & if\ z < k, \\ \frac{z-k}{l-k}, & if\ k \le z < l, \\ \frac{m-z}{m-l}, & if\ l \le z \le m, \\ 0, & if\ z > m, \end{cases} \tag{1}$$

Definition 2 ([72]). *Let $\tilde{x} = (a_1,\ b_1,\ c_1)$ and $\tilde{y} = (a_2,\ b_2,\ c_2)$ be two non-negative TFNs. According to the extension principle, the arithmetic operations are defined as follows:*

- $\tilde{x} \oplus \tilde{y} = (a_1 + a_2,\ b_1 + b_2,\ c_1 + c_2)$;
- $\tilde{x} \ominus \tilde{y} = (a_1 - c_2,\ b_1 - b_2,\ c_1 - a_2)$;
- $\alpha \odot \tilde{x} = (\alpha.a_1,\ \alpha.b_1,\ \alpha.c_1)$;
- $\tilde{x}^{-1} \cong \left(\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}\right)$;
- $\tilde{x} \otimes \tilde{y} \cong (a_1 \times a_2,\ b_1 \times b_2,\ c_1 \times c_2)$;
- $\tilde{x} \oplus \tilde{y} \cong (a_1/c_2,\ b_1/b_2,\ c_1/a_2)$.

3. The Proposed Hybrid Fuzzy MEREC-G and Fuzzy RATMI Methods

Figure 1 illustrates the proposed fuzzy MEREC-G and fuzzy RATMI methods in three main phases. The first phase involves defining the problem under study by specifying the alternatives and criteria with their objective. The decision-maker invites the experts who will provide their initial fuzzy decision matrices between the alternatives and criteria. The second phase applies the fuzzy MEREC-G method to assign weights to each criterion based on the information from the first phase. The third step uses the fuzzy RATMI method to rank the alternatives according to the weighted fuzzy criteria obtained in the second phase. The following sections explain these phases in more detail.

3.1. Phase 1: Formulate the Problem Using the MCDM Model

Step 1.1: The decision-maker identifies "m" possible alternatives, "n" relevant criteria, and the nature of each criterion (i.e., whether it is a benefit criterion that should be maximized or a non-benefit criterion that should be minimized) for the problem at hand.

Step 1.2: The decision-maker determines "k" experts who have knowledge and experience about the problem to participate in the decision-making process by providing either subjective or objective input data represented by triangular fuzzy numbers (TFNs).

Step 1.3: The experts, $E = \{E_1,\ E_2,\ \ldots,\ E_k\}$, will provide a realistic evaluation of each alternative in $A = \{A_1,\ A_2,\ \ldots,\ A_m\}$ based on each criterion in $C = \{C_1,\ C_2,\ \ldots,\ C_n\}$, which is represented by the fuzzy number $x_{ij}^u = \left(a_{ij}^u,\ b_{ij}^u, c_{ij}^u\right)$, $i = 1, \ldots, m; j = 1, \ldots, n; u = 1, \ldots, k$. The fuzzy decision matrix, X^u, for each expert, "u", can be constructed using Equation (2).

$$X^u = \left[x_{ij}^u\right]_{mxn} = \begin{bmatrix} A/C & C_1 & C_2 & \cdots & C_n \\ A_1 & x_{11}^u & x_{12}^u & \cdots & x_{1n}^u \\ A_2 & x_{21}^u & x_{22}^u & \cdots & x_{2n}^u \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & x_{m1}^u & x_{m2}^u & \cdots & x_{mn}^u \end{bmatrix} \tag{2}$$

Step 1.4: Construct the combined fuzzy decision matrix, $\tilde{X}$, using Equation (3).

$$\tilde{X} = [\tilde{x}_{ij}]_{mxn} \tag{3}$$

where

$$\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}) , a_{ij} = min_k\left(a_{ij}^k\right) , b_{ij} = \frac{1}{k}\left(\sum_{u=1}^{k} b_{ij}^u\right) , and\ c_{ij} = max_k\left(c_{ij}^k\right).$$

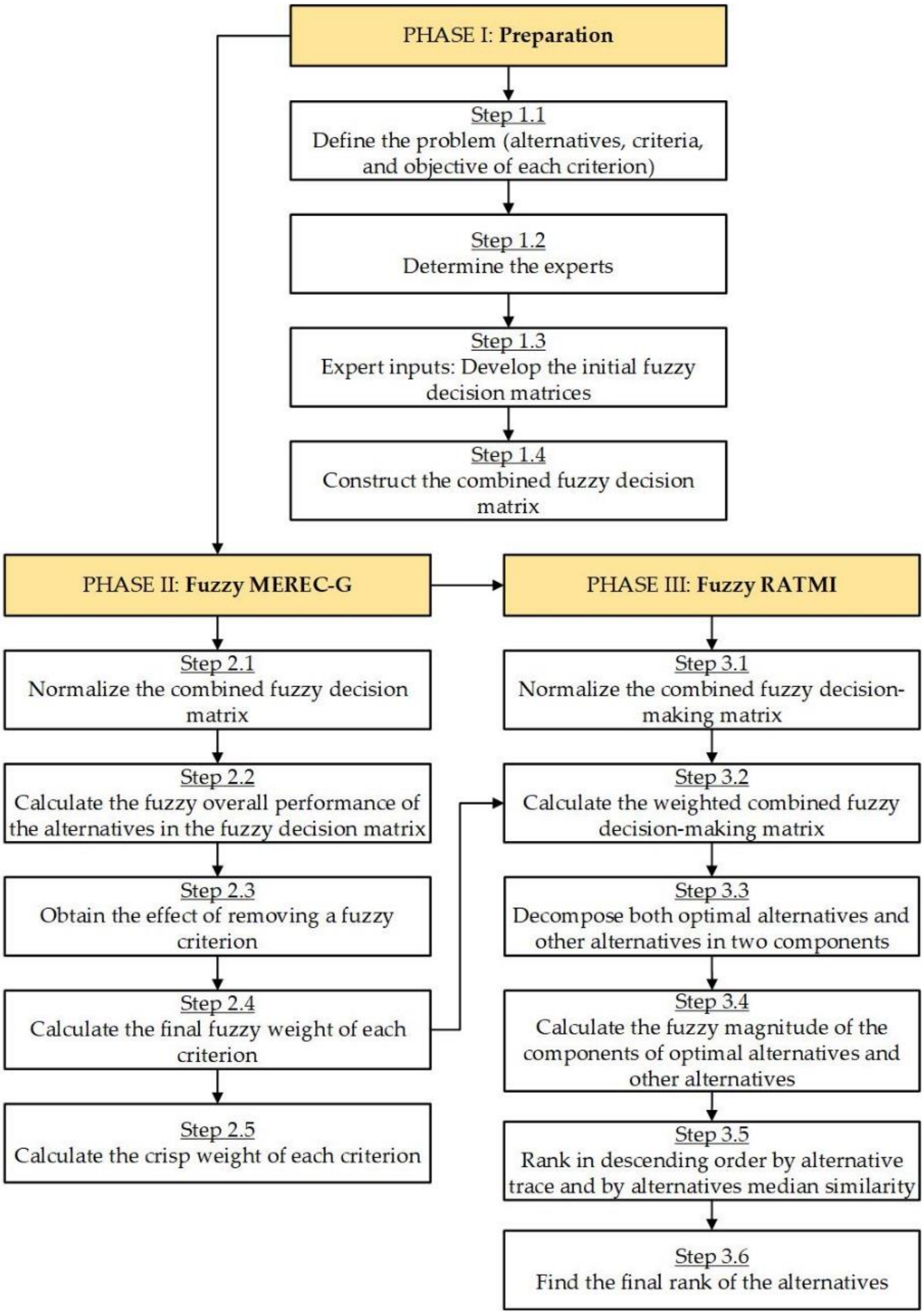

Figure 1. The framework of the proposed hybrid fuzzy MEREC-G and fuzzy RATMI methods.

