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APPLICABILITY ASSESSMENT OF THE CURLIA METHODOLOGY FOR MACHINE SELECTION

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Abstract. *Machine selection constitutes a vital yet highly intricate process and can be classified as a Multi-Criteria Decision-Making (MCDM) task because it requires the simultaneous assessment of multiple conflicting criteria. This study evaluates the applicability of the CURLIA methodology to machine selection problems. Seven individual MCDM techniques, including RAM, TOPSIS, EDAS, SREM, PIV, MOORA, and Probability, were initially employed to determine the rankings of candidate machines. Subsequently, the CURLIA framework was utilized to aggregate the decision data generated by these baseline techniques. Two practical engineering applications were evaluated: the ranking of thirteen hand-held polishing machines and the ranking of six wood planers. For each application, sensitivity analysis was conducted using alternative weighting schemes to determine the importance of the criteria. The candidate rankings synthesized using CURLIA exhibited excellent agreement with those produced by the constituent MCDM algorithms. The mean Spearman rank correlation coefficient between CURLIA and the individual constituent MCDM techniques ranged from 0.8823 to 1.0000. Across the evaluated engineering applications, the results indicate that CURLIA provides a consistent aggregation of the rankings generated by the constituent MCDM methods.*

Key words: *CURLIA method, MCDM, Machine ranking, Sensitivity analysis*

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1. INTRODUCTION

Selecting appropriate machinery represents a critical decision that directly affects an enterprise's long-term survival and competitiveness [1]. Optimal machine selection enhances operational efficiency, increases productivity, and minimizes production-line disruptions caused by technical failures. For operating personnel, smoothly functioning equipment with high safety standards reduces operational stress, protects worker health, and improves overall workplace morale. Machine selection also plays a fundamental role in determining product quality by ensuring manufacturing consistency, reducing defect rates, thereby strengthening customer confidence through reliable delivery schedules and consistent product quality [2,3].

Nevertheless, machine selection is rarely a straightforward task; rather, it is an inherently complex multi-criteria problem that requires comprehensive evaluation across numerous technical and economic parameters, ranging from capital investment cost, operating power, precision, and warranty duration to operational ergonomics [4]. This complexity arises because these criteria often conflict with one another across candidate alternatives [5] Multi-Criteria Decision-Making (MCDM) methodologies are specifically designed to support decision-makers in addressing multiple competing objectives [6,7]. MCDM algorithms have been extensively applied to machine selection problems [3,8–13] and are widely recognized as effective analytical frameworks for evaluating candidate solutions across diverse performance metrics [14]. However, owing to differences in the underlying algorithms, distinct MCDM methodologies may produce divergent alternative rankings when applied to the same dataset [15–17]. Consequently, researchers have advocated for synthesized decision frameworks that integrate multiple MCDM methods to enhance decision reliability and robustness [18,19]. In this context, selecting an appropriate data aggregation technique to synthesize the results obtained from individual MCDM methods becomes a paramount consideration for decision-makers seeking optimal solutions [20,21].

A variety of data aggregation techniques have been employed in the literature, including Copeland [22–24], Condorcet theory [25], the Rank Average method, Borda count [26], Half-Quadratic Programming [27], Minimum of Ranks [28,29], Ranked Pairs, the Schulze method [30], and Arrow's theorem [31]. Beyond synthesizing decision outcomes, data aggregation methodologies provide diagnostic insights into the constituent MCDM algorithms employed [32]. Nevertheless, not all data aggregation techniques are universally suitable across different contexts because of numerical variations inherent in specific domain applications [33]. Empirical evidence has demonstrated that different aggregation models can produce divergent consensus rankings for the evaluated candidate alternatives [33]. Although Copeland and Borda count are among the most widely adopted aggregation approaches for synthesizing MCDM output data, their application may yield hybrid solution rankings that do not necessarily guarantee optimal selections [34]. Furthermore, both Copeland and Borda count exhibit substantially increased computational complexity as the number of constituent MCDM algorithms increases [32]. Consequently, validating a straightforward, low-complexity aggregation framework capable of synthesizing multi-MCDM outputs would contribute to the existing literature while addressing key operational limitations associated with the traditional Copeland and Borda techniques.

CURLI-AGGREGATOR (CURLIA) [35] is a recently proposed data aggregation methodology, developed as an extension of the Collaborative Unbiased Rank List integration (CURLI) [36] method, that has been reported to outperform the Copeland method in approximately 78.3% of the simulated scenarios. This comparative evaluation between CURLIA and Copeland was conducted across 1,000 simulated scenarios involving the synthesis of multi-MCDM outputs for mobile phone selection, COVID-19 control strategy ranking, and electric vehicle selection [35]. However, owing to its recent introduction, to the best of our knowledge, no existing study has applied the CURLIA framework to aggregate MCDM outcomes beyond those investigated in its original study. Given the novelty of this technique, whether CURLIA can maintain high decision-making efficacy when aggregating machine ranking outputs, a critical application domain highlighted earlier in this section, remains an open research question, which provides the primary impetus for the present study.

The remainder of this article is structured as follows. Section 2 describes the computational procedure for applying the CURLIA algorithm to synthesize multi-MCDM outputs, together with the constituent MCDM algorithms employed and the evaluation protocol used to validate the applicability of CURLIA. Section 3 presents the empirical evaluation results for two distinct machine selection applications, with each case incorporating sensitivity analysis using different criteria weighting schemes. Section 4 provides a comprehensive discussion of the key research findings. Finally, Section 5 summarizes the main conclusions and outlines potential directions for future research.

2. Materials and Methods

Following the ranking of candidate machines using the constituent MCDM techniques, the computational framework for aggregating the resulting decision outcomes using CURLIA proceeds as follows [35]:

Step 1: Construct the initial aggregation matrix by synthesizing the candidate alternative rankings obtained from l distinct constituent MCDM techniques, as formulated in Eq. (1), where l denotes the total number of decision-making methodologies applied, m represents the total number of candidate alternatives, R denotes the initial aggregation matrix, and r_{ij} represents the ranking position of the i-th alternative obtained using the j-th MCDM methodology. The indices i and j refer to alternatives $i = 1, \dots, m$ and MCDM methodologies $j = 1, \dots, l$, respectively.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1l} \\ r_{21} & r_{22} & \cdots & r_{2l} \\ \cdots & \cdots & r_{ij} & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{ml} \end{bmatrix} \tag{1}$$

Step 2: Formulate l square matrices of order m, corresponding to the pairwise alternative comparison matrices for each constituent MCDM technique. Assign matrix elements values of -1, 0, or 1 according to the decision rules defined in Eq. (2), where S_{il} denotes the pairwise comparison result between alternatives i and k under the l-th MCDM methodology, while r_i and r_k represent the ranking positions of alternatives i and k, respectively, obtained using that methodology. The indices i and k refer to the alternatives being compared, with $(i \neq k)$.

$$S_{il} = \begin{cases} -1 & if \quad r_i > r_k, i \neq k \\ 1 & if \quad r_i < r_k, i \neq k \\ 0 & if \quad r_i = r_k, i \neq k \end{cases} \tag{2}$$

Step 3: Calculate overall performance scores R_i for each candidate alternative using Eq. (3). The final ranking of the candidate machines is determined by sorting their respective aggregate R_i scores in descending order.

$$R_i = \sum_{j=1}^{l} S_{il} \tag{3}$$

To apply CURLIA to the synthesis of machine rankings, candidate machines must first be evaluated using baseline MCDM methodologies. Seven constituent algorithms were selected: RAM, TOPSIS, EDAS, SREM, PIV, MOORA, and Probability. The rationale for selecting these methodologies is as follows. RAM represents a straightforward decision-making model that employs a radical transformation mechanism to balance benefit- and cost-type criteria [37]. TOPSIS and MOORA are among the most established and widely applied MCDM techniques [38]. EDAS evaluates alternatives based on their distances from average solution values across all candidates, offering distinct structural advantages and enhanced resistance to extreme outliers [39]. SREM is a newly developed MCDM algorithm featuring a novel candidate-ranking logic [40,41]. SREM simultaneously incorporates squared and square-root data transformations in calculating performance scores, thereby minimizing sensitivity to outlier values. PIV evaluates candidate performance deviations from the ideal solution and suppresses rank reversal when alternatives are added or removed [42]. Probability avoids additive aggregation operations when evaluating alternative scores [43]. Although each MCDM algorithm follows distinct operational logic, this overview highlights the structural diversity among the seven selected techniques. Integrating structurally diverse constituent methodologies provides a more objective basis for evaluating CURLIA's aggregation efficacy.

Criteria weights serve as important inputs in MCDM applications and substantially influence final alternative rankings [44–47]. Relying on a single weighting method may introduce subjective bias or lead to unstable ranking outcomes [45,48]. To ensure objective evaluations, seven objective weighting schemes were employed: Equal, SD, SPC, LOPCOW, LODECI, Entropy, and MEREC. An integrated weighting scheme, the eighth approach, was also established by calculating the arithmetic mean of the criteria weights obtained from the seven individual objective weighting methods. Synthesizing criteria weights through integrated weighting models is widely recognized in the specialized literature as a robust methodology [49]. When aggregating data, validating synthesized outcomes against rankings produced by individual constituent MCDM algorithms is essential. High statistical agreement indicates that the aggregation model can be considered reliable [28]. Accordingly, under each criteria weighting scenario, candidate alternatives were ranked using the seven constituent MCDM methods, followed by aggregation using CURLIA. Ranking consistency between CURLIA and each constituent MCDM algorithm was quantified using Spearman's rank correlation coefficient, one of the most widely used rank correlation measures. In this study, a Spearman correlation coefficient above 0.80 is interpreted as indicating a strong level of ranking agreement. Based on these principles, the overall procedural framework for machine ranking using the CURLIA methodology is illustrated in Fig. 1.

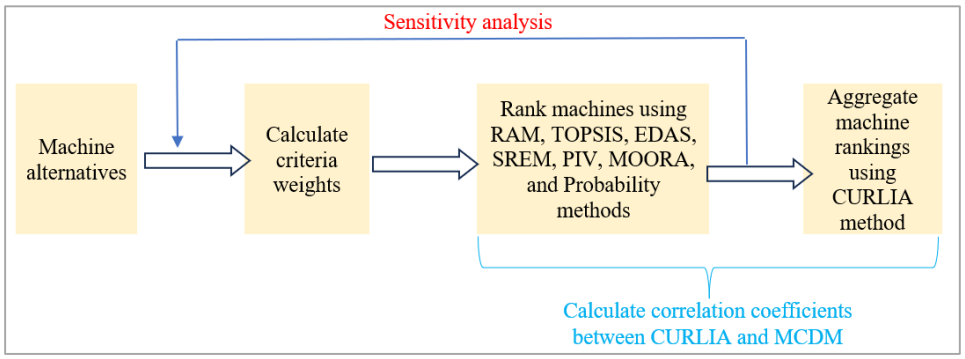

Fig. 1 Algorithmic flowchart for machine ranking using the CURLIA methodology

As shown in Fig. 1, the CURLIA-based machine ranking framework consists of a sequence of operational stages: identifying machine candidates and evaluation criteria, determining criteria weights, ranking alternatives using the constituent MCDM methods, aggregating decision data using CURLIA, and calculating Spearman's rank correlation coefficients between CURLIA and the constituent algorithms. Sensitivity analysis is performed by systematically varying the criteria weighting schemes and subsequently reinitiating the computational workflow from the constituent MCDM ranking stage onward [50].

3. Application of the CURLIA Methodology for Machine Selection

3.1. Example 1

This example evaluates a decision problem involving the ranking of thirteen hand-held polishing machine candidates, designated A1 through A13. The performance attributes specified for each alternative comprise one cost-type parameter (C), namely purchase price (C1), and five benefit-type parameters (B): power capacity (C2), polishing disc diameter (C3) (mm), no-load speed (C4) (rev/min), operating weight (C5) (kg), and warranty period (C6). The technical data for all thirteen polishing machines are summarized in Table 1 [51], with the corresponding parameter units are provided in the final row. Note that C1 is expressed in VNDT (thousands of Vietnamese Dong), where 1 VNDT ≈ 1/24.5USD.

Inspection of the raw attribute values reveals that the minimum purchase price (C1 = 390 VNDT) corresponds to alternative A8; the maximum power (C2 = 2000 W) corresponds to A5; the maximum polishing disc diameter (C3 = 180 mm) is shared by A1, A2, A3, A4, A5, A6, A7, and A10; the maximum no-load speed (C4 = 24000 rev/min) corresponds to A9; the maximum operating weight (C5 = 4.7 kg) corresponds to A11; and the maximum warranty period (C6 = 12 months) is shared by A2, A7, and A12. Consequently, no single polishing machine outperforms the competing alternatives across all six evaluation criteria simultaneously, necessitating multi-criteria decision analysis to determine the optimal selection. To evaluate candidate alternatives, criteria weighting was performed using eight distinct weighting schemes, Equal, SD, SPC, LOPCOW, LODECI, Entropy, MEREC, and Combination, representing scenarios S1 through S8, respectively. The resulting criteria weights are compiled in Table 2.

Table 1 Technical specifications of polishing machine candidates in Example 1 [51]

Machine	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
Unit	VNDT	W	mm	rev/min	kg	month

Table 2 Criteria weights derived across weighting scenarios in Example 1

Method	Scenario	C1	C2	C3	C4	C5	C6
Equal	S1	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
SD	S2	0.2158	0.0608	0.0026	0.7204	0.0001	0.0003
SPC	S3	0.0010	0.0023	0.0095	0.0004	0.7609	0.2258
LOPCOW	S4	0.0003	0.0015	0.0112	0.0002	0.6557	0.3311
LODECI	S5	0.2121	0.1754	0.0862	0.2169	0.1648	0.1446
Entropy	S6	0.2516	0.1531	0.0097	0.4106	0.1150	0.0600
MEREC	S7	0.2217	0.3021	0.0604	0.1812	0.1952	0.0394
max/min		838.67	201.4	64.12	3602	7609	1103.67
Combination	S8	0.1527	0.1231	0.0495	0.2423	0.2941	0.1383

The weighting results across the six criteria (C1–C6) under scenarios S1–S8 reveal pronounced discrepancies in criteria priorities, directly reflecting the distinct underlying algorithms of the respective weighting technique. Except for scenario S1 (Equal weighting), which assigns uniform importance to all criteria (all criteria weights are 0.1667), the remaining objective weighting methods exhibit distinct patterns of weight concentration. Specifically, SD (S2) and Entropy (S6) assign the highest priority to criterion C4 (0.7204 and 0.4106, respectively), while also placing considerable emphasis on C1. Conversely, SPC (S3) and LOPCOW (S4) exhibit extreme weight concentration on criterion C5 (0.7609 and 0.6557, respectively), followed by C6, while assigning near-zero weights to the remaining criteria. In contrast, LODECI (S5) and MEREC (S7) produce more balanced weight distributions. LODECI assigns relatively stable weights to C1, C2, C4, and C5 (ranging from 0.1648 to 0.2169), whereas MEREC assigns the highest importance to C2 (0.3021), followed by C1, C5, and C4.

The divergence among the weighting techniques is prominently illustrated by the maximum-to-minimum weight ratio (max/min) for each criterion. Criterion C5 exhibits the highest instability across the evaluated scenarios, with an extreme max/min ratio of 7609, followed by C4 (3602) and C6 (1103.67). In contrast, C3 demonstrates the highest stability across the weighting methods, with a max/min ratio of only 64.12, although its weight remains relatively low across most scenarios. These substantial fluctuations indicate that

relying solely on a single objective weighting technique may introduce structural bias or inadvertently exclude critical criteria from the decision framework. To mitigate this limitation, the Combination weighting method (S8), derived by averaging the criteria weights obtained from the seven individual objective techniques, effectively harmonizes algorithmic disparities and reduces extreme weight concentrations. The weights obtained under S8 exhibit a balanced and comprehensive distribution across all parameters: C5 retains the highest importance (0.2941), followed by C4 (0.2423), C1 (0.1527), C6 (0.1383), C2 (0.1231), and C3 (0.0495). This synthesis ensures an objective, multi-dimensional representation of each parameter within the MCDM framework [49].

Following criteria weighting, candidate machines were ranked using the constituent MCDM algorithms under each weighting scenario. Table 3 presents the machine ranking results obtained using seven MCDM techniques, RAM, TOPSIS, EDAS, SREM, PIV, MOORA, and Probability, under the Equal weighting scheme (scenario S1). Ranking results corresponding to the remaining weighting profiles are evaluated in the sensitivity analysis section.

Table 3 Candidate machine rankings in Example 1 under weighting scenario S1

Machine	RAM	TOPSIS	EDAS	SREM	PIV	MOORA	Probability
A1	10	11	12	9	11	13	12
A2	6	8	7	6	6	10	10
A3	5	6	5	7	5	6	4
A4	11	12	11	12	13	11	11
A5	2	2	1	3	2	2	1
A6	4	4	4	5	4	3	3
A7	12	13	13	8	12	12	13
A8	13	7	10	2	10	4	8
A9	1	1	3	1	1	1	6
A10	8	10	6	10	7	9	5
A11	3	3	2	4	3	5	2
A12	9	9	8	13	8	8	7
A13	7	5	9	11	9	7	9

The numerical results presented in Table 3 demonstrate inconsistencies in the rankings generated by the different constituent MCDM techniques, a phenomenon that has been widely documented in decision theory due to structural differences among algorithms [15]. This divergence provides a rationale for applying a data aggregation model following the individual MCDM evaluations. The CURLIA aggregation procedure is performed through the following computational steps:

Step 1: Construct the initial aggregation matrix using the individual ranking data presented in Table 3.

Step 2: Formulate seven square pairwise comparison matrices of order 13 (corresponding to the $l = 7$ constituent MCDM methods) according to Eq. (2). For conciseness, Table 4 presents the pairwise alternative comparison matrix derived specifically from the RAM methodology under scenario S1.

Table 4 Pairwise alternative comparison matrix for the RAM method in Example 1 (S1)

RAM	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13
A1	0	-1	-1	1	-1	-1	1	1	-1	-1	-1	-1	-1
A2	1	0	-1	1	-1	-1	1	1	-1	1	-1	1	1
A3	1	1	0	1	-1	-1	1	1	-1	1	-1	1	1
A4	-1	-1	-1	0	-1	-1	1	1	-1	-1	-1	-1	-1
A5	1	1	1	1	0	1	1	1	-1	1	1	1	1
A6	1	1	1	1	-1	0	1	1	-1	1	-1	1	1
A7	-1	-1	-1	-1	-1	-1	0	1	-1	-1	-1	-1	-1
A8	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1
A9	1	1	1	1	1	1	1	1	0	1	1	1	1
A10	1	-1	-1	1	-1	-1	1	1	-1	0	-1	1	-1
A11	1	1	1	1	-1	1	1	1	-1	1	0	1	1
A12	1	-1	-1	1	-1	-1	1	1	-1	-1	-1	0	-1
A13	1	-1	-1	1	-1	-1	1	1	-1	1	-1	1	0

Step 3: Based on the seven pairwise comparison matrices, the composite R_i performance scores for each candidate machine were calculated using Eq. (3), as presented in Table 5. Table 5 also presents the aggregate machine rankings derived from the R_i scores.

Table 5 Composite R_i scores and aggregated machine rankings in Example 1 (S1)

Machine	R_i	Rank
A1	-58	11
A2	-8	6
A3	22	5
A4	-64	12
A5	72	1
A6	44	4
A7	-68	13
A8	-10	7
A9	70	2
A10	-12	8
A11	54	3
A12	-26	10
A13	-16	9

Comparison of the data in Table 3 and 5 confirms strong agreement between the CURLIA aggregated rankings and the individual constituent MCDM outputs. For instance, alternative A5 secures first rank under CURLIA, EDAS, and Probability; second rank under RAM, TOPSIS, PIV, and MOORA; and third rank under SREM. Similarly, candidate A9 obtains second rank under CURLIA while achieving first rank under RAM, TOPSIS, SREM, PIV, and MOORA. Strong agreement is also observed among the lower-ranked candidates: alternative A7 ranks thirteenth under CURLIA, TOPSIS, EDAS, and Probability, and twelfth under RAM, PIV, and MOORA. Candidate A4 ranks twelfth under CURLIA, TOPSIS, and SREM, and eleventh under RAM, EDAS, MOORA, and Probability. Overall, CURLIA aggregation establishes candidate machine rankings that are highly consistent with the individual constituent MCDM outcomes. To quantify this

consensus, Table 6 summarizes the Spearman rank correlation coefficients between CURLIA and each constituent methodology.

Table 6 Spearman correlation coefficients between CURLIA and constituent MCDM algorithms in Example 1 (S1)

	RAM	TOPSIS	EDAS	SREM	PIV	MOORA	Probability
CURLIA	0.8736	0.9231	0.9396	0.7747	0.9505	0.8681	0.8462
Average				0.8823			

Spearman rank correlation coefficients between CURLIA and the constituent methodologies remain high, reaching 0.9505 relative to PIV. Of the seven correlation values, six exceed the 0.80 benchmark threshold for robust ranking consensus. The minimum correlation value (0.7747) is observed between CURLIA and SREM. Although slightly below 0.80, inspection of Tables 3 and 5 reveals only minimal differences in rank positions between these two methods: A9 ranks first under SREM and second under CURLIA; A5 ranks first under CURLIA and third under SREM; both methods assign sixth rank to A2 and twelfth rank to A4. Crucially, the mean Spearman rank correlation coefficient between CURLIA and all seven constituent algorithms equals 0.8823, substantially exceeding the 0.80 threshold. This result verifies that, under scenario S1, CURLIA aggregation successfully synthesizes candidate machine rankings with high statistical fidelity relative to the constituent algorithms. The candidate preference ordering under S1 is established as follows: A5 > A9 > A11 > A6 > A3 > A2 > A8 > A10 > A13 > A12 > A1 > A4 > A7. Accordingly, the top three recommended polishing machine candidates under S1 are A5, A9, and A11.

This concludes the candidate evaluation under scenario S1. For the remaining scenarios, S2 through S8, candidate machine rankings were similarly obtained using the seven constituent MCDM techniques, followed by CURLIA aggregation, thereby constituting the sensitivity analysis for Example 1. The candidate alternative rankings across scenarios S2–S8 are depicted in Figs. 2-8, respectively.

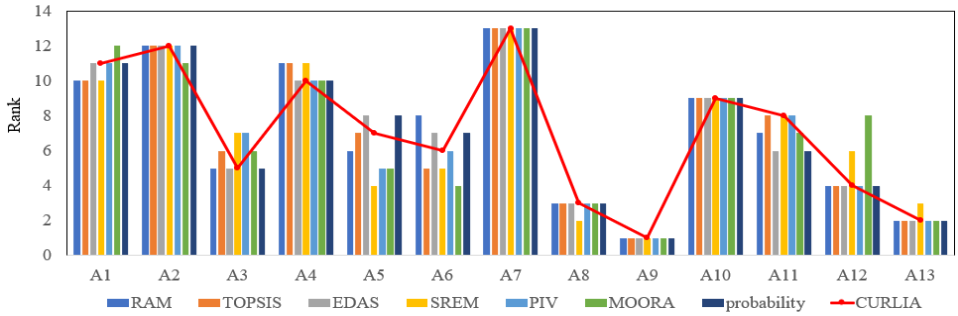

Fig. 2 Candidate alternative rankings in Example 1 under scenario S2

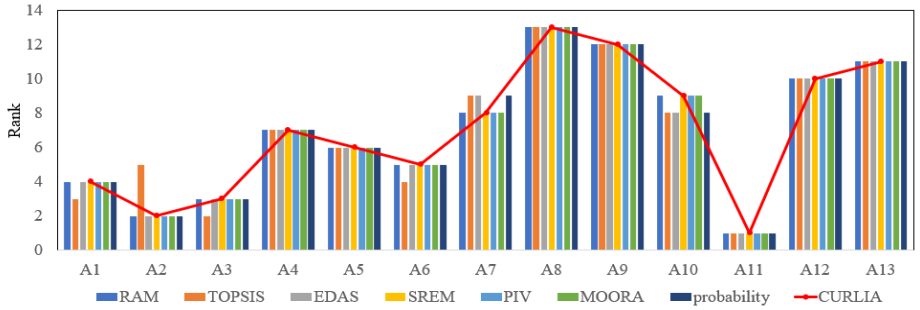

Fig. 3 Candidate alternative rankings in Example 1 under scenario S3

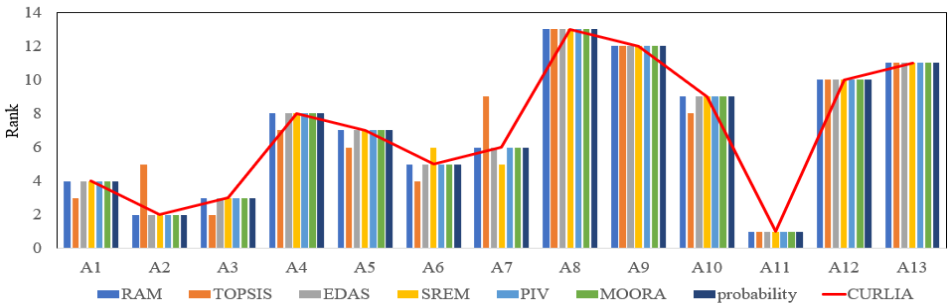

Fig. 4 Candidate alternative rankings in Example 1 under scenario S4

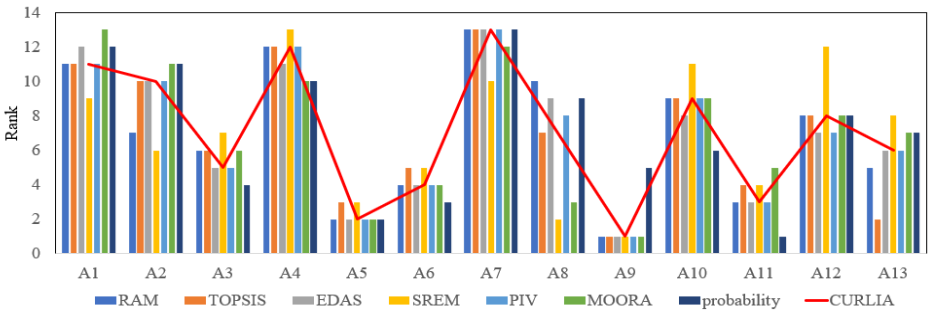

Fig. 5 Candidate alternative rankings in Example 1 under scenario S5

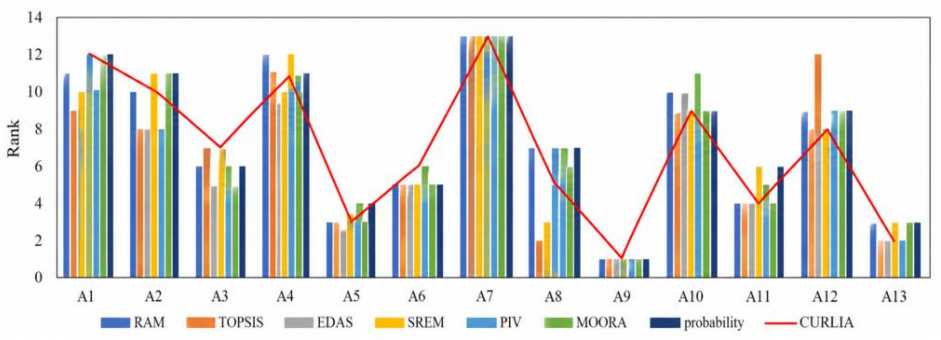

Fig. 6 Candidate alternative rankings in Example 1 under scenario S6

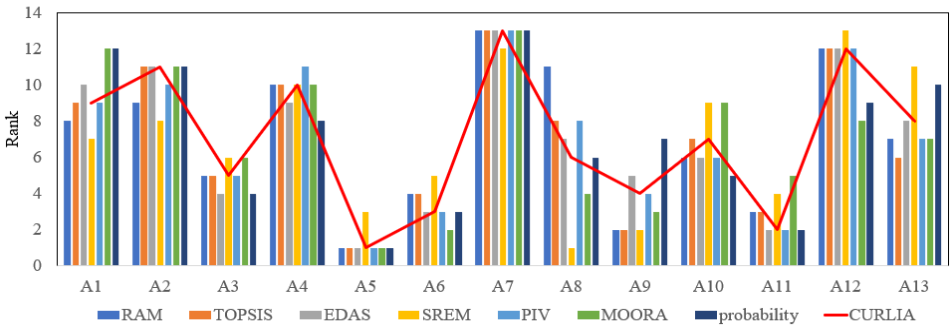

Fig. 7 Candidate alternative rankings in Example 1 under scenario S7

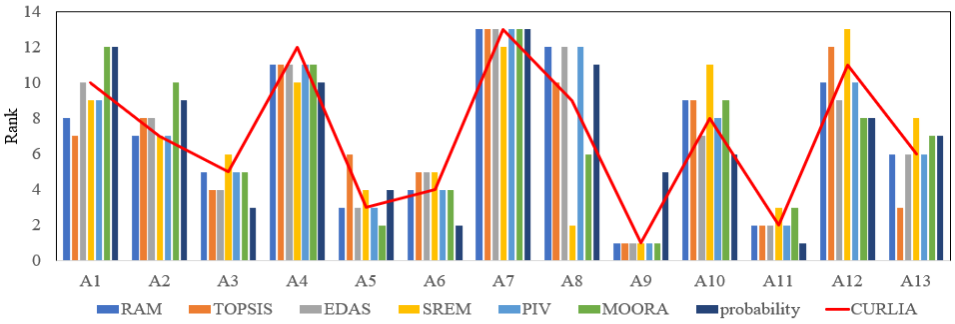

Fig. 8 Candidate alternative rankings in Example 1 under scenario S8

Table 7 summarizes the Spearman rank correlation coefficients between CURLIA and the constituent MCDM techniques across these scenarios.

Table 7 Spearman rank correlation coefficients comparing CURLIA against constituent MCDM methods in Example 1

Scenario	MCDM methods							Average
	RAM	TOPSIS	EDAS	SREM	PIV	MOORA	Probability	
S2	0.9780	0.9890	0.9835	0.9396	0.9780	0.9231	0.9835	0.9678
S3	1.0000	0.9615	0.9945	1.0000	1.0000	1.0000	0.9945	0.9929
S4	1.0000	0.9341	1.0000	0.9945	1.0000	1.0000	1.0000	0.9898
S5	0.9451	0.9451	0.9780	0.7637	0.9945	0.9121	0.8846	0.9176
S6	0.9780	0.9560	0.9670	0.9286	0.9835	0.9341	0.9725	0.9600
S7	0.8956	0.9615	0.9835	0.8077	0.9780	0.8736	0.8901	0.9129
S8	0.9560	0.9066	0.9505	0.7912	0.9670	0.9011	0.8462	0.9027

Prior to identifying the top-performing machine selections across the evaluated scenarios, it is essential to assess whether CURLIA aggregation maintains balanced alignment with the constituent MCDM algorithms. The quantitative metrics presented in Table 7 demonstrate consistently high Spearman rank correlation coefficients between CURLIA and all constituent decision techniques. The lowest correlation value is 0.7637, observed between CURLIA and SREM under scenario S5, followed by the second-lowest value of 0.7912, also observed relative to SREM under scenario S8. Across all remaining weighting scenarios, the Spearman correlation coefficients between CURLIA and the constituent algorithms consistently exceed the 0.80 benchmark. Notably, complete rank identity (Spearman coefficients = 1.0000) is achieved in specific cases, including RAM, SREM, PIV, and MOORA under S3, as well as RAM, EDAS, PIV, MOORA, and Probability under S4. The average Spearman rank correlation coefficient (AS) between CURLIA and all constituent MCDM methods remains exceptionally high across all scenario, with the lowest mean value of 0.9027 recorded under scenario S8, substantially exceeding the 0.80 benchmark. These empirical results demonstrate that the candidate machine rankings synthesized through CURLIA exhibit a high degree of consistency with the individual constituent MCDM outputs, confirming the suitability of CURLIA as an aggregation framework for this evaluation case.

Analysis of the candidate machine rankings across the individual scenarios yields the following insights:

Under scenario S2 (Fig. 2), alternatives A8, A9, and A13 constitute the top three preferred options. CURLIA and all seven constituent MCDM methods unanimously identify A9 as the optimal candidate. Alternative A13 achieves second rank under CURLIA, RAM, TOPSIS, EDAS, PIV, MOORA, and Probability, while securing third rank under SREM. Similarly, CURLIