The Combined PSI-ROC Weight Model

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ABSTRACT

The assignment of weights to criteria plays a vital role in addressing multi-objective optimization problems in general and Multi-Criteria Decision-Making (MCDM) problems in particular. This study introduces a new approach for calculating criteria weights, referred to as the Combined PSI-ROC Weight method, and operates in two stages. First, the Preference Selection Index (PSI) method is applied to determine the priority order of the criteria, and then the Rank Order Centroid (ROC) method is used to calculate the weights based on this established order. The effectiveness of the Combined PSI-ROC weight method was tested using two randomly generated numerical examples and one case study involving the evaluation of fire-resistant material criteria. The results indicate that the proposed method outperforms the PSI and Entropy weight methods in maintaining the rank stability of alternatives when assessed by different MCDM techniques. Specifically, the average Spearman correlation coefficients between rankings generated by MCDM methods reached 0.9467, 0.8933, and 0.9444, respectively, when using PSI-ROC weights. In comparison, the PSI method achieved coefficients of 0.8067, 0.8076, and 0.9016, while the Entropy method produced values of 0.9267, 0.7162, and 0.8873.

Keywords-Multi-Criteria Decision-Making (MCDM); criteria weighting; PSI method; ROC method; combined PSI-ROC method; rank stability

I. INTRODUCTION

When solving MCDM problems, it is often necessary to use several different methods simultaneously, as each may yield a ranking of alternative solutions that is not entirely consistent with the others [1]. Several factors contribute to this situation, including the use of different algorithms within each method, the application of various data normalization techniques, and the implementation of distinct weighting methods [2]. The weights of the criteria reflect their importance and have a significant impact on the results of multi-objective optimization problems [3]. Also, the choice of a weighting method for the criteria needs to ensure the stability of the alternative rankings when they are ranked by different MCDM methods [4]. However, selecting an appropriate weighting method is challenging due to the wide variety of available approaches, ranging from objective to subjective methods [5].

Different strategies have been explored to address this challenge. Some studies have focused on comparing existing weighting methods [6], while others have combined multiple methods to achieve improved performance [7, 8]. Researchers have begun repurposing criteria ranking methods as weighting methods. For example, the R method, originally designed to rank alternatives, has been adapted to calculate criteria weights. It has been shown that applying these weights within other MCDM methods produces more reliable results than using the R method directly for ranking. Nonetheless, when used in this way, the R method becomes a subjective approach, as the weights depend on the decision maker’s personal judgments regarding the importance of criteria [9].

The PSI method, also intended for ranking alternatives, has similarly been adapted for calculating criteria weights. These weights have then been applied in methods such as TOPSIS and MABAC, yielding better performance compared to directly applying PSI for ranking [10]. In [11], PSI-derived weights were integrated with RAPS and MCRAT methods, again demonstrating improved results over using PSI alone. These findings suggest that employing PSI as a weighting method is an innovative and effective approach. However, because PSI is classified as an objective weighting method, it does not incorporate expert judgments on the importance of the criteria.

So, it may sometimes lead to decisions that overlook valuable domain knowledge [12, 13].

Both purely subjective and purely objective weighting methods have inherent limitations. To overcome the latter, the present study proposes a combined approach that integrates subjective and objective elements, thereby capitalizing on the strengths of each while reducing their weaknesses. The PSI method was selected as the subjective component for its demonstrated advantages, while the ROC method was chosen as the objective component. ROC has been reported to achieve up to 96% accuracy in identifying the best alternative [14], and its key advantage lies in minimizing the errors associated with individual weight assignments by determining the "centroid of potential weights" while maintaining the established ranking order.

II. THE PROPOSED MODEL

The steps for the PSI method [15], which is one of the two components of the developed model, are:

Step 1: Construct a decision matrix consisting of *m* alternatives and *n* criteria. Let y_{ij} be the value of criterion *j* for alternative *i*, where *j*=1…*n* and *i*=1…*m*.

Step 2: Classify the criteria "larger is better" as B and "smaller is better" as C, and normalize the data using:

$$n_{ij} = \begin{cases} \dfrac{y_{ij}}{max y_{ij}}, \text{ if } j \in \mathrm{B} \\ \dfrac{min y_{ij}}{y_{ij}}, \text{ if } j \in \mathrm{C} \end{cases} \quad (1)$$

Step 3: Calculate the mean $\bar{n}_j$ of the normalized data using:

$$\bar{n}_j = \frac{1}{n}\sum_{i=1}^{n} n_{ij} \quad (2)$$

Step 4: Determine the deviation in preference values using:

$$\varnothing_j = 1 - \sum_{i=1}^{n}\left[n_{ij} - \bar{n}_j\right]^2 \quad (3)$$

Step 5: Calculate the weights for the criteria using:

$$w_{jPSI} = \frac{\varnothing_j}{\sum_{i=1}^{m}\varnothing_i} \quad (4)$$

The second method of the model is ROC [16] and its steps are:

Step 1: Rank the criteria in descending order of priority, where the most important criterion is ranked as 1 and the least important is ranked as *n*.