3.2. Phase 2: Fuzzy MEREC-G Method

Step 2.1: Normalize the combined fuzzy decision matrix to reduce the disparity between the magnitude of alternatives and dimensions, with a normalized value within

[0, 1]. The component of a normalized matrix, $\tilde{e}_{ij}$, will be produced by the triangular fuzzy number (TFN) according to [69] using Equation (4) for benefit criteria and Equation (5) for non-benefit criteria.

$$\tilde{e}_{ij} = \left(r_{ij}^{l},\ r_{ij}^{m},\ r_{ij}^{u}\right) = \left(\frac{a_{ij}}{c_j^{max}},\ \frac{b_{ij}}{c_j^{max}},\ \frac{c_{ij}}{c_j^{max}}\right) \quad \forall\, i \in [1,\ \ldots,\ m]\ ,\ \forall\, j \in [1,\ \ldots,\ n] \tag{4}$$

$$\tilde{e}_{ij} = \left(r_{ij}^{l},\ r_{ij}^{m},\ r_{ij}^{u}\right) = \left(\frac{a_j^{min}}{c_{ij}},\ \frac{a_j^{min}}{b_{ij}},\ \frac{a_j^{min}}{a_{ij}}\right) \quad \forall\, i \in [1,\ \ldots,\ m]\ ,\ \forall\, j \in [1,\ \ldots,\ n] \tag{5}$$

Step 2.2: Calculate the fuzzy overall performance value, $\tilde{P}_i$, of the alternatives using the geometric mean of the fuzzy normalized matrix, as presented by Equation (6).

$$\tilde{P}_i = \left(\sqrt[n]{\prod_{j=1}^{n} r_{ij}^{l}},\ \sqrt[n]{\prod_{j=1}^{n} r_{ij}^{m}}\ ,\ \sqrt[n]{\prod_{j=1}^{n} r_{ij}^{u}}\right) \quad \forall\, i \in [1,\ \ldots,\ m] \tag{6}$$

Step 2.3: This step considers the core of the classical MEREC-G [65], in which the changes in the overall performance value of the alternatives will be calculated by removing the effect of each criterion from the overall performance. This step can be calculated for the fuzzy MEREC-G using Equation (7) to find the changes represented by the fuzzy number, $\tilde{t}_{ij}$.

$$\tilde{t}_{ij} = \left(\sqrt[n]{\frac{\prod_{j=1}^{n} r_{ij}^{l}}{r_{ik}^{l}}}\ ,\ \sqrt[n]{\frac{\prod_{j=1}^{n} r_{ij}^{m}}{r_{ik}^{m}}}\ ,\ \sqrt[n]{\frac{\prod_{j}^{n} r_{ij}^{u}}{r_{ik}^{u}}}\right) \quad \forall\, i \in [1, \ldots, m]\ ,\ k \neq j \tag{7}$$

Step 2.4: Find the removal effect, $\tilde{E}_j$, using Equation (8) to obtain the final fuzzy weights, $\tilde{w}_j$, of each criterion using Equation (9) and Equation (10).

$$\tilde{E}_j = \left(\sum_{i=1}^{m} \tilde{t}_{ij}^{l}\ ,\sum_{i=1}^{m} \tilde{t}_{ij}^{m}\ ,\ \sum_{i=1}^{m} \tilde{t}_{ij}^{u}\right) \quad \forall\, j \in [1, \ldots, n] \tag{8}$$

$$\tilde{w}_j = \left(\frac{\sum_{i=1}^{m} \tilde{t}_{ij}^{l}}{\sum_{j=1}^{n} \tilde{E}_j^{u}}\ ,\ \frac{\sum_{i=1}^{m} \tilde{t}_{ij}^{m}}{\sum_{j=1}^{n} \tilde{E}_j^{m}}\ ,\ \frac{\sum_{i=1}^{m} \tilde{t}_{ij}^{u}}{\sum_{j=1}^{n} \tilde{E}_j^{l}}\right) \quad \forall\, j \in [1, \ldots, n] \tag{9}$$

$$\tilde{w}_j = \left(w_j^{l}\ ,\ w_j^{m}\ , w_j^{u}\right) \quad \forall\, j \in [1, \ldots, n] \tag{10}$$

Step 2.5: To obtain the crisp weights, w_j^*, of the criteria, the obtained fuzzy weights, $\tilde{w}_j$, are converted using Equation (11). The sum of the crisp weights equals one.

$$w_j^* = \frac{w_j^{l} + 4w_j^{m} + w_j^{u}}{6} \tag{11}$$

3.3. Phase 3: Fuzzy RATMI Method

Step 3.1: The values in the combined fuzzy decision-making matrix will be normalized by the Equations (4) and (5) that are used for the fuzzy MEREC-G technique.

Step 3.2: The fuzzy weights of the criteria are multiplied by the fuzzy normalized values to obtain fuzzy weighted normalized values using Equation (12).

$$\tilde{g}_{ij} = \left(g_{ij}^{l},\ g_{ij}^{m},\ g_{ij}^{u}\right) = \tilde{w}_j \times \tilde{e}_{ij} = \left(w_j^{l} \times r_{ij}^{l}, w_j^{m} \times r_{ij}^{m},\ w_j^{l} \times r_{ij}^{u}\right) \tag{12}$$

Step 3.3: Determine the fuzzy optimal alternative using Equations (13) and (14). Then, decompose the fuzzy optimal alternative into two components using Equations (15) and (16), followed by decomposing the other alternatives into two components using Equations (17) and (18).

$$\tilde{q}_j = max\left(\tilde{g}_{ij} \middle| 1 \leq j \leq n\right) \tag{13}$$

$$\tilde{Q} = \{\tilde{q}_1,\ \tilde{q}_2,\ \ldots,\ \tilde{q}_n\} \tag{14}$$

$$\tilde{Q} = \tilde{Q}^{max} \cup \tilde{Q}^{min} \tag{15}$$

$$\tilde{Q} = \{\tilde{q}_1,\ \tilde{q}_2,\ \ldots,\ \tilde{q}_k\} \cup \{\tilde{q}_1,\ \tilde{q}_2,\ \ldots,\ \tilde{q}_h\}; k+h=j \tag{16}$$

$$\tilde{V} = \tilde{V}^{max} \cup \tilde{V}^{min} \tag{17}$$

$$\tilde{V} = \{\tilde{v}_1,\ \tilde{v}_2,\ \ldots,\ \tilde{v}_k\} \cup \{\tilde{v}_1,\ \tilde{v}_2,\ \ldots,\ \tilde{v}_h\}; k+h=j \tag{18}$$

