A Novel Approach for Criteria Weight Determination: A Case Study in Machine Ranking

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Received: 25 October 2025 | Revised: 17 November 2025 | Accepted: 25 November 2025

 DOI: https://doi.org/10.48084/etasr.15778

ABSTRACT

Machine ranking plays a crucial role in manufacturing, influencing both economic efficiency and technical performance. However, this task is inherently complex because each machine must be evaluated simultaneously across multiple, often conflicting, criteria. This challenge highlights the need for Multi-Criteria Decision-Making (MCDM) methods. This study proposes a new criteria weighting approach, the SITDER method, that aims to improve the stability of machine ranking results across different MCDM techniques. SITDER integrates two methods: Skewness Impact Through Distributional Evaluation (SITDE) and Rank Order Centroid (ROC). In the first stage, SITDE is used to determine the relative importance of the criteria. In the second stage, ROC is applied to compute the final criterion weights. The effectiveness of SITDER was validated using two case studies involving the ranking of 13 handheld polishers and 12 grinding machines. In both examples, the rank correlation coefficients among the MCDM methods were consistently higher when using SITDER compared to SITDE alone. In Example 1, the average Spearman coefficient increased from 0.6282 (SITDE) to 0.739 (SITDER). In Example 2, it increased from 0.9643 to 0.9744. These results demonstrate that SITDER is a highly effective weighting method and a valuable addition to the set of available criteria weighting techniques.

Keywords-weight method; SITDE method; ROC weight; SITDER method; MCDM

I. INTRODUCTION

Machinery spans applications from heavy industry to everyday life, and serves as a fundamental tool for enhancing labor productivity. Machines also deliver high precision and consistency in processed products, at levels that are difficult to achieve manually. In this sense, machinery is not merely a tool but the backbone of the modern economy, helping reduce human labor, driving economic growth, and ultimately improving overall quality of life [1]. These advantages have encouraged manufacturers to develop numerous machine alternatives for the same purpose [2]. However, this abundance of options makes selecting the most suitable machine a challenging task for users. Machine selection typically involves multiple criteria, which often vary among alternatives and may even conflict. For example, a machine with a low purchase price may have reduced power or precision, while a high-power machine may offer less operational convenience. To address this complexity, MCDM methods have been widely adopted in machine selection across various applications [3]. Within these methods, choosing an appropriate criterion weighting technique is crucial, as it significantly affects the final ranking of alternatives [4]. Criteria weighting methods are generally classified into two groups: subjective and objective approaches [5]. In machine selection research, numerous studies have applied objective weighting methods. Examples include the use of Criteria Importance Through Intercriteria Correlation (CRITIC) and Integrated Determination of Objective Criteria Weights (IDOCRIW) for weighting sawing machine criteria [6]; the combined use of Entropy and the Method based on the Removal Effects of Criteria (MEREC) for determining forklift criteria weights [7]; the application of the Symmetry Point of Criteria (SPC) method for woodworking machines [8]; and the use of equal weighting for grinding, drilling, and milling machines [9]. Similarly, many studies have employed subjective weighting methods. These include the application of the Analytic Hierarchy Process (AHP) to determine the criteria weights of CNC lathes [10, 11], and the use of Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA) for weighting criteria of both new and used CNC lathes and universal lathes [12]. The PIPRECIA method has also been used to determine criteria weights for welding robots [13].

Both objective and subjective weighting methods have been widely applied in machine selection. However, using objective weighting methods calculates criteria weights solely based on impersonal numerical data, disregarding user preferences. This can sometimes result in the final selected alternative not aligning with the user's expectations. Conversely, reliance on subjective weighting methods can introduce human error due to a user's incomplete understanding of the criteria or a potential bias towards a specific criterion [14]. Consequently, novel weighting methods, integrating objective and subjective approaches, have been proposed. In this integrative manner, criteria weights are calculated in two stages: first, weights are determined using an objective method to establish the priority order of the criteria; and second, the final weights are calculated by applying the formulas of a subjective weighting method. This two-stage process aims to leverage the strengths and mitigate the weaknesses of both component methods. The PSI-ROC weighting method calculates the subjective weights for the criteria using the Preference Selection Index (PSI) method and then calculates the weights for the criteria deploying the objective ROC method [15]. The SIWEC-ROC method performs weight calculation in two stages: first, weights are calculated using the SIWEC method, and then the criteria weights are calculated employing the ROC method [16]. The ER method performs weight calculation in two stages: first, weights are calculated using the Entropy method, and then the criteria weights are calculated utilizing the ROC method [17]. The IDOCRIW method determines the criteria weights by taking the harmonic mean of the weights calculated using two methods: Entropy and Criterion Impact Loss Method (CILOS) [18]. SITDE is a recently developed objective weighting method that determines criteria weights by incorporating Skewness [19]. This approach is particularly suitable for machine criteria where the distribution of values across different alternatives may span a wide range. However, as an objective method, SITDE is subject to the aforementioned inherent limitations. To exploit the advantage of SITDE, its calculation process is based on the criterion of Skewness, while simultaneously addressing its purely objective nature. This research proposes the integration of the SITDE method with the ROC method, yielding a new hybrid approach named SITDER. The ROC method was chosen for its proven effectiveness in combination with objective weighting methods and because it has been validated to be up to 96% accurate in selecting the best alternative [20]. This high accuracy stems from ROC's notable advantage: it minimizes errors related to individual weights by determining the "center of potential weights" while preserving the rank order of the objectives [18].

