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A NOVEL DNMEREC-BORDA-COCOSO MULTI-CRITERIA GROUP DECISION-MAKING FRAMEWORK

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Abstract. *This study aims to propose a multi-criteria group decision-making framework under a probabilistic hesitant fuzzy environment, named DNMEREC (Double Normalization Method based on the Removal Effects of Criteria)-Borda-CoCoSo (Combined Compromise Solution). In this decision-making framework, we improve DNMEREC to determine the criteria weights and use an enhanced Borda rule to refine the CoCoSo ranking method. The Borda rule considers both the scores and the rankings in the ranking process, addressing the limitation of CoCoSo, which only considers the scores. Additionally, we account for the issue of standardization overlap between DNMEREC and CoCoSo. Finally, we validate the proposed decision-making framework using a case study on supplier selection. The study shows that through improvements, the correlation of CoCoSo has been increased by 15.14%.*

Keywords: Improved DNMEREC, Borda rule, Improved CoCoSo method, Probability hesitant fuzzy set, Multi-criteria group decision-making

1. **Introduction.** Multi-Criteria Decision-Making (MCDM) methods are effective tools for solving complex decision problems [1-3]. Over several decades of development, many classical MCDM methods have been established, including TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), ELECTRE (Elimination and Choice Expressing Reality), CoCoSo, BWM (Best-Worst Method) and CRITIC (Criteria Importance Through Intercriteria Correlation) [4-7]. These methods have also been extended to various uncertain environments. For example, interval-valued intuitionistic fuzzy TOPSIS, spherical fuzzy ELECTRE, spherical fuzzy CoCoSo, and Pythagorean hesitant fuzzy MULTIMOORA (multi-objective optimization by ratio analysis plus the full multiplicative form) are some of the adaptations that have been developed to handle uncertainty in decision-making contexts [8-10]. Scholars have also combined these methods with some classical weighting methods to propose hybrid multi-criteria decision-making frameworks.

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For example, Xiao et al. [11] combined MULTIMOORA with CRITIC to propose a comprehensive decision-making framework. Liu et al. [12] combined the entropy weight method with TOPSIS to propose the entropy weight TOPSIS method. Akram et al. [13] integrated SWARA (Stepwise Weight Assessment Ratio Analysis) and ELECTRE to create the SWARA-ELECTRE multi-criteria decision-making model. These combinations have the disadvantage that they do not take account of the overlapping factors between different methods during the standardization process. To address this issue, this paper integrates DNMEREC and CoCoSo in a probabilistic hesitant fuzzy environment to propose a DNMEREC-Borda-CoCoSo multi-criteria decision-making method. This method not only takes account of the overlapping factors in the standardization process but also optimizes the CoCoSo method through the improved Borda ranking rule.

In this study, the DNMEREC method is an improved approach for objective weight determination, derived from the MEREC method [14] as an enhancement of the method introduced by Keshavarz-Ghorabaee et al. [15]. The MEREC method calculates criterion weights by considering the removal effect of each criterion on the overall performance of alternative solutions. The method posits that a criterion has a greater weight when its removal results in a more significant impact on the overall performance of alternative solutions. Meanwhile, the DNMEREC method improves upon the MEREC method by refining the normalization process into a dual normalization process. It takes account of the impact of both the maximum evaluation value and the minimum value on the normalization process for each criterion. The final weight is a comprehensive weight derived from the combination of weights under maximum and minimum normalizations. Compared to a single weight value, this weight is more comprehensive.

The CoCoSo (Combined Compromise Solution) is a Multi-Criteria Decision-Making (MCDM) method proposed in 2019. Since its introduction, this method has garnered significant attention and has been applied to various MCDM scenarios, including healthcare, transportation, supply chains, and more. Additionally, it has been widely improved and extended. For example, Wan et al. [16] integrated MEREC with CoCoSo to develop the MEREC-CoCoSo decision-making framework. Bouraima et al. [17] utilized an integrated IRN (Interval Rough Number) SWARA and IRN CoCoSo model to evaluate alternative railway systems for sustainable transportation. Ecer et al. [18] analyzed the sustainability performance of micro-mobility solutions in urban transportation using a novel IVFNN (Interval-Valued Fuzzy Neutrosophic Number)-Delphi-LOPCOW (Logarithmic Percentage Change-Driven Objective Weighting)-CoCoSo framework. In the context of named data networking, Negara et al. [19] employed a multi-criteria decision-making method based on CRITIC-CoCoSo to develop a caching placement strategy for efficient content distribution. Through these studies, CoCoSo has been expanded and improved. However, the ranking rule of the CoCoSo method does not consider the ranking issue of alternatives under different scores. To address this issue, this study employs an improved Borda ranking rule to enhance the ranking process of CoCoSo. The improved Borda ranking is a classical ranking method that considers both the ranking values and the ranks themselves. Currently, this method has been widely used in the ranking process of MULTIMOORA.

In summary, to address the limitations of existing research, we proposed an improved DNMEREC-Borda-CoCoSo decision-making framework. In this method, we enhanced the weight aggregation process of the DNMEREC method and introduced the Borda rule to improve the ranking process of the CoCoSo method. Throughout the decision-making process, the normalization procedures of DNMEREC and CoCoSo were shared.