Step 3.4: Calculate the fuzzy magnitude of optimal alternative components using Equations (19) and (20) and the fuzzy magnitude of other alternative components using Equations (21) and (22).

$$\tilde{Q}_k = \left(q_k^l,\ q_k^m,\ q_k^u\right) = \left(\sqrt{\left(q_1^l\right)^2 + \left(q_2^l\right)^2 + \ldots + \left(q_k^l\right)^2}, \sqrt{\left(q_1^m\right)^2 + \left(q_2^m\right)^2 + \ldots + \left(q_k^m\right)^2},\ \sqrt{\left(q_1^u\right)^2 + \left(q_2^u\right)^2 + \ldots + \left(q_k^u\right)^2}\right) \tag{19}$$

$$\tilde{Q}_h = \left(q_h^l,\ q_h^m,\ q_h^u\right) = \left(\sqrt{\left(q_1^l\right)^2 + \left(q_2^l\right)^2 + \ldots + \left(q_h^l\right)^2}, \sqrt{\left(q_1^m\right)^2 + \left(q_2^m\right)^2 + \ldots + \left(q_h^m\right)^2},\ \sqrt{\left(q_1^u\right)^2 + \left(q_2^u\right)^2 + \ldots + \left(q_h^u\right)^2}\right) \tag{20}$$

$$\tilde{V}_k = \left(v_k^l,\ v_k^m,\ v_k^u\right) = \left(\sqrt{\left(v_1^l\right)^2 + \left(v_2^l\right)^2 + \ldots + \left(v_k^l\right)^2}, \sqrt{\left(v_1^m\right)^2 + \left(v_2^m\right)^2 + \ldots + \left(v_k^m\right)^2},\ \sqrt{\left(v_1^u\right)^2 + \left(v_2^u\right)^2 + \ldots + \left(v_k^u\right)^2}\right) \tag{21}$$

$$\tilde{V}_h = \left(v_h^l,\ v_h^m,\ v_h^u\right) = \left(\sqrt{\left(v_1^l\right)^2 + \left(v_2^l\right)^2 + \ldots + \left(v_h^l\right)^2}, \sqrt{\left(v_1^m\right)^2 + \left(v_2^m\right)^2 + \ldots + \left(v_h^m\right)^2},\ \sqrt{\left(v_1^u\right)^2 + \left(v_2^u\right)^2 + \ldots + \left(v_h^u\right)^2}\right) \tag{22}$$

Step 3.5: In this step, the alternatives will be ranked twice. The first uses the fuzzy MCRAT [48], and the second uses fuzzy RAMS as a part of the proposed fuzzy RATMI. Ranking by fuzzy MCRAT uses the following sub-steps:

Step 3.5.1: Create the matrix, $\tilde{Y}$, composed of the optimal alternative component, as shown in Equation (23).

$$\tilde{Y} = \begin{bmatrix} \tilde{Q}_k & 0 \\ 0 & \tilde{Q}_h \end{bmatrix} \tag{23}$$

Step 3.5.2: Create the matrix, $\tilde{B}_i$, composed of the alternative's component using Equation (24).

$$\tilde{B}_i = \begin{bmatrix} \tilde{V}_{ik} & 0 \\ 0 & \tilde{V}_{ih} \end{bmatrix} \tag{24}$$

Step 3.5.3: Create the matrix, $\tilde{Z}_i$, using Equation (25).

$$\tilde{Z}_i = \tilde{Y} \times \tilde{B}_i = \begin{bmatrix} \tilde{z}_{11;i} & 0 \\ 0 & \tilde{z}_{22;i} \end{bmatrix} \tag{25}$$

Step 3.5.4: Then, the fuzzy trace of the matrix, $\tilde{Z}_i$, can be obtained using Equation (26).

$$tr\left(\tilde{Z}_i\right) = \tilde{z}_{11;i} + \tilde{z}_{22;i} = \left(z_{11,i}^l + z_{22,i}^l,\ z_{11,i}^m + z_{22,i}^m,\ z_{11,i}^u + z_{22,i}^u\right) \tag{26}$$

In Equation (26), $tr\left(\tilde{Z}_i\right) = \left(Z_i^l,\ Z_i^m,\ Z_i^u\right)$ indicates the fuzzy trace of the Z_i matrix, and the value is defuzzied to obtain $tr(Z_i)$ by using Equation (27). Here, rank the alternatives in descending order of the $tr(Z_i)$ values.

$$Z_i = \frac{Z_j^l + 4Z_j^m + Z_j^u}{6} \tag{27}$$

Ranking by fuzzy alternatives median similarity (RAMS) uses the following sub-steps:

Step 3.5.5: Determine the fuzzy median of similarity of the optimal alternative using Equation (28).

$$\tilde{D} = \left(d^l,\ d^m,\ d^u\right) = \left(\sqrt{\tilde{Q}_k^2 + \tilde{Q}_h^2}\right)/2 \tag{28}$$

Step 3.5.6: Determine the fuzzy median of similarity of the alternatives using Equation (29).

$$\tilde{D}_i = \left(d_i^l,\ d_i^m,\ d_i^l\right) = \left(\sqrt{\tilde{V}_{ik}^2 + \tilde{V}_{ih}^2}\right)/2 \tag{29}$$

Step 3.5.7: Calculate the fuzzy median similarity, $ms(\tilde{M}_i)$, which represents the ratio between the perimeter of each alternative and the optimal alternative using Equation (30).

$$ms(\tilde{M}_i) = \frac{\tilde{D}_i}{\tilde{D}} = \left(\frac{d_i^l}{d^u}, \frac{d_i^m}{d^m}, \frac{d_i^u}{d^l}\right) \tag{30}$$

In Equation (30), $ms(\tilde{M}_i) = \left(M_i^l,\ M_i^m,\ M_i^u\right)$ indicates the median similarity of the M_i matrix, and the value is defuzzied to obtain $ms(M_i)$ by using Equation (31). Here, rank the alternatives in descending order of the $ms(M_i)$ values.

$$M_i = \frac{M_j^l + 4M_j^m + M_j^u}{6} \tag{31}$$

Step 3.6: If v is the weight of fuzzy MCRAT's strategy, and $(1 - v)$ is the weight of RAMS's strategy, then the majority index, E_i, between the two strategies can be calculated using Equation (32). Then, find the final rank of the alternatives in descending order of E_i.

$$E_i = v\frac{(tr(Z_i) - tr^*)}{(tr^- - tr^*)} + (1 - v)\frac{(ms(M_i) - ms^*)}{(ms^- - ms^*)} \tag{32}$$

where
$tr^* = \min(tr(Z_i),\ \forall i \in [1,\ 2,\ \ldots,\ m])$;
$tr^- = \max\ (tr(Z_i), \forall i \in [1,\ 2,\ \ldots,\ m])$;
$ms^* = \min\ (ms(M_i), \forall i \in [1,\ 2,\ \ldots,\ m])$;
$ms^- = \max(ms(M_i),\ \forall i \in [1,\ 2,\ \ldots,\ m])$;
v is a value from 0 to 1. Here, v = 0.5.

4. Applications and Results

This section applies the proposed hybrid fuzzy MEREC-G and fuzzy RATMI methods using the data from Ulutaş et al. [48] to purchase a forklift that laborers can use in the warehouse. The following is an application of the three phases previously mentioned to rank the alternatives based on weighted criteria.