II. MATERIALS AND METHODS

The determination of criteria weights using the SITDE method is carried out according to the following sequence [19]:

- Construction of the decision matrix with m rows and n columns, where m is the number of alternatives to be ranked, n is the number of criteria for evaluating each alternative, and x_{ij} is the value of criterion j for alternative i, with $i=1$ *to* m, and $j=1$ *to* n.

- Normalizing the decision matrix using (1), where the letters J and H represent the benefit-type criteria (larger is better) and the cost-type criteria (smaller is better), respectively:

$$z_{ij}=\begin{cases}\dfrac{min x_{ij}}{x_{ij}} & if \quad j\in j\\ \dfrac{x_{ij}}{max x_{ij}} & if \quad j\in H\end{cases} \qquad (1)$$

- Calculating the Skewness for criterion j using (2). Here, $\overline{z_j}$ is the mean value of the normalized scores for criterion j, and σ_j is the standard deviation of the normalized scores for criterion j:

$$K_j=\frac{m}{(m-1)(m-2)}\sum_{i=1}^{m}\left(\frac{z_{ij}-\overline{z_j}}{\sigma_j}\right)^3 \qquad (2)$$

- Calculating the distribution-derived deviation of the criteria j using:

$$LK_j=log\left|\left((K_j+1)+\left(\left|\min(K_j)\right|+1\right)\right)\right| \qquad (3)$$

- Calculating the weights of the criteria using:

$$W_j=\frac{LK_j}{\sum_{j=1}^{n}LK_j} \qquad (4)$$

The determination of criteria weights using the ROC method is performed in the following sequence [21].

- Ranking the criteria in descending order of their priority level.

- Calculating the weights of the criteria using (5), where t is the priority rank of criterion j:

$$W_j=\frac{1}{n}\sum_{t}^{n}\frac{1}{t} \qquad (5)$$

Based on the criteria weighting procedures for the SITDE and ROC methods, the block diagram of the proposed method is illustrated in Figure 1.

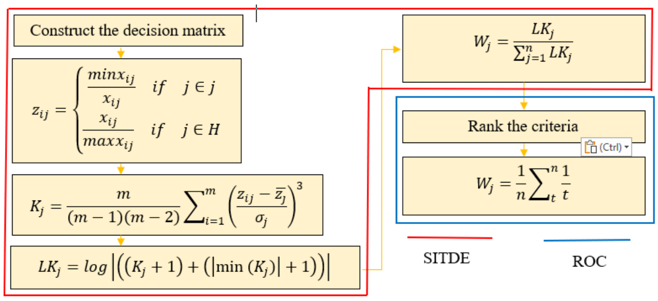

Fig. 1. Block diagram of the SITDER method.

To evaluate the effectiveness of the proposed method, it is necessary to apply several different MCDM techniques to rank the alternatives and then assess the consistency of these rankings using Spearman's Rank Correlation Coefficient (referred to as the Spearman coefficient). This study employs four MCDM methods, each with distinct characteristics: Multi-Objective Optimization based on Ratio Analysis (MOORA), one of the most widely used methods; Probability, a non-additive approach; Simple Additive Weighting (SAW), the oldest and simplest method; and Faire Un Choix Adéquat (FUCA), which does not require data normalization. The Spearman coefficient is calculated using (6), where D_i denotes the difference in the rank of the i-th alternative across the applied MCDM methods [22].