The remainder of this paper is organized as follows. Section 2 introduces the probabilistic hesitant fuzzy set and its calculation rules. Section 3 proposes the DNMEREC-Borda-

CoCoSo multi-criteria decision-making framework. Section 4 summarizes the model proposed. Section 5 validates the proposed method using a case study on supplier selection and further verifies the method through comparative analysis. Section 6 concludes the study and provides directions for future research.

2. **Preliminaries.**

Definition 2.1. [20-22]. *Let X be a non-empty set, and for each element x in X, associated with which is a probability hesitation element $PH(x)$, which is represented by a set of membership degrees and their corresponding probability distributions. It is defined as follows:*

$$PH(x) = \{\langle x, h_x(p_x)\rangle | x \in X\} \tag{1}$$

where, $h_x(p_x) = \{(x_i|p_i)|i = 1, 2, 3, \dots, n\}$ represents the Probability Hesitant Fuzzy Element (PHFE), x_i is the i-th element in the PHFE and represents membership degree, p_i represents the probability of the i-th element in the PHFE, and $0 \leq p_i \leq 1$, $\sum_{i=1}^{n} p_i = 1$.

Definition 2.2. [23]. *Let $hp = \{(x_i|p_i)|i = 1, 2, 3, \dots, n\}$ be a PHFE, and its scoring function S and deviation degree D are calculated as follows:*

$$S(hp) = \sum_{i=1}^{n} x_i p_i, \quad D(hp) = \sum_{i=1}^{n} [x_i - S(hp)]^2 p_i \tag{2}$$

According to S and D, for any two PHFEs hp_a and hp_b, there exists the following relationship: If $S(hp_a) > S(hp_b)$, then $hp_a \succ hp_b$; If $S(hp_a) = S(hp_b)$, then: If $D(hp_a) > D(hp_b)$, then $hp_a \succ hp_b$; if $D(hp_a) = D(hp_b)$, then $hp_a \approx hp_b$.

This study employs Probabilistic Hesitant Fuzzy Sets (PHFSs) to represent the decision-making information provided by decision-makers. Therefore, the fundamental computational rules of probabilistic hesitant fuzzy sets serve as the foundation of this research. We present the following computational rules for probabilistic hesitant fuzzy sets.

Definition 2.3. [24,25]. *For any three PHFE hp, hp_1, hp_2, and $\theta > 0$, the following computation rules exist:*

a) $(hp)^c = \bigcup_{i=1,2,\dots,n} \{(1 - x_i)|p_i\}$,

b) $(hp)^\theta = \bigcup_{i=1,2,3,\dots,n} \left\{(x_i)^\theta \middle| p_i\right\}$,

c) $\theta hp = \bigcup_{i=1,2,3,\dots,n} \left\{1 - (1 - x_i)^\theta \middle| p_i\right\}$,

d) $hp_1 \oplus hp_2 = \bigcup_{i_1=1,2,3,\dots,n, i_2=1,2,3,\dots,n} \{(x_{i_1} + x_{i_2} - x_{i_1}x_{i_2})|p_{i_1}p_{i_2}\}$,

e) $hp_1 \otimes hp_2 = \bigcup_{i_1=1,2,3,\dots,n, i_2=1,2,3,\dots,n} \{x_{i_1}x_{i_2}|p_{i_1}p_{i_2}\}$.

3. **The DNMEREC-Borda-CoCoSo Framework.** The DNMEREC method is a recently proposed approach for objective weight determination. This method was introduced by Puška et al. [14] as an improvement to the MEREC method [15] using dual standardization. In the DNMEREC method, the dual normalization process maximizes and minimizes all data, avoiding the influence of extreme values on the decision results. However, since its proposal, few scholars have extended and applied this method to probabilistic hesitant fuzzy environments. To address this, we extend and apply the DNMEREC method by incorporating the characteristics of probabilistic hesitant fuzzy sets.

CoCoSo (Combined Compromise Solution) is a multi-attribute decision support method used to evaluate and select the best options in scenarios involving multiple criteria or attributes. This method integrates three popular decision-making techniques: the Simple Additive Weighting (SAW), the Weighted Aggregated Sum Product Assessment (WASPAS), and the Multiplicative Exponent Weighted (MEW) [26]. The CoCoSo method has been modified and extended to different fuzzy environments. However, issues still exist with overlap in the standardization process and ranking rules that only consider numerical values. In this section, we improve the CoCoSo ranking rules using the Borda count method. Combining the two aforementioned methods, we propose a new multi-criteria group decision-making framework, DNMEREC-Borda-CoCoSo. The specific process of this decision-making framework is as follows.

Step 1: Construct the probability hesitant fuzzy decision matrix. The matrix is evaluated by decision-makers, who integrate their professional background and knowledge to assess decision solutions under various decision criteria. By combining the decision values of all decision-makers, a probability hesitation fuzzy element is obtained, ultimately resulting in a complete decision matrix M.

$$M = [p_{ij}]_{m\times n} \tag{3}$$

where, m represents the number of decision alternatives, n represents the number of decision criteria, and p_{ij} denotes the decision value of the i-th alternative under the j-th criterion, which is expressed using Probabilistic Hesitant Fuzzy Elements (PHFEs).