4.1. Phase 1: Formulate the Problem Using the MCDM Model

Following step 1.1, the decision-maker determined eight criteria and six forklifts as alternatives. The criteria for assessment of the forklifts were C_1 (purchasing price), C_2 (lifting height), C_3 (lowering speed), C_4 (loading capacity), C_5 (lifting speed), C_6 (movement area requirement), C_7 (image of the manufacturer company), and C_8 (supply of spare parts). Only two criteria (C_1 and C_6) were non-benefit, and the others were benefit criteria. Using steps 1.2, 1.3, and 1.4, the decision maker determined six experts to evaluate the performance of the forklifts under each criterion using the linguistic phrases shown in Stanković et al. [31]. The experts' assessments were transformed into fuzzy values using those linguistic phrases and aggregated using Equation (3). The combined fuzzy decision matrix, as given by Ulutaş et al. [48], is presented in Table 1.

Table 1. The combined fuzzy decision matrix [48].

Alternatives	C_1	C_2	C_3	C_4
A1	(4.0000, 5.6670, 6.0000)	(5.3330, 6.3330, 7.3330)	(2.0000, 3.0000, 4.0000)	(5.6670, 6.6670, 7.6670)
A2	(5.0000, 5.6670, 7.0000)	(5.3330, 6.3330, 7.3330)	(3.6670, 5.0000, 5.6670)	(4.0000, 5.0000, 6.0000)
A3	(5.6670, 7.3330, 7.6670)	(6.6670, 7.3330, 8.6670)	(4.0000, 5.6670, 6.0000)	(5.6670, 6.6670, 7.6670)
A4	(5.6670, 7.3330, 7.6670)	(5.6670, 6.6670, 7.6670)	(4.0000, 5.6670, 6.0000)	(5.6670, 6.6670, 7.6670)
A5	(5.0000, 6.0000, 7.0000)	(5.6670, 6.6670, 7.6670)	(4.0000, 5.6670, 6.0000)	(4.0000, 5.0000, 6.0000)
A6	(5.0000, 6.0000, 7.0000)	(5.6670, 6.3330, 7.6670)	(4.0000, 5.6670, 6.0000)	(4.0000, 5.0000, 6.0000)
Alternatives	C_5	C_6	C_7	C_8
A1	(4.3330, 5.3330, 6.3330)	(5.3330, 6.3330, 7.3330)	(5.3330, 6.0000, 7.3330)	(4.6670, 5.6670, 6.6670)
A2	(4.3330, 5.3330, 6.3330)	(6.3330, 7.3330, 8.3330)	(6.0000, 6.6670, 8.0000)	(5.6670, 6.0000, 7.6670)
A3	(6.0000, 7.0000, 8.0000)	(6.3330, 7.3330, 8.3330)	(6.0000, 7.0000, 8.0000)	(5.0000, 6.0000, 7.0000)
A4	(6.0000, 7.0000, 8.0000)	(6.3330, 7.3330, 8.3330)	(5.3330, 6.0000, 7.3330)	(4.6670, 5.6670, 6.6670)
A5	(4.3330, 6.0000, 6.3330)	(5.3330, 6.3330, 7.3330)	(5.6670, 6.0000, 7.6670)	(5.0000, 6.0000, 7.0000)
A6	(4.3330, 5.6670, 6.3330)	(5.0000, 5.6670, 7.0000)	(5.0000, 5.6670, 7.0000)	(5.6670, 6.3330, 7.6670)

4.2. Phase 2: Application and Results of the Fuzzy MEREC-G Method

Equations (4) and (5) of step 2.1 have been used to determine the fuzzy decision matrix with normalization. Table 2 presents the results obtained from this step.

Table 2. The normalized fuzzy decision matrix.

Alternatives	C_1	C_2	C_3	C_4
A1	(0.6667, 0.7058, 1.0000)	(0.6153, 0.7307, 0.8461)	(0.3333, 0.5000, 0.6667)	(0.7391, 0.8696, 1.0000)
A2	(0.5714, 0.7058, 0.8000)	(0.6153, 0.7307, 0.8461)	(0.6112, 0.8333, 0.9445)	(0.5217, 0.6521, 0.7826)
A3	(0.5217, 0.5455, 0.7058)	(0.7692, 0.8461, 1.0000)	(0.6667, 0.9445, 1.0000)	(0.7391, 0.8696, 1.0000)
A4	(0.5217, 0.5455, 0.7058)	(0.6539, 0.7692, 0.8846)	(0.6667, 0.9445, 1.0000)	(0.7391, 0.8696, 1.0000)
A5	(0.5714, 0.6667, 0.8000)	(0.6539, 0.7692, 0.8846)	(0.6667, 0.9445, 1.0000)	(0.5217, 0.6521, 0.7826)
A6	(0.5714, 0.6667, 0.8000)	(0.6539, 0.7307, 0.8846)	(0.6667, 0.9445, 1.0000)	(0.5217, 0.6521, 0.7826)
Alternatives	C_5	C_6	C_7	C_8
A1	(0.5416, 0.6666, 0.7916)	(0.6818, 0.7895, 0.9376)	(0.6666, 0.7500, 0.9166)	(0.6087, 0.7391, 0.8696)
A2	(0.5416, 0.6666, 0.7916)	(0.6000, 0.6818, 0.7895)	(0.7500, 0.8334, 1.0000)	(0.7391, 0.7826, 1.0000)
A3	(0.7500, 0.8750, 1.0000)	(0.6000, 0.6818, 0.7895)	(0.7500, 0.8750, 1.0000)	(0.6521, 0.7826, 0.9130)
A4	(0.7500, 0.8750, 1.0000)	(0.6000, 0.6818, 0.7895)	(0.6666, 0.7500, 0.9166)	(0.6087, 0.7391, 0.8696)
A5	(0.5416, 0.7500, 0.7916)	(0.6818, 0.7895, 0.9376)	(0.7084, 0.7500, 0.9584)	(0.6521, 0.7826, 0.9130)
A6	(0.5416, 0.7084, 0.7916)	(0.7143, 0.8823, 1.0000)	(0.6250, 0.7084, 0.8750)	(0.7391, 0.8260, 1.0000)

Steps 2.2 and 2.3 have been applied with the help of Equations (6) and (7), respectively, to calculate the overall performance of alternatives in the fuzzy decision matrix and then calculate the changes in this overall performance by removing each fuzzy number. Table 3 shows the results of Equation (7) of step 2.3.

Table 3. The changes in the overall performance of alternatives.