Step 2: Calculate the weights of the criteria using:

$$w_{jROC} = \frac{1}{n}\sum_{k=i}^{n}\frac{1}{k} \quad (5)$$

where *k* is the rank of criterion *j*.

From the criteria weight values calculated by the PSI method, the priority ranking of the criteria can be determined, which corresponds to Step 1 of the ROC method. The criteria weights calculated by the ROC method then become the criteria weights of the hybrid PSI-ROC method (Figure 1).

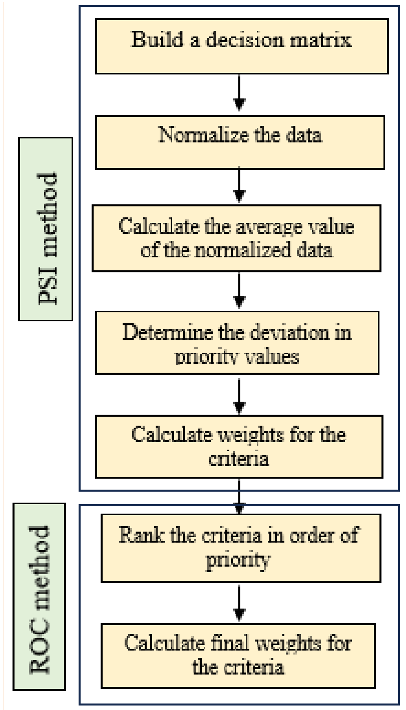

Fig. 1. PSI-ROC combined weighting method.

III. MODEL EVALUATION

To evaluate the performance of the combined PSI-ROC weighting method, three case studies were conducted. In the first case, criteria weights were calculated for a decision-making problem involving five alternatives (A1-A5), each characterized by four "larger-is-better" (B-type) criteria (C1-C4). In the second case, criteria weights were determined for six alternatives (A1-A6), each evaluated using five "smaller-is-better" (C-type) criteria (C1-C5). In the third case, criteria weights were obtained for ranking eight types of fire-resistant materials, where each alternative was assessed using four B-type criteria and one C-type criterion.

For all three cases, the weights were computed using the PSI method, the proposed PSI-ROC method, and the widely used Entropy method. The resulting weights were then applied in six MCDM techniques: MOORA, ROV, COCOSO, TOPSIS, PIV, and RAM, to rank the alternatives. Ranking stability across these MCDM methods was assessed using Spearman's rank correlation coefficient [17, 18], denoted as S, which is calculated by:

$$S = 1 - \frac{6\sum D_i^2}{m\left(m^2 - 1\right)} \quad (6)$$

where D_i is the difference in ranking of the alternative i across methods, and m is the number of alternatives.

A. Case 1

In the first case, the decision problem involved five alternatives (A1-A5) and four B-type criteria (C1-C4). Using (1-4) on input data (Table I), the criteria weights were obtained with the PSI method. The corresponding priority order was then applied in (5) to determine the ROC-based weights, leading to the combined PSI-ROC weighting. The results were then compared with those of the Entropy method (Table II). The alternatives were ranked using the six MCDM methods for each weighting approach (Tables III-V), and the Spearman coefficients between methods were then calculated (Tables VI-VIII).

TABLE I. CASE 1 INPUT DATA

Alt.	C1	C2	C3	C4
A1	21	5.5	102	68
A2	24	5	106	64
A3	20	4.8	100	70
A4	25	4	101	66
A5	18	4.3	94	65

TABLE II. CRITERIA WEIGHTS

Weight method	C1	C2	C3	C4
PSI	0.2434	0.2453	0.2554	0.2559
	Priority order			
	4	3	2	1
PSI-ROC	0.063	0.146	0.271	0.521
Entropy	0.2457	0.3078	0.2211	0.2254

TABLE III. ALTERNATIVE RANKINGS FOR THE PSI METHOD

Alt.	MOORA	ROV	COCOSO	TOPSIS	PIV	RAM
A1	2	1	1	2	2	2
A2	1	2	3	1	1	1
A3	4	3	2	4	4	4
A4	3	4	4	3	3	3
A5	5	5	5	5	5	5

TABLE IV. ALTERNATIVE RANKINGS FOR THE PSI-ROC METHOD

Alt.	MOORA	ROV	COCOSO	TOPSIS	PIV	RAM
A1	1	2	2	1	1	1
A2	3	3	3	3	3	3
A3	2	1	1	2	2	2
A4	4	4	4	4	4	4
A5	5	5	5	5	5	5

TABLE V. ALTERNATIVE RANKINGS FOR THE ENTROPY METHOD

Alt.	MOORA	ROV	COCOSO	TOPSIS	PIV	RAM
A1	1	1	1	2	1	1
A2	2	2	3	1	2	2
A3	3	3	2	3	3	3
A4	4	4	4	4	4	4
A5	5	5	5	5	5	5

TABLE VI. SPEARMAN COEFFICIENTS FOR THE PSI METHOD

Method	ROV	COCOSO	TOPSIS	PIV	RAM
MOORA	0.8000	0.5000	1.0000	1.0000	1.0000
ROV		0.9000	0.8000	0.8000	0.8000
COCOSO			0.5000	0.5000	0.5000
TOPSIS				1.0000	1.0000
PIV					1.0000
Average	0.8067				

TABLE VII. SPEARMAN COEFFICIENTS FOR THE PSI-ROC METHOD

Method	ROV	COCOSO	TOPSIS	PIV	RAM
MOORA	0.9000	0.9000	1.0000	1.0000	1.0000
ROV		1.0000	0.9000	0.9000	0.9000
COCOSO			0.9000	0.9000	0.9000
TOPSIS				1.0000	1.0000
PIV					1.0000
Average	0.9467				

TABLE VIII. SPEARMAN COEFFICIENTS FOR THE ENTROPY METHOD

Method	ROV	COCOSO	TOPSIS	PIV	RAM
MOORA	1.0000	0.9000	0.9000	1.0000	1.0000
ROV		0.9000	0.9000	1.0000	1.0000
COCOSO			0.7000	0.9000	0.9000
TOPSIS				0.9000	0.9000
PIV					1.0000
Average	0.9267				

The findings showed that PSI-ROC achieved the highest stability with all Spearman coefficients, meaning greater than 0.9 and an average of 0.9467, in contrast with the PSI method, which had an average of 0.8067, and the Entropy method, which obtained 0.9267. This indicates that PSI-ROC significantly enhances the ranking consistency across different MCDM methods [19].

B. Case 2

In the second case, six alternatives (A1-A6) were evaluated using five C-type criteria (Table IX). Following the same procedure as in case one, the weights were determined using PSI, PSI-ROC, and Entropy, and then the rankings and Spearman coefficients were calculated (Tables X-XII).

TABLE IX. CASE 2 INPUT DATA

Alt.	C1	C2	C3	C4	C5
A1	205	1.7	77	22.1	41
A2	200	1.8	65	23	38
A3	208	2.5	60	18.4	40
A4	210	2.3	72	22	44
A5	212	1.6	70	23.1	50
A6	223	2	74	25.2	43.5

TABLE X. SPEARMAN COEFFICIENTS FOR THE PSI METHOD

Method	ROV	COCOSO	TOPSIS	PIV	RAM
MOORA	1.0000	0.8286	0.5714	1.0000	1.0000
ROV		0.8286	0.5714	1.0000	1.0000
COCOSO			0.5143	0.8286	0.8286
TOPSIS				0.5714	0.5714
PIV					1.0000
Average	0.8076				

TABLE XI. SPEARMAN COEFFICIENTS FOR THE PSI-ROC METHOD

Method	ROV	COCOSO	TOPSIS	PIV	RAM
MOORA	1.0000	0.9429	0.7143	1.0000	1.0000
ROV		0.9429	0.7143	1.0000	1.0000
COCOSO			0.7714	0.9429	0.9429
TOPSIS				0.7143	0.7143
PIV					1.0000
Average	0.8933				

TABLE XII. SPEARMAN COEFFICIENTS FOR THE ENTROPY METHOD

Method	ROV	COCOSO	TOPSIS	PIV	RAM
MOORA	0.8000	0.5714	0.7429	1.0000	1.0000
ROV		0.7143	0.3143	0.8000	0.8000
COCOSO			0.3714	0.5714	0.5714
TOPSIS				0.7429	0.7429
PIV					1.0000
Average	0.7162				

The lowest Spearman coefficient was 0.5143 for PSI and 0.3143 for Entropy, compared with a much higher 0.7143 for PSI-ROC. The average correlation was also the highest for PSI-ROC (0.8933), compared with PSI (0.8076) and Entropy (0.7162). Both of these observations demonstrate that PSI-ROC improves the ranking stability.

C. Case 3

In the third case, the evaluation focused on 8 fire-resistant materials: PVC, 5ATH/PVC, 10ATH/PVC, 15ATH/PVC, 5ZB/PVC, 10ZB/PVC, 15ZB/PVC, and 5ATH/5ZB/PVC. The parameters taken into account when processing the data (Table XIII) were the tensile strength at break, the elongation at break, the elastic modulus, the total burning time, and the limiting oxygen index (C1–C5). Among these, C4 was a C-type criterion, while the rest were B-type.

TABLE XIII. CASE 3 INPUT DATA

Alt.	C1	C2	C3	C4	C5
PVC	25.7	289.5	30.1	7.5	25.5
5ATH/PVC	24.8	260.6	32.7	3.5	28.1
10ATH/PVC	22.5	205.1	33.1	1.9	30
15ATH/PVC	23.5	274.1	33.6	0.5	32
5ZB/PVC	21.4	257.3	32	3.8	27.8
10ZB/PVC	21.4	257.3	32.3	2.1	29.8
15ZB/PVC	19.2	240	33	0.7	31.7
5ATH/5ZB/PVC	24.2	271	33.3	1.7	30.3

The results of the Spearman coefficients (Tables XIV-XVI) also confirmed in this case that the PSI-ROC method delivered the most consistent rankings, with an average coefficient of 0.9444, compared with 0.9016 for PSI and 0.8873 for Entropy.

TABLE XIV. SPREARMAN COEFFICIENTS FOR THE PSI METHOD

Method	ROV	COCOSO	TOPSIS	PIV	RAM
MOORA	0.8095	0.8095	0.9048	0.9048	0.9762
ROV		0.8571	0.9048	0.9762	0.8571
COCOSO			0.9524	0.8810	0.8810
TOPSIS				0.9286	0.9524
PIV					0.9286
Average	0.9016				

TABLE XV. SPEARMAN COEFFICIENTS FOR THE PSI-ROC METHOD

Method	ROV	COCOSO	TOPSIS	PIV	RAM
MOORA	0.9524	0.8571	0.9762	0.9762	1.0000
ROV		0.8810	0.9762	0.9762	0.9524
COCOSO			0.9048	0.9048	0.8571
TOPSIS				1.0000	0.9762
PIV					0.9762
Average	0.9444				

TABLE XVI. SPEARMAN COEFFICIENTS FOR THE ENTROPY METHOD

Method	ROV	COCOSO	TOPSIS	PIV	RAM
MOORA	0.8810	0.7143	1.0000	0.9762	1.0000
ROV		0.8810	0.8810	0.9048	0.8810
COCOSO			0.7143	0.8095	0.7143
TOPSIS				0.9762	1.0000
PIV					0.9762
Average	0.8873				

In all three examples, the PSI-ROC method consistently achieved higher average Spearman coefficients compared with PSI and Entropy. Despite the differences in the problem size and criteria types, PSI-ROC repeatedly outperformed the other two methods. Its advantage arises from combining the objective nature of PSI with the ranking-based robustness of ROC, thus capturing the "centroid of potential weights" perspective.

It is revealed that the PSI-ROC method provides more stable and reliable alternative rankings across different MCDM approaches. It is, therefore, proposed as an effective alternative to both PSI and Entropy for calculating criteria weights.

IV. CONCLUSIONS

This study combined two methods, Preference Selection Index (PSI) and Rank Order Centroid (ROC), and introduced the weighting approach PSI-ROC, which integrates the strengths of both methods. The effectiveness of PSI-ROC was validated through three cases. The findings demonstrated that when PSI-ROC is employed to calculate criteria weights, the resulting alternative rankings consistently exhibit higher stability across multiple Multi-Criteria Decision-Making (MCDM) methods, outperforming both the PSI and Entropy approaches.

For future work, applying PSI-ROC to other decision-making problems in place of PSI or Entropy is proposed. However, it should be noted that PSI-ROC cannot be applied directly when the maximum value of a B-type criterion equals zero or when any C-type criterion takes the value zero. In such cases, alternative data normalization procedures must be adopted. This limitation highlights the need for further research into handling these special cases. In addition, extending the PSI-ROC framework to accommodate qualitative criteria represents an important direction for future studies, which could further enhance the robustness and applicability of the method.

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