Step 2: Transform the probability hesitant fuzzy decision matrix. The purpose of the transformation is to facilitate subsequent standardization. Here, we use the scoring function from Definition 2.2 to convert each PHFE into a precise value for standardization. The transformed decision matrix is as follows:

$$X = [x_{ij}]_{m\times n} \tag{4}$$

where, x_{ij} represents the probabilistic hesitant fuzzy score value of the i-th alternative under the j-th criterion, which is a precise value.

Step 3: Standardize the decision matrix. Here, the decision criteria are divided into positive and negative criteria. Different methods are employed for handling criteria of different types. The specific methods are as follows:

$$\begin{cases} N_{ij} = \dfrac{x_{ij}}{\max_i x_{ij}},\ N_{ij}^{*} = \dfrac{\min_i x_{ij}}{x_{ij}}, & \text{for positive criteria;} \\ N_{ij} = \dfrac{\min_i x_{ij}}{x_{ij}},\ N_{ij}^{*} = \dfrac{x_{ij}}{\max_i x_{ij}}, & \text{for negaitive criteria} \end{cases} \tag{5}$$

where, N_{ij} and N_{ij}^{*} respectively represent the two types of standardized evaluation values of the i-th alternative under the j-th criterion. After standardization, the following two normalized decision matrices are obtained:

$$NM = [N_{ij}]_{m\times n}, \quad NM^{*} = \left[N_{ij}^{*}\right]_{m\times n} \tag{6}$$

Step 4: Calculate the overall performance of each decision alternative, T_i and T_i^{*}. The calculation process is as follows:

$$T_i = \ln\left(1 + \left(\frac{1}{m}\sum_{j=1}^{m}\left|\ln\left(N_{ij}\right)\right|\right)\right), \quad T_i^{*} = \ln\left(1 + \left(\frac{1}{m}\sum_{j=1}^{m}\left|\ln\left(N_{ij}^{*}\right)\right|\right)\right) \tag{7}$$

Step 5: Calculate the influence of each criterion on decision alternatives. In this step, the impact of criteria on alternatives is excluded during the calculation. The specific process is as follows:

$$ef_{ij} = \ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j}^{m}\left|\ln\left(N_{ik}\right)\right|\right)\right), \quad ef_{ij}^{*} = \ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j}^{m}\left|\ln\left(N_{ik}^{*}\right)\right|\right)\right) \tag{8}$$

Step 6: Calculate the removal effect of each decision criterion. The specific process is as follows:

$$RE_j = \sum_i \left|T_i - ef_{ij}\right|, \quad RE_j^{*} = \sum_i \left|T_i^{*} - ef_{ij}^{*}\right| \tag{9}$$

Step 7: By employing the removal effect obtained in Step 6, the calculation of the dual-standardized weights $\left(w_j, w_j^{*}\right)$ and comprehensive weights (cw_j) for each decision criterion is conducted as follows:

$$w_j = \frac{RE_j}{\sum_k RE_k}, \quad w_j^{*} = \frac{RE_j^{*}}{\sum_k RE_k^{*}}, \quad cw_j = \frac{w_j w_j^{*}}{\sum_{j=1}^{n} w_j w_j^{*}} \tag{10}$$

Step 8: Calculate both the weighted comparability sum (S_i) and the power-weighted comparability sequences sum (P_i). The detailed procedure for this computation is as follows:

$$S_i = \sum_{j=1}^{n}\left(cw_j N_{ij}\right), \quad P_i = \sum_{j=1}^{n}\left(cw_j\right)^{N_{ij}} \tag{11}$$

where, cw_j represents the weights obtained by Step 7.

Step 9: To determine the relative weights of the evaluation criteria, three aggregate scores are defined: the mean of the sum of scores from the Weighted Sum Method (WSM) and Weighted Product Method (WPM), the total relative scores compared to the best alternative in WSM and WPM models, and the balance compromise score in WSM and WPM models. Although $0 \leq \lambda \leq 1$, it is typically set at a threshold of 0.50.

$$k_{ia} = \left(S_i + P_i\right) \Big/ \sum_{i=1}^{m}\left(S_i + P_i\right), \quad k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i},$$
$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\lambda \max_i S_i + (1-\lambda)\max_i P_i} \tag{12}$$

Step 10: To determine the final ranking of alternatives using the improved Borda rule, one must integrate the three aggregate scores and rankings as mentioned previously. The improved Borda rule obviates the necessity for manual comparisons and additional conditions, streamlining the process for decision-makers. By combining these three aggregate scores (k_{ia}, k_{ib}, k_{ic}), the method yields a final ranking of solutions, offering a more accessible and effective approach than traditional methods. This enhanced Borda rule is notably more comprehensive, accounting for inter-method relationships better than the conventional CoCoSo ranking method. The calculation procedure is as follows:

$$k_{ia}^{*} = k_{ia} \Big/ \sqrt{\sum_{i=1}^{m}\left(k_{ia}\right)^2}, \quad k_{ib}^{*} = k_{ib} \Big/ \sqrt{\sum_{i=1}^{m}\left(k_{ib}\right)^2}, \quad k_{ic}^{*} = k_{ic} \Big/ \sqrt{\sum_{i=1}^{m}\left(k_{ic}\right)^2} \tag{13}$$

$$BR(i) = k_{ia}^{*}\frac{m - rank(k_{ia}) + 1}{m(m+1)/2} + k_{ib}^{*}\frac{m - rank(k_{ib}) + 1}{m(m+1)/2} + k_{ic}^{*}\frac{m - rank(k_{ic}) + 1}{m(m+1)/2} \tag{14}$$

In Formula (14), $BR(i)$ represents the Borda rule calculation value for the i-th alternative, and $rank(k_{ia})$, $rank(k_{ib})$, $rank(k_{ic})$ represent the rankings under the three aggregate scores, respectively. A higher value of $BR(i)$ indicates a better alternative.