Alternatives	C_1	C_2	C_3	C_4
A1	(0.6231, 0.7428, 0.8718)	(0.6294, 0.7396, 0.8902)	(0.6795, 0.7755, 0.9171)	(0.6151, 0.7237, 0.8718)
A2	(0.6585, 0.7653, 0.8892)	(0.6524, 0.7620, 0.8830)	(0.6530, 0.7496, 0.8709)	(0.6660, 0.7729, 0.8917)
A3	(0.7331, 0.8544, 0.9599)	(0.6984, 0.8088, 0.9190)	(0.7110, 0.7977, 0.9190)	(0.7019, 0.8060, 0.9190)
A4	(0.7018, 0.8223, 0.9294)	(0.6823, 0.7877, 0.9035)	(0.6806, 0.7677, 0.8898)	(0.6719, 0.7757, 0.8898)
A5	(0.6662, 0.7981, 0.9049)	(0.6551, 0.7840, 0.8936)	(0.6535, 0.7641, 0.8800)	(0.6738, 0.8003, 0.9074)
A6	(0.6701, 0.7981, 0.9122)	(0.6589, 0.7890, 0.9008)	(0.6573, 0.7641, 0.8871)	(0.6777, 0.8003, 0.9147)

Table 3. *Cont.*

Alternatives	C_5	C_6	C_7	C_8
A1	(0.5999, 0.7178, 0.8839)	(0.5805, 0.7006, 0.8628)	(0.5824, 0.7058, 0.8656)	(0.5900, 0.7073, 0.8721)
A2	(0.6251, 0.7427, 0.8757)	(0.6160, 0.7403, 0.8761)	(0.5967, 0.7194, 0.8470)	(0.5979, 0.7259, 0.8470)
A3	(0.6659, 0.7808, 0.9080)	(0.6874, 0.8092, 0.9392)	(0.6659, 0.7808, 0.9080)	(0.6793, 0.7934, 0.9199)
A4	(0.6335, 0.7474, 0.8751)	(0.6540, 0.7745, 0.9051)	(0.6442, 0.7640, 0.8860)	(0.6526, 0.7656, 0.8927)
A5	(0.6335, 0.7599, 0.8934)	(0.6130, 0.7544, 0.8721)	(0.6096, 0.7599, 0.8694)	(0.6169, 0.7553, 0.8754)
A6	(0.6377, 0.7661, 0.9017)	(0.6130, 0.7425, 0.8721)	(0.6248, 0.7661, 0.8889)	(0.6100, 0.7495, 0.8721)

Equations (8)–(10) from step 2.4 have been used to calculate the fuzzy criteria weight of each criterion. Then, Equation (11) from step 2.5 was used to calculate the crisp value of each criterion. Table 4 shows the results of these calculations.

Table 4. Resulting effect and weights of the fuzzy MEREC-G.

Removal effect	$\tilde{E}_1$	$\tilde{E}_2$	$\tilde{E}_3$	$\tilde{E}_4$
	(4.0527, 4.7810, 5.4674)	(3.9764, 4.6710, 5.3902)	(4.0348, 4.6188, 5.3640)	(4.0064, 4.6790, 5.3944)
	$\tilde{E}_5$	$\tilde{E}_6$	$\tilde{E}_7$	$\tilde{E}_8$
	(3.7955, 4.5147, 5.3378)	(3.7639, 4.5214, 5.3273)	(3.7236, 4.4961, 5.2648)	(3.7467, 4.4970, 5.2792)
Fuzzy weights	$\tilde{w}_1$	$\tilde{w}_2$	$\tilde{w}_3$	$\tilde{w}_4$
	(0.0946, 0.1300, 0.1758)	(0.0929, 0.1270, 0.1733)	(0.0942, 0.1256, 0.1725)	(0.0936, 0.1272, 0.1735)
	$\tilde{w}_5$	$\tilde{w}_6$	$\tilde{w}_7$	$\tilde{w}_8$
	(0.0886, 0.1228, 0.1716)	(0.0879, 0.1229, 0.1713)	(0.0869, 0.1222, 0.1693)	(0.0875, 0.1223, 0.1697)
Crisp weights	w_1^*	w_2^*	w_3^*	w_4^*
	0.1317	0.1290	0.1282	0.1293
	w_5^*	w_6^*	w_7^*	w_8^*
	0.1252	0.1252	0.1242	0.1244

4.3. Phase 3: Application and Results of the Fuzzy RATMI Method

The fuzzy MEREC-G method is used to determine the fuzzy criteria weights, which are then combined with the decision matrix to form the decision-making matrix. The fuzzy RATMI method is applied to this matrix to rank the alternatives. From step 3.1, the fuzzy decision-making matrix is normalized using Equations (4) and (5), which are the same as those used in the fuzzy MEREC-G. The fuzzy weighted decision-making matrix is obtained using Equation (12) from step 3.2 and shown in Table 5.

First, the fuzzy optimal alternatives are determined using Equations (13) and (14), and then they are decomposed into their components using Equations (15) and (16). Next, Equations (17) and (18) are used to decompose the alternatives into their components. Finally, the fuzzy magnitude of the components is calculated using Equations (19) and (20). The values of the fuzzy magnitude of components are shown in Table 6.

The same process is performed for the alternatives using Equations (21) and (22). Then, with Equations (23)–(25), the values of $\tilde{z}_{11;i}$ and $\tilde{z}_{22;i}$, which are the elements of the $\tilde{Z}_i$, are found. Equation (26) is used to obtain the fuzzy trace, $tr(\tilde{Z}_i)$, of the matrix, $\tilde{Z}_i$. Finally, this fuzzy value is defuzzified using Equation (27). Table 7 shows these values and the results of the fuzzy MCRAT method.

Table 5. The fuzzy weighted decision-making matrix.

Alternatives	C_1	C_2	C_3	C_4
A1	(0.0631, 0.0918, 0.1758)	(0.0571, 0.0928, 0.1466)	(0.0314, 0.0628, 0.1150)	(0.0691, 0.1106, 0.1735)
A2	(0.0541, 0.0918, 0.1406)	(0.0571, 0.0928, 0.1466)	(0.0576, 0.1047, 0.1629)	(0.0488, 0.0830, 0.1357)
A3	(0.0494, 0.0709, 0.1241)	(0.0714, 0.1075, 0.1733)	(0.0628, 0.1186, 0.1725)	(0.0691, 0.1106, 0.1735)
A4	(0.0494, 0.0709, 0.1241)	(0.0607, 0.0977, 0.1533)	(0.0628, 0.1186, 0.1725)	(0.0691, 0.1106, 0.1735)
A5	(0.0541, 0.0867, 0.1406)	(0.0607, 0.0977, 0.1533)	(0.0628, 0.1186, 0.1725)	(0.0488, 0.0830, 0.1357)
A6	(0.0541, 0.0867, 0.1406)	(0.0607, 0.0928, 0.1533)	(0.0628, 0.1186, 0.1725)	(0.0488, 0.0830, 0.1357)
Alternatives	C_5	C_6	C_7	C_8
A1	(0.0480, 0.0818, 0.1359)	(0.0599, 0.0971, 0.1606)	(0.0580, 0.0917, 0.1552)	(0.0533, 0.0904, 0.1476)
A2	(0.0480, 0.0818, 0.1359)	(0.0527, 0.0838, 0.1352)	(0.0652, 0.1019, 0.1693)	(0.0647, 0.0957, 0.1697)
A3	(0.0665, 0.1074, 0.1716)	(0.0527, 0.0838, 0.1352)	(0.0652, 0.1070, 0.1693)	(0.0571, 0.0957, 0.1550)
A4	(0.0665, 0.1074, 0.1716)	(0.0527, 0.0838, 0.1352)	(0.0580, 0.0917, 0.1552)	(0.0533, 0.0904, 0.1476)
A5	(0.0480, 0.0921, 0.1359)	(0.0599, 0.0971, 0.1606)	(0.0616, 0.0917, 0.1622)	(0.0571, 0.0957, 0.1550)
A6	(0.0480, 0.0870, 0.1359)	(0.0628, 0.1085, 0.1713)	(0.0543, 0.0866, 0.1481)	(0.0647, 0.1010, 0.1697)

Table 6. The fuzzy magnitude of components' values.

Components	Magnitude
$\tilde{Q}_k$	(0.1633, 0.2665, 0.4205)
$\tilde{Q}_h$	(0.0890, 0.1421, 0.2455)

Table 7. Results of the fuzzy MCRAT method.

Alternatives	$\tilde{V}_{ik}$	$\tilde{V}_{ih}$	$\tilde{z}_{11;i}$	$\tilde{z}_{22;i}$
A1	(0.1324, 0.2192, 0.3594)	(0.0870, 0.1336, 0.2381)	(0.0216, 0.0584, 0.1511)	(0.0077, 0.0190, 0.0584)
A2	(0.1404, 0.2295, 0.3774)	(0.0755, 0.1243, 0.1951)	(0.0229, 0.0612, 0.1587)	(0.0067, 0.0177, 0.0479)
A3	(0.1605, 0.2646, 0.4147)	(0.0722, 0.1098, 0.1835)	(0.0262, 0.0705, 0.1744)	(0.0064, 0.0156, 0.0451)
A4	(0.1517, 0.2529, 0.3983)	(0.0722, 0.1098, 0.1835)	(0.0248, 0.0674, 0.1675)	(0.0064, 0.0156, 0.0451)
A5	(0.1392, 0.2378, 0.3748)	(0.0807, 0.1301, 0.2135)	(0.0227, 0.0634, 0.1576)	(0.0072, 0.0185, 0.0524)
A6	(0.1395, 0.2341, 0.3754)	(0.0829, 0.1388, 0.2216)	(0.0228, 0.0624, 0.1578)	(0.0074, 0.0197, 0.0544)
Alternatives	$tr(\tilde{Z}_i)$	$tr(Z_i)$	**Rankings**	
A1	(0.0294, 0.0774, 0.2095)	0.0914	6	
A2	(0.0296, 0.0788, 0.2066)	0.0919	5	
A3	(0.0326, 0.0861, 0.2194)	0.0994	1	
A4	(0.0312, 0.0830, 0.2125)	0.0960	2	
A5	(0.0299, 0.0819, 0.2100)	0.0946	4	
A6	(0.0302, 0.0821, 0.2122)	0.0952	3	

Another ranking will be obtained by the fuzzy RAMS method. In this method, the alternatives are ranked based on the median similarity between the optimal alternatives and other alternatives by applying Equations (28)–(31). This was followed by finding the majority index between the fuzzy MCRAT and fuzzy RAMS methods using Equation (32) with $v = 0.5$. The results of these calculations are shown in Tables 8 and 9, along with the alternative rankings according to the fuzzy RATMI method.

Table 8. Results of the fuzzy RAMS technique.

Alternatives	Max	Min	Median	Median similarity
	$\tilde{Q}_k$	$\tilde{Q}_h$	$\tilde{D}$	$ms(\tilde{M}_i)$
	(0.1633, 0.2665, 0.4205)	(0.0890, 0.1421, 0.2455)	(0.0930, 0.1510, 0.2434)	
	$\tilde{V}_{ik}$	$\tilde{V}_{ih}$	$\tilde{D}_i$	
A1	(0.1324, 0.2192, 0.3594)	(0.0870, 0.1336, 0.2381)	(0.0792, 0.1284, 0.2155)	(0.3254, 0.8500, 2.3175)
A2	(0.1404, 0.2295, 0.3774)	(0.0755, 0.1243, 0.1951)	(0.0797, 0.1305, 0.2124)	(1.4031, 2.2837, 15.0859)
A3	(0.1605, 0.2646, 0.4147)	(0.0722, 0.1098, 0.1835)	(0.0880, 0.1432, 0.2268)	(1.5398, 2.4381, 16.5554)
A4	(0.1517, 0.2529, 0.3983)	(0.0722, 0.1098, 0.1835)	(0.0840, 0.1379, 0.2193)	(1.4822, 2.3577, 15.9359)
A5	(0.1392, 0.2378, 0.3748)	(0.0807, 0.1301, 0.2135)	(0.0804, 0.1355, 0.2157)	(1.4571, 2.3188, 15.6662)
A6	(0.1395, 0.2341, 0.3754)	(0.0829, 0.1388, 0.2216)	(0.0811, 0.1361, 0.2180)	(1.4634, 2.3434, 15.7337)
Alternatives	$ms(M_i)$	**Rankings**		
A1	1.0071	6		
A2	1.0113	5		
A3	1.0989	1		
A4	1.0591	2		
A5	1.0398	4		
A6	1.0470	3		

Table 9. Alternatives rankings according to the fuzzy RATMI method.

Alternatives	Fuzzy MCRAT	Fuzzy RAMS	Majority Index	Rankings
	$tr^* = 0.0914$	$ms^* = 1.0071$		
	$tr^- = 0.0094$	$ms^- = 1.0989$	E_i	
	$tr(Z_i)$	$ms(M_i)$		
A1	0.0914	1.0071	0.0000	6
A2	0.0919	1.0113	0.0538	5
A3	0.0994	1.0989	1.0000	1
A4	0.0960	1.0591	0.5670	2
A5	0.0946	1.0398	0.3742	4
A6	0.0952	1.0470	0.4502	3

Another application of the proposed fuzzy MCDM approach was conducted using two other problems [61,62] that are demonstrated in Table 10. The computations of these two examples are attached in the Supplementary Materials as Table S1 for Example 1 and Table S2 for Example 2.

Table 10. Details of the selected problems and comparisons with the proposed approaches.

Prob No.	Ref. No.	Problem Field	Objective of the Study	Fuzzy MCDM Tool(s) Used	Comparison of Results with the Proposed and Used Fuzzy Approaches
1	[61]	Food security	This study examined the various supplier selection approaches to determine Jordan's primary wheat suppliers and rank them according to specified criteria. The fuzzy VIKOR approach assessed, selected, and ranked the best wheat suppliers in Jordan.	Fuzzy VIKOR with the following characteristics: • 12 experts • seven criteria • five wheat suppliers as alternatives (Romania, Ukraine, Syria, Russia, and Australia)	• The used approach found Romania is the best supplier, followed by Ukraine. • The proposed approach found that Ukraine is a better supplier than Romania. • The Spearman's *rho* and Kendall's *tau_b* correlations between the alternative rankings of the two methods are 60% and 40%, respectively. • The used approach used crisp weights as input to the fuzzy VIKOR matrix, while the proposed approach used fuzzy weights created by fuzzy MEREC-G to be an input to the fuzzy RATMI decision matrix.
2	[62]	Waste management	This study used a fuzzy TOPSIS to evaluate the performance of five waste disposal locations in Park Avenue, Vijayashanti apartments in Chennai, Tamil Nadu (India)	Fuzzy TOPSIS with the following characteristics: • one expert • five criteria • five garbage disposal places as alternatives	• The used approach ranked the five disposal sites in the order S5, S4, S3, S1, and S2. • The proposed approach ranked the fice disposal sites in the order S5, S4, S3, S2, and S1. • The Spearman's *rho* and Kendall's *tau_b* correlations between the alternative rankings of the two methods are 90% and 78%, respectively. • The used approach applied, given fuzzy weights as input to the fuzzy TOPSIS matrix, while the proposed approach used fuzzy weights obtained from fuzzy MEREC-G.