$$S=1-\frac{6\sum_{i=1}^{m}D_i^2}{m(m^2-1)} \qquad (6)$$

III. RESULTS AND DISCUSSION

A. Example 1

This study utilized data concerning 13 types of polishing machines from [23]. The machines were encoded from A1 to A13. Each alternative was characterized by six criteria: Selling Price, Power, Polishing Disc Diameter, No-load Speed, Weight, and Warranty Period, denoted as C1-C6, respectively. High power output is essential for strong operation, allowing the machine to maintain excellent speed and efficiency even under heavy load. A larger polishing pad diameter is crucial as it enables the machine to cover a greater surface area, significantly reducing the overall working time. Furthermore, a high no-load speed signifies the machine's ability to achieve greater polishing velocity, which helps in rapidly addressing scratches and attaining a high-gloss finish. Machines with a heavier weight (above the typical range) often feature a more powerful motor and robust construction, providing increased stability and reduced operational vibration. Finally, a long warranty period serves as a strong indicator of the manufacturer's confidence in the product's quality and long-term durability. The data for these machines are summarized in Table I. Among these, only C1 is an H-type criterion, while all other criteria belong to the J-type. The calculation of criteria weights using the SITDE method, the ranking of criteria, and the determination of criteria weights using the SITDER method were performed following the sequence outlined in the flowchart in Figure 1. The results are outlined in Table II.

Table III presents the rankings of the alternatives obtained from the four MCDM methods, MOORA, Probability, SAW, and FUCA, under two weighting scenarios: criteria weights computed using SITDE and criteria weights computed using SITDER. It is observed that the rankings of the polishing machines differ across MCDM methods and between the two weighting approaches. This variability is expected and has been widely documented, as each MCDM method relies on different computational principles and decision-making frameworks [24]. To evaluate the effectiveness of the proposed SITDER method, the Spearman Rank Correlation Coefficient was calculated for both weighting scenarios using (6). The corresponding results are displayed in Table IV.

TABLE I. POLISHING MACHINES

Alt	C1	C2	C3	C4	C5	C6
A1	5230	1200	180	3200	3.5	6
A2	5175	1200	180	3000	3	12
A3	1500	1020	180	3600	3.6	6
A4	4832	1200	180	3000	3	6
A5	1250	2000	180	3000	3	6
A6	1200	1400	180	3200	3.4	6
A7	5021	900	180	2000	2.2	12
A8	390	600	150	4500	1	6
A9	1171	240	125	24000	1.1	6
A10	3450	1250	180	3000	2.8	6
A11	1750	1400	150	3500	4.7	6
A12	1925	440	150	4700	1.2	12
A13	1400	240	125	12000	1.2	6

TABLE II. WEIGHTS AND PRIORITY ORDER OF CRITERIA

Method	C1	C2	C3	C4	C5	C6
SITDE weight	0.1784	0.2101	0.1988	0.1384	0.1890	0.0853
Priority order	4	1	2	5	3	6
SITDER weight	0.103	0.408	0.242	0.061	0.158	0.028

TABLE III. RANKING OF POLISHING MACHINES

Alt	SITDE weight				SITDER weight			
	MOORA	Probability	SAW	FUCA	MOORA	Probability	SAW	FUCA
A1	12	11	6	5	12	8	4	6
A2	11	10	4	7	11	7	5	8
A3	6	4	5	3	4	4	7	5
A4	10	7	8	8	10	6	8	7
A5	1	1	1	2	1	1	1	1
A6	2	3	3	1	2	2	2	2
A7	13	13	10	11	13	9	9	9
A8	4	6	9	9	5	10	10	10
A9	3	8	11	12	7	12	12	12
A10	9	5	7	6	6	5	6	4
A11	5	2	2	4	3	3	3	3
A12	8	9	12	10	9	11	11	11
A13	7	12	13	13	8	13	13	13

TABLE IV. SPEARMAN COEFFICIENTS BETWEEN MCDM METHODS

Method	SITDE weight			SITDER weight		
	Probability	SAW	FUCA	Probability	SAW	FUCA
MOORA	0.7363	0.3022	0.3407	0.6044	0.4286	0.5769
Probability		0.7143	0.7582		0.9066	0.978
SAW			0.9176			0.9396
Average	0.6282			0.739		

The average Spearman coefficient among the MCDM methods, when employing SITDER for criteria weighting, is 0.739, which is significantly higher than the average of 0.6282 obtained when using the SITDE method. This reflects that utilizing the SITDER method for criteria weighting ensures a higher stability in the rank order of alternatives when evaluated by different MCDM methods compared to using SITDE. This implicitly suggests that the SITDER method is more effective than the SITDE method.

B. Example 2

In this example, the effectiveness of the proposed method is evaluated in the case of ranking 12 types of grinding machines, denoted as A1-A12, respectively. Eight criteria were used to describe each type of machine, including the maximum travel of the table along the X-axis (C1), the maximum travel of the table along the Y-axis (C2), the maximum travel of the table along the Z-axis (C3), the maximum grinding wheel diameter that can be mounted on the machine (C4), the maximum speed of the grinding wheel (C5), the power of the machine (C6), the achievable accuracy of the machine (C7), and the year the machine was manufactured (C8). Among these, only C7 is an H-type criterion, while all remaining criteria are of the j-type. The data for this example are depicted in Table V [10].

Performing similarly to Example 1, the criteria weights were calculated, as summarized in Table VI. The alternative options were ranked, as presented in Table VII, while the values of the Spearman coefficient among the MCDM methods are illustrated in Table VIII.

TABLE V. TYPES OF GRINDING MACHINES

Alt	C1	C2	C3	C4	C5	C6	C7	C8
A1	315	110	300	205	38.5	2.2	0.005	2016
A2	600	300	350	305	28	3.7	0.005	2016
A3	600	300	350	305	28	3.7	0.005	1998
A4	600	400	380	305	28	3.7	0.005	1992
A5	315	110	300	205	38.5	2.2	0.005	2002
A6	315	110	300	205	38.5	2.2	0.002	2009
A7	500	200	350	205	31.5	3.7	0.005	2009
A8	510	205	355	205	31.5	3.7	0.005	2014
A9	1280	550	600	510	53.5	3.4	0.002	2017
A10	600	500	400	355	37	3.7	0.002	2018
A11	1600	720	650	510	53.5	4.2	0.002	2014
A12	510	205	355	205	31.5	3.7	0.005	2016

TABLE VI. WEIGHTS AND PRIORITY ORDER OF CRITERIA (EXAMPLE 2)

Method	C1	C2	C3	C4	C5	C6	C7	C8
SITDE weight	0.1356	0.1511	0.0747	0.1081	0.1074	0.1663	0.0915	0.1653
Priority order	4	3	8	5	6	1	7	2
SITDER weight	0.1106	0.1522	0.0156	0.0793	0.0543	0.3397	0.0335	0.2147

TABLE VII. RANKING OF GRINDING MACHINES

Alt.	SITDE weight				SITDER weight			
	MOORA	Probability	SAW	FUCA	MOORA	Probability	SAW	FUCA
A1	11	11	11	10	11	11	11	10
A2	5	5	5	4	5	5	6	4
A3	6	6	6	8	6	6	7	8
A4	4	4	4	7	4	4	4	6
A5	12	12	12	12	12	12	12	12
A6	10	10	10	11	10	10	10	11
A7	9	9	9	9	9	9	9	9
A8	8	8	8	6	8	8	8	7
A9	2	2	2	3	2	2	2	2
A10	3	3	3	2	3	3	3	3
A11	1	1	1	1	1	1	1	1
A12	7	7	7	5	7	7	5	5

TABLE VIII. SPEARMAN COEFFICIENTS BETWEEN MCDM METHODS (EXAMPLE 2)

Method	SITDE weight			SITDER weight		
	Probability	SAW	FUCA	Probability	SAW	FUCA
MOORA	1	1	0.9286	1	0.9835	0.956
Probability		1	0.9286		0.9835	0.956
SAW			0.9286			0.967
Average	0.9643			0.9744		

Based on the data in Table VII, it is observed that A11 is consistently identified as the best grinding machine when both SITDE and SITDER are used to calculate the criteria weights, and when all four MOORA, Probability, SAW, and FUCA methods are utilized to rank the alternatives. Conversely, A5 is consistently identified as the worst machine. According to the data in Table VIII, the Spearman coefficient among the MCDM methods is very high in both cases where SITDE and SITDER are used to calculate the criteria weights. Specifically, the average value of the Spearman coefficient among the MCDM methods is 0.9643 when using SITDE to calculate the criteria weights, and 0.9744 when using SITDER. This indicates that SITDER has also shown an advantage over SITDE in this example. As such, by comparing these two methods in calculating the criteria weights when ranking 13 handheld polishers and 12 grinders, it was observed that SITDER is more effective than SITDE. All obtained results are sufficient to affirm that this study has taken an innovative approach to create a new method, SITDER, for calculating criteria weights that is more effective than the existing method, SITDE.

IV. CONCLUSIONS

This study introduced a new criteria weighting method, SITDER, which integrates the SITDE and ROC approaches. The case studies on handheld polishing machines and grinding machines demonstrated that SITDER provides more stable ranking results than SITDE. In the polishing machine example, the average Spearman coefficient among the MCDM methods increased from 0.6282 (using SITDE) to 0.739 (using SITDER). In the grinding machine example, this value increased from 0.9643 to 0.9744. Future research should further evaluate SITDER across different application domains and compare its performance with other established weighting techniques under various operational conditions. Another important area for development involves extending SITDE and SITDER to handle qualitative criteria, as neither method can currently process such data, highlighting the need for fuzzy versions of both approaches. Additionally, the existing SITDE normalization procedure (as described in (1)) becomes invalid when a J-type criterion contains a zero value for any alternative or when an H-type criterion has a maximum value of zero across all alternatives. Addressing this limitation by identifying or developing an alternative normalization technique is therefore an essential direction for future work.

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