4. **Decision Model.** Based on the improved DNMEREC and CoCoSo methods, we propose a DNMEREC-Borda-CoCoSo framework. In this method, the improved DNMEREC and CoCoSo methods share two steps. Subsequently, the weights obtained from the improved DNMEREC are input into the CoCoSo method for decision information weighting. Finally, the decision alternatives are ranked based on the Borda rule. The decision-making steps of the proposed method are as follows.

Step 1: Invite decision-makers to evaluate all decision alternatives and obtain the decision matrix.

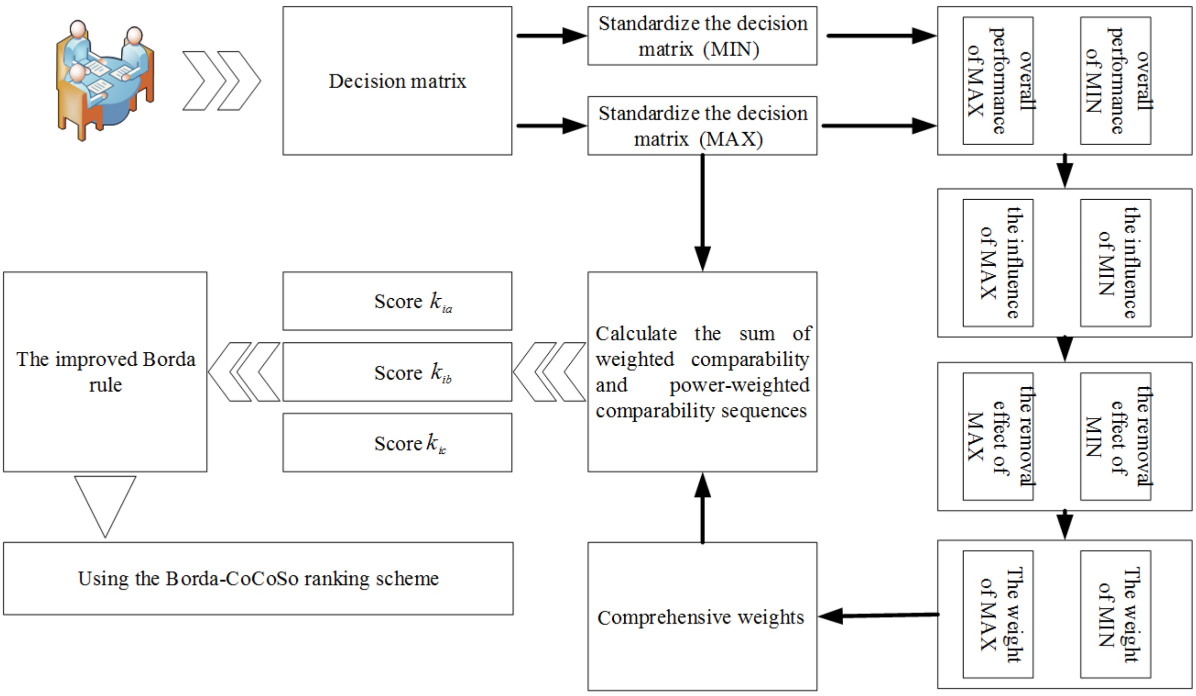
Step 2: Transform the probabilistic hesitant fuzzy decision matrix into a score matrix based on Definition 2.2.

Step 3: Normalize the decision matrix using Equation (5).

Step 4: Calculate the weights of all decision criteria using Equations (7)-(10).

Step 5: Rank all decision alternatives using Equations (11)-(14) to assist decision-makers in making a decision.

The process is shown in Figure 1.



Note: In Figure 1, "MIN" and "MAX" represent the normalization process in Equation (5). k_{ia}, k_{ib}, and k_{ic} represent the comprehensive scheme scores in Equation (12). The flowchart in the figure illustrates the decision-making process of this study.

FIGURE 1. Decision model

5. **Method Validation.** To validate the feasibility and effectiveness of the proposed method, we apply the decision framework to the supplier selection problem of a dairy plant based on the study by Divsalar et al. [27]. In this study, the case company is a major dairy supplier; thus, special attention is needed for the packaging process. Aluminum foil, being one of the main materials, has a large monthly consumption in the packaging process of the case company. Given these details, it is crucial to procure aluminum foil at a reasonable price, with appropriate quality, and at the correct time. Therefore, the supplier selection issue is one of the main concerns for managers. Currently, there are four suppliers cooperating with the case company. The decision criteria are shown in Table 1. Table 2 lists the 10 criteria selected from the literature review. In Table 2, each

Table 1. The decision criteria

Criterion	Mark	References
Quality	C_1	Jain and Singh [28], Divsalar et al. [27]
Cost	C_2	Stević et al. [29], Divsalar et al. [27]
Delivery	C_3	Jain and Singh [28]
Reliability	C_4	Jain and Singh [28], Divsalar et al. [27]
Flexibility	C_5	Jain and Singh [28]
Warranties	C_6	Jain and Singh [28]
Eco-design	C_7	Kannan et al. [30]
Long-term relationship	C_8	Jain and Singh [28], Divsalar et al. [27]
Reputation	C_9	Divsalar et al. [27]
Availability	C_{10}	Divsalar et al. [27]

Table 2. Decision data

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.6(0.2), 0.7(0.4), 0.9 (0.4)	0.5(0.7), 0.7(0.2), 0.8 (0.1)	0.3(0.4), 0.6(0.4), 0.9 (0.2)	0.4(0.3), 0.5(0.3), 0.9 (0.4)	0.5(0.4), 0.6(0.5), 0.8 (0.1)	0.6(0.4), 0.7(0.4), 0.8 (0.2)	0.4(0.5), 0.6(0.2), 0.8 (0.3)	0.3(0.3), 0.6(0.4), 0.7 (0.3)	0.4(0.4), 0.5(0.2), 0.7 (0.4)	0.5(0.4), 0.7(0.5), 0.9 (0.1)
A_2	0.7(0.3), 0.8(0.4), 0.9 (0.3)	0.5(0.3), 0.8(0.3), 0.9 (0.4)	0.4(0.5), 0.7(0.2), 0.8 (0.3)	0.5(0.4), 0.6(0.3), 0.7 (0.3)	0.4(0.3), 0.6(0.5), 0.8 (0.2)	0.5(0.6), 0.6(0.3), 0.9 (0.1)	0.3(0.5), 0.5(0.1), 0.6 (0.4)	0.4(0.4), 0.6(0.3), 0.8 (0.3)	0.5(0.5), 0.6(0.3), 0.8 (0.2)	0.5(0.4), 0.6(0.5), 0.8 (0.1)
A_3	0.5(0.4), 0.6(0.3), 0.8 (0.3)	0.6(0.2), 0.7(0.4), 0.9 (0.4)	0.4(0.4), 0.5(0.4), 0.7 (0.2)	0.5(0.4), 0.6(0.4), 0.7 (0.2)	0.6(0.6), 0.7(0.2), 0.8 (0.2)	0.5(0.5), 0.7(0.2), 0.8 (0.3)	0.4(0.5), 0.5(0.4), 0.7 (0.1)	0.4(0.5), 0.6(0.3), 0.7 (0.2)	0.5(0.4), 0.7(0.2), 0.8 (0.4)	0.5(0.6), 0.7(0.3), 0.9 (0.1)
A_4	0.5(0.4), 0.6(0.3), 0.9 (0.3)	0.5(0.5), 0.7(0.1), 0.9 (0.4)	0.2(0.3), 0.4(0.5), 0.7 (0.2)	0.4(0.3), 0.5(0.5), 0.7 (0.2)	0.3(0.2), 0.5(0.4), 0.7 (0.4)	0.4(0.3), 0.6(0.3), 0.8 (0.4)	0.4(0.3), 0.7(0.3), 0.8 (0.4)	0.2(0.3), 0.5(0.6), 0.7 (0.1)	0.4(0.3), 0.6(0.5), 0.7 (0.2)	0.4(0.2), 0.5(0.5), 0.7 (0.3)

evaluation value is a probabilistic hesitant fuzzy element. For example, the evaluation value $\{0.6(0.2), 0.7(0.4), 0.9\,(0.4)\}$ under C_1 for A_1 indicates that there are three evaluation values, 0.6, 0.7, and 0.9, with their corresponding probabilities being 0.2, 0.4, and 0.4, respectively.

Based on the decision data in Table 2, we use the proposed DNMEREC-Borda-CoCoSo decision framework to assist the case company in selecting suppliers. The specific process is as follows.

Step 1: Based on Definition 2.2, the probabilistic hesitant fuzzy set matrix is converted into a scoring matrix, and the results are shown in Table 3.

Table 3. The transformed decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.76	0.57	0.54	0.63	0.58	0.68	0.56	0.54	0.54	0.64
A_2	0.8	0.75	0.58	0.59	0.58	0.57	0.44	0.58	0.59	0.58
A_3	0.62	0.76	0.5	0.58	0.66	0.63	0.47	0.52	0.66	0.6
A_4	0.65	0.68	0.4	0.51	0.54	0.62	0.65	0.43	0.56	0.54

Step 2: The scoring results are normalized, and the maximum and minimum normalized results are shown in Tables 4 and 5.

Step 3: Based on Equations (7)-(10), the weights of the decision criteria are calculated, and the decision results are shown in Table 6.

TABLE 4. The decision matrix after maximum normalization

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.82	0.75	0.93	1.00	0.88	1.00	0.86	0.93	0.82	1.00
A_2	0.78	0.99	1.00	0.94	0.88	0.84	0.68	1.00	0.89	0.91
A_3	1.00	1.00	0.86	0.92	1.00	0.93	0.72	0.90	1.00	0.94
A_4	0.95	0.89	0.69	0.81	0.82	0.91	1.00	0.74	0.85	0.84

TABLE 5. The decision matrix after minimum normalization

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.95	1.00	0.74	0.81	0.93	0.84	0.79	0.80	1.00	0.84
A_2	1.00	0.76	0.69	0.86	0.93	1.00	1.00	0.74	0.92	0.93
A_3	0.78	0.75	0.80	0.88	0.82	0.90	0.94	0.83	0.82	0.90
A_4	0.81	0.84	1.00	1.00	1.00	0.92	0.68	1.00	0.96	1.00

TABLE 6. The weights of the decision criteria

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Maximum normalized weights	0.102	0.112	0.095	0.092	0.092	0.092	0.129	0.097	0.099	0.091
Minimum normalized weights	0.105	0.124	0.114	0.091	0.093	0.084	0.104	0.104	0.100	0.083
Comprehensive weights	0.107	0.138	0.107	0.082	0.084	0.076	0.133	0.099	0.098	0.075

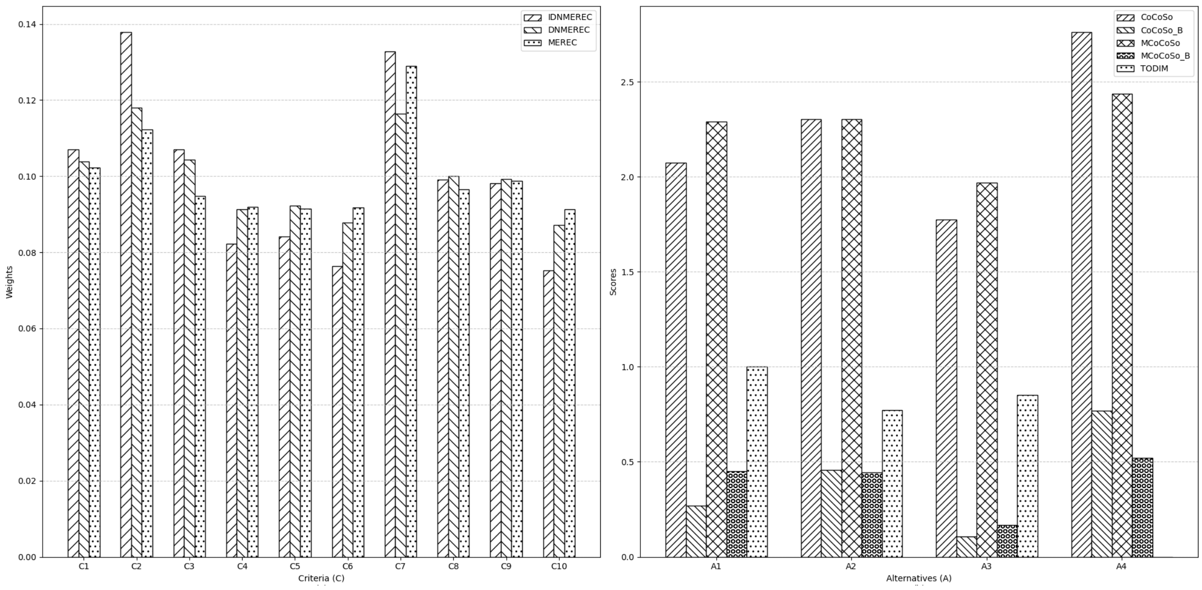
Step 4: Based on Equations (11)-(14), the decision alternatives are ranked, and the ranking results are shown in Table 7.

TABLE 7. The decision results

	A_1	A_2	A_3	A_4
k_{ia}	0.4	0.251	0.242	0.259
k_{ib}	2.107	2.129	2.075	3
k_{ic}	0.931	0.942	0.7	0.973
k_{ia}^*	0.677	0.425	0.41	0.439
k_{ib}^*	0.446	0.451	0.44	0.636
k_{ic}^*	0.521	0.527	0.392	0.545
$BR(i)$	0.4642	0.3784	0.1242	0.6041

In summary, with the improved DNMEREC method, we obtain the weights for different decision criteria: $w = [0.107, 0.138, 0.107, 0.082, 0.084, 0.076, 0.133, 0.099, 0.098, 0.075]$. Based on these decision criterion weights and the decision data in Table 2, we rank the four suppliers as $A_4(0.6196) \succ A_2(0.4518) \succ A_1(0.2976) \succ A_3(0.1457)$. Therefore, A_4 is identified as the optimal cooperative supplier.

To further validate the proposed method, we compared the improved DNMEREC with the original DNMEREC [14] and MEREC [15]. Additionally, we compared Borda-CoCoSo with CoCoSo [26] and Choquet integral-PHF-TODIM [27]. The results are shown in Figure 2. As can be seen from Figure 2(a), the improved DNMEREC (IDNMEREC) exhibits the same trend as DNMEREC and MEREC. However, IDNMEREC makes the differences



(a) (b)

Figure 2. Comparison of different methods

Table 8. k_{ia}, k_{ib} and k_{ic}

	A_1	A_2	A_3	A_4
k_{ia}	**0.227(0.400)**	0.264	0.157	0.352
Ranking	3	2	4	1
k_{ib}	3.112	3.354	2.983	**3.741(3.000)**
Ranking	3	2	4	1
k_{ic}	0.613	0.715	**0.426(0.700)**	0.952
Ranking	3	2	4	1

Note: The values in parentheses in Table 8 represent the modified values to achieve different rankings. These values are intended to verify the impact of different rankings of k_{ia}, k_{ib}, and k_{ic} on the proposed method.

between different criteria more pronounced. As shown in Figure 2(b) and Table 8, after introducing the Borda rule for ranking, Borda-CoCoSo and CoCoSo have the same ranking since the rankings under k_{ia}, k_{ib} and k_{ic} are consistent. When adjusting the values of k_{ia}, k_{ib} and k_{ic} to make the rankings inconsistent, Borda-CoCoSo and CoCoSo show different rankings due to the introduction of the Borda rule, which considers the rankings under different scores (as shown by MCoCoSo and MCoCoSo_B in Figure 2). Compared to Choquet integral-PHF-TODIM, there are differences in the decision results because this method considers the preference relationships between the two schemes. To further demonstrate the advantages of the proposed method, we used the Pearson coefficient to calculate the correlations of different methods. The results are shown in Table 9. The results indicate that the introduction of the correlation coefficient in this paper improved the correlation of CoCoSo, achieving an increase of 15.14%.

6. **Conclusion.** To address multi-criteria group decision-making problems under a probabilistic hesitant fuzzy environment, this study proposes a novel multi-criteria decision-making framework, DNMEREC-Borda-CoCoSo. In this framework, we improve the weight aggregation method of DNMEREC and the alternative ranking method of CoCoSo. Additionally, we validate the proposed decision-making framework through a case study

Table 9. The Pearson correlation of different methods

	CoCoSo	CoCoSo_B	MCoCoSo	MCoCoSo_B	TODIM
CoCoSo	1	0.8837	0.909	0.8486	−0.8644
CoCoSo_B	0.8837	1	0.9736	0.9629	−0.6226
MCoCoSo	0.909	0.9736	1	0.9918	−0.5942
MCoCoSo_B	0.8486	0.9629	0.9918	1	−0.4877
TODIM	−0.8644	−0.6226	−0.5942	−0.4877	1
Mean	0.5554	**0.6395**	0.6560	**0.6631**	−0.3138

on supplier selection. The results indicate that the proposed framework can effectively facilitate decision-making. Overall, the contributions of this study are as follows: first, it improves the DNMEREC and CoCoSo methods; second, it extends the application of probabilistic hesitant fuzzy sets; third, it combines these improvements to propose a multi-criteria decision-making framework that assists decision-makers in multi-criteria group decision-making.

In future research, we will use the proposed method to address some prominent multi-criteria decision-making problems, such as green supplier selection, sustainable investment scheme decision-making, and knowledge sharing decision-making. Additionally, we will further refine the proposed method. For instance, we will apply the method to uncertain environments such as interval-valued intuitionistic fuzzy sets, linguistic term sets, and intuitionistic fuzzy sets.

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REFERENCES

[1] J. Su, D. Wang, B. Xu, F. Zhang and N. Zhang, An interval-valued intuitionistic fuzzy group decision-making method for evaluating online knowledge payment products, *Applied Soft Computing*, vol.150, 111046, 2024.

[2] H. Taherdoost and A. Mohebi, Using smart method for multi-criteria decision making: Applications, advantages and limitations, *Archives of Advanced Engineering Science*, pp.1-10, 2024.

[3] J.-F. Ding and L.-M. Hsu, Electrocardiogram monitor supplier selection based on fuzzy MCDM evaluation method, *International Journal of Innovative Computing, Information and Control*, vol.19, no.2, pp.465-486, 2023.

[4] P. Wang, Y. Lin and Z. Wang, An integrated BWM-CRITIC approach based on neutrosophic set for sustainable supply chain finance risk evaluation, *International Journal of Innovative Computing, Information and Control*, vol.18, no.6, pp.1735-1754, 2022.

[5] X. Yu, W. Yang and S. Suntrayuth, A new approach to solving TOPSIS rank reversal based on S-type utility function, *International Journal of Innovative Computing, Information and Control*, vol.19, no.5, pp.1501-1516, 2023.

[6] P. Wang, Y. Lin and Z. Wang, An integrated multi criteria group decision-making model applying fuzzy TOPSIS-CRITIC method with unknown weight information, *International Journal of Innovative Computing, Information and Control*, vol.18, no.3, pp.815-836, 2022.

[7] Y. Yang and J. He, A novel method based on fixed point iteration and improved TOPSIS method for multi-attribute group decision making, *International Journal of Innovative Computing, Information and Control*, vol.17, no.1, pp.15-29, 2021.

[8] J. Su, B. Xu, H. Liu, Y. Chen and X. Zhang, Green knowledge management capability assessment based on interval-valued intuitionistic fuzzy EWM-TOPSIS-Sort-B, *Journal of Intelligent & Fuzzy Systems*, pp.1-19, 2024.
[9] T. K. Paul, C. Jana and M. Pal, Enhancing multi-attribute decision making with pythagorean fuzzy hamacher aggregation operators, *Journal of Industrial Intelligence*, vol.1, no.1, pp.30-54, 2023.
[10] M. Palanikumar and A. Iampan, Spherical fermatean interval valued fuzzy soft set based on multi criteria group decision making, *International Journal of Innovative Computing, Information and Control*, vol.18, no.2, pp.607-619, 2022.
[11] J. Xiao, Z. Xu and X. Wang, An improved MULTIMOORA with CRITIC weights based on new equivalent transformation functions of nested probabilistic linguistic term sets, *Soft Computing*, vol.27, no.16, pp.11629-11646, 2023.
[12] J. Liu, M. Xie, S. Chen, G. Xu, T. Wu and W. Li, TS-REPLICA: A novel replica placement algorithm based on the entropy weight TOPSIS method in spark for multimedia data analysis, *Information Sciences*, vol.626, pp.133-148, 2023.
[13] M. Akram, F. Ilyas and M. Deveci, Interval rough integrated SWARA-ELECTRE model: An application to machine tool remanufacturing, *Expert Systems with Applications*, vol.238, 122067, 2024.
[14] A. Puška, D. Božanić, Z. Mastilo and D. Pamuèar, Extension of MEREC-CRADIS methods with double normalization-case study selection of electric cars, *Soft Computing*, vol.27, no.11, pp.7097-7113, 2023.
[15] M. Keshavarz-Ghorabaee, M. Amiri, E. K. Zavadskas, Z. Turskis and J. Antucheviciene, Determination of objective weights using a new method based on the removal effects of criteria (MEREC), *Symmetry*, vol.13, no.4, 525, 2021.
[16] G. Wan, Y. Rong and H. Garg, An efficient spherical fuzzy MEREC-CoCoSo approach based on novel score function and aggregation operators for group decision making, *Granular Computing*, vol.8, no.6, pp.1481-1503, 2023.
[17] M. B. Bouraima, Y. Qiu, Ž. Stević and V. Simić, Assessment of alternative railway systems for sustainable transportation using an integrated IRN SWARA and IRN CoCoSo model, *Socio-Economic Planning Sciences*, vol.86, 101475, 2023.
[18] F. Ecer, H. Küçükönder, S. K. Kaya and Ö. F. Görçün, Sustainability performance analysis of micro-mobility solutions in urban transportation with a novel IVFNN-Delphi-LOPCOW-CoCoSo framework, *Transportation Research Part A: Policy and Practice*, vol.172, 103667, 2023.
[19] R. M. Negara, N. R. Syambas and E. Mulyana, C3CPS: CRITIC-CoCoSo-based caching placement strategy using multi-criteria decision method for efficient content distribution in Named Data Networking, *Journal of King Saud University – Computer and Information Sciences*, vol.35, no.9, 101714, 2023.
[20] W. Zhou and Z. Xu, Probability calculation and element optimization of probabilistic hesitant fuzzy preference relations based on expected consistency, *IEEE Transactions on Fuzzy Systems*, vol.26, no.3, pp.1367-1378, 2018.
[21] B. Zhu, *Decision Method for Research and Application Based on Preference Relation*, Ph.D. Thesis, Southeast University, Nanjing, 2014.
[22] J. Su, B. Xu, L. Jiang, H. Liu, Y. Chen, Y. Li and N. Zhang, Cross-Organizational knowledge sharing partner selection based on Fogg Behavioral Model in probabilistic hesitant fuzzy environment, *Expert Systems with Applications*, vol.260, 125348, 2025.
[23] J. Gao, Z. Xu and H. Liao, A dynamic reference point method for emergency response under hesitant probabilistic fuzzy environment, *International Journal of Fuzzy Systems*, vol.19, no.5, pp.1261-1278, 2017.
[24] Z. Xu and W. Zhou, Consensus building with a group of decision makers under the hesitant probabilistic fuzzy environment, *Fuzzy Optimization and Decision Making*, vol.16, no.4, pp.481-503, 2016.
[25] J. Li and Z.-X. Wang, Consensus building for probabilistic hesitant fuzzy preference relations with expected additive consistency, *International Journal of Fuzzy Systems*, vol.20, no.5, pp.1495-1510, 2018.
[26] M. Yazdani, P. Zarate, E. K. Zavadskas and Z. Turskis, A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems, *Management Decision*, vol.57, no.9, pp.2501-2519, 2019.
[27] M. Divsalar, M. Ahmadi, E. Ebrahimi and A. Ishizaka, A probabilistic hesitant fuzzy Choquet integral-based TODIM method for multi-attribute group decision-making, *Expert Systems with Applications*, vol.191, 116266, 2022.

[28] N. Jain and A. R. Singh, Sustainable supplier selection under must-be criteria through fuzzy inference system, *Journal of Cleaner Production*, vol.248, 119275, 2020.
[29] Ž. Stević, D. Pamuèar, A. Puška and P. Chatterjee, Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS), *Computers & Industrial Engineering*, vol.140, 106231, 2020.
[30] D. Kannan, H. Mina, S. Nosrati-Abarghooee and G. Khosrojerdi, Sustainable circular supplier selection: A novel hybrid approach, *Science of the Total Environment*, vol.722, 137936, 2020.

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