5. Discussion

The numerical application of the proposed hybrid MCDM approach based on fuzzy MEREC-G and fuzzy RATMI methods in this research study showed that it can generate alternative rankings. However, ensuring its validity and checking how those generated alternative rankings compare with rankings of other fuzzy MCDM methods is essential. Moreover, it is also necessary to check the sensitivity of the proposed model. Therefore, the validity and sensitivity analyses are provided in the following subsections.

5.1. Validity Analysis of the Proposed Approach

The validity of the resulting alternative rankings from the fuzzy MCRAT, fuzzy RAMS, and fuzzy RATMI methods presented in Tables 7–9, respectively, are checked. This was done by comparing these rankings from the proposed methods in this study with those resulting from multiple fuzzy MCDM methods presented in Table 11. Those other MCDM methods are the fuzzy ARAS, fuzzy MARCOS, fuzzy TOPSIS, fuzzy MABAC, fuzzy VIKOR, and fuzzy MAIRCA. It is worth mentioning that the researchers who created these fuzzy MCDM methods applied criteria with established fuzzy weights. In contrast, in this research study, the fuzzy weights were unknown and determined by the proposed MEREC-G method. The nonparametric correlation coefficients of ranked data, Spearman's *rho*, and Kendall's *tau_b*, which might be better for smaller samples [73], were found as shown in Tables 12 and 13, respectively. The correlation analyses show high correlations with statistical significance levels between the resulting alternative rankings from the fuzzy MCRAT, fuzzy RAMS, and fuzzy RATMI methods and those resulting from the other fuzzy MCDM methods. This result indicates high accuracy and consistency between the alternative rankings of the proposed hybrid MCDM approach based on fuzzy MEREC-G and fuzzy RATMI methods in this research study and the other fuzzy MCDM methods. Therefore, the proposed approach is deemed valid.

Table 11. Alternative rankings resulted from multiple fuzzy MCDM methods.

Alternatives	Fuzzy ARAS *	Fuzzy MARCOS *	Fuzzy TOPSIS *	Fuzzy MABAC *	Fuzzy VIKOR *	Fuzzy MAIRCA *	Fuzzy MCRAT **	Fuzzy RAMS **	Fuzzy RATMI **
A1	5	6	6	5	6	5	6	6	6
A2	6	5	5	6	5	6	5	5	5
A3	1	1	1	1	1	1	1	1	1
A4	2	2	2	2	2	2	2	2	2
A5	4	4	4	4	4	4	4	4	4
A6	3	3	3	3	3	3	3	3	3

* Alternative ranking adopted from [48]. ** Alternative ranking based on Tables 7–9.

Table 12. Spearman's *rho* correlation coefficients between alternative rankings resulted from multiple fuzzy MCDM methods.

	Fuzzy ARAS	Fuzzy MARCOS	Fuzzy TOPSIS	Fuzzy MABAC	Fuzzy VIKOR	Fuzzy MAIRCA	Fuzzy MCRAT	Fuzzy RAMS	Fuzzy RATMI
Fuzzy ARAS		0.943	0.943	1.000	0.943	1.000	0.943	0.943	0.943
Fuzzy MARCOS			1.000	0.943	1.000	0.943	1.000	1.000	1.000
Fuzzy TOPSIS				0.943	1.000	0.943	1.000	1.000	1.000
Fuzzy MABAC					0.943	1.000	0.943	0.943	0.943
Fuzzy VIKOR						0.943	1.000	1.000	1.000
Fuzzy MAIRCA							0.943	0.943	0.943
Fuzzy MCRAT								1.000	1.000
Fuzzy RAMS									1.000
Fuzzy RATMI									

Note: All Spearman's *rho* correlation coefficients are significant at the $p \leq 0.01$ level (2-tailed).

Table 13. Kendall's *tau_b* correlation coefficients between alternative rankings resulted from multiple fuzzy MCDM methods.

	Fuzzy ARAS	**Fuzzy MARCOS**	**Fuzzy TOPSIS**	**Fuzzy MABAC**	**Fuzzy VIKOR**	**Fuzzy MAIRCA**	**Fuzzy MCRAT**	**Fuzzy RAMS**	**Fuzzy RATMI**
Fuzzy ARAS		0.867 *	0.867 *	1.000 **	0.867 *	1.000 **	0.867 *	0.867 *	0.867 *
Fuzzy MARCOS			1.000 **	0.867 *	1.000 **	0.867 *	1.000 **	1.000 **	1.000 **
Fuzzy TOPSIS				0.867 *	1.000 **	0.867 *	1.000 **	1.000 **	1.000 **
Fuzzy MABAC					0.867 *	1.000 **	0.867 *	0.867 *	0.867 *
Fuzzy VIKOR						0.867 *	1.000 **	1.000 **	1.000 **
Fuzzy MAIRCA							0.867 *	0.867 *	0.867 *
Fuzzy MCRAT								1.000 **	1.000 **
Fuzzy RAMS									1.000 **
Fuzzy RATMI									

* Correlation is significant at the $p \leq 0.05$ level (2-tailed). ** Correlation is significant at the $p \leq 0.01$ level (2-tailed).

5.2. Sensitivity Analysis of the Proposed Approach

The sensitivity of the proposed MCDM approach in this study is checked by analyzing the effect of different criteria weights on the resulting rankings of alternatives (A1–A6) from the fuzzy RATMI. The sensitivity analysis was performed by calculating different fuzzy criteria weights of each of the eight criteria (C1–C8) based on a range of 10% to 90% with 10% increments and equally distributing the remainder of the 100% on the reset of criteria in each scenario. This has created a total of 72 run scenarios of the fuzzy RATMI algorithm (i.e., nine sets of criteria weights $\times$ eight criteria = 72 run scenarios). This procedure enabled comparing the effect of different weights of each criterion on the resulting alternative rankings.

Figure 2 shows the resulting alternative rankings from the sensitivity analysis. As shown in Figure 2a, criterion C1 demonstrated its sensitivity in most of the alternative rankings in the 10% and 20% scenarios and provided consistent rankings for the 30% to 90% scenarios. Figure 2b shows that criterion C2 changed the rankings of the alternatives A3 and A4 only in the 10% scenario and showed consistent alternative rankings in the 20% to 90% scenarios. For criterion C3, the analysis shows that it gave consistent alternative rankings for the whole range of scenarios from 10% to 90%, as presented in Figure 2c, indicating that changing its weight does not influence the decision-making problem. Figure 2d shows that criterion C4 changed the rankings of the alternatives in the 10%, 80%, and 90% scenarios and gave consistent alternative rankings in the 20% to 70% scenarios. Figure 2e shows that criterion C5 changed the rankings of the alternatives A2, A3, and A4 only in the 10% scenario and showed consistent alternative rankings in the 20% to 90% scenarios. Figure 2f shows that criterion C6 changed the rankings of the alternatives in the 10% and 20% scenarios while giving consistent alternative rankings in the 30% to 90% scenarios. Figure 2g shows that criterion C7 changed the rankings of the alternatives in the 10%, 20%, and 70% scenarios while giving consistent alternative rankings in the other scenarios. Finally, Figure 2h shows that criterion C8 changed the rankings of the alternatives in the 10%, 20%, and 30% scenarios and gave consistent alternative rankings in the 40% to 90% scenarios. These results indicate that the proposed approach is sensitive enough to changes in the criteria weights and reflects those changes on the alternative rankings, yet not too sensitive and capable of producing consistent rankings based on alternatives' performance scoring.

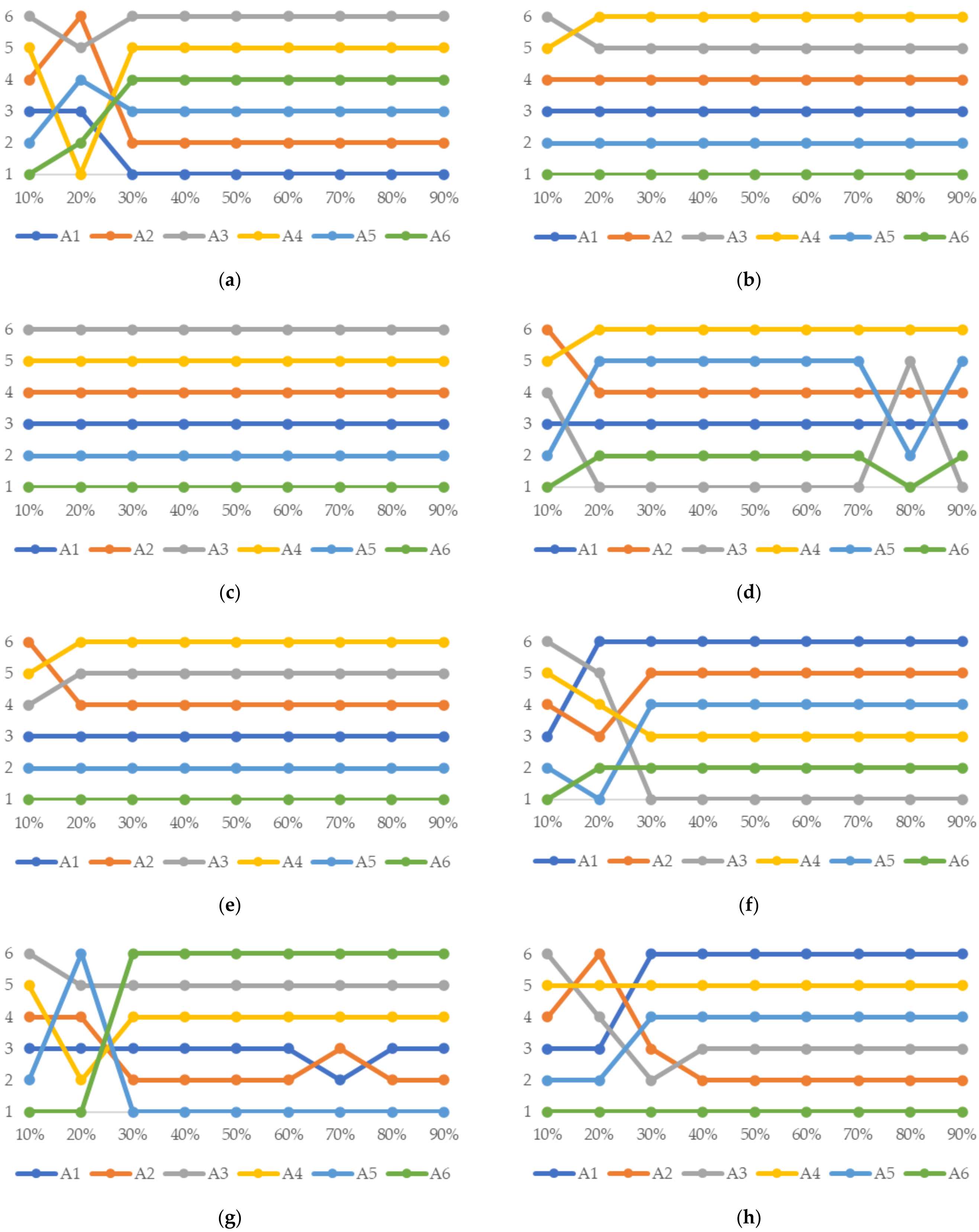

Figure 2. Sensitivity analysis of alternative rankings resulted from using different criteria weight percentages for (**a**) C1; (**b**) C2; (**c**) C3; (**d**) C4; (**e**) C5; (**f**) C6; (**g**) C7; and (**h**) C8.

6. Conclusions

Decision-making can be challenging when faced with multiple conflicting criteria and uncertain or vague information. Fuzzy logic can model the uncertainty and ambiguity in the decision process and provide a framework for fuzzy MCDM methods. These methods help decision-makers assign weights to the criteria and rank the alternatives systematically. This paper introduces a new hybrid fuzzy MCDM approach that combines two novel methods: fuzzy MEREC-G for criteria weighting and fuzzy RATMI for alternative rankings. The new approach was tested with real-world problem data adopted from Ulutaş et al. [48] and compared with other MCDM methods: fuzzy ARAS, fuzzy MARCOS, fuzzy TOPSIS, fuzzy MABAC, fuzzy VIKOR, and fuzzy MAIRCA, fuzzy MCRAT, and fuzzy RAMS. The validity and sensitivity of the proposed hybrid MCDM approach were evaluated. The validity was measured using the nonparametric Spearman's *rho* and Kendall's *tau_b* correlation coefficients of ranked data. The correlation coefficients were 0.943 and 1.00 using Spearman's *rho* methodology, while they were 0.867 and 1.00 using Kendall's *tau_b* methodology. These figures indicate that the proposed approach was valid and can be applied to different real problems with fuzzy data, such as supplier selection [49,52] and selecting pandemic hospital sites [55]. The sensitivity was checked by analyzing how different criteria weights affected the alternative rankings from the fuzzy RATMI, which showed that the approach was sensitive enough to reflect the changes in the criteria weights on the alternative rankings, but not too sensitive and able to produce consistent rankings based on the alternatives' performance scorings. Therefore, this study's new hybrid fuzzy approach is deemed valid.

There are always opportunities for further studies in any new approach. The following are possible future directions to extend the study on the proposed hybrid fuzzy MEREC-G and fuzzy RATMI approach:

- Using the proposed fuzzy hybrid approach for different problems in multi-disciplines can further ensure its effectiveness in solving research and industrial decision-making problems.
- Conduct comparative studies between the new hybrid fuzzy approach and different hybrid fuzzy methods in the literature or to be developed in the future.
- Study the efficacy of the proposed fuzzy hybrid approach when the number of decision criteria increases.
- Apply other variations and extensions of traditional fuzzy set theory, such as intuitionistic, hesitant, and Pythagorean fuzzy, in the developed method, which might better handle the uncertainty and vagueness of inputs in decision-making problems.
- For further comparative analyses, the proposed fuzzy hybrid approach could apply to other studies, such as the recent study presented by Görçün et al. [63].

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/math11173773/s1, Table S1: Example 1; Table S2: Example 2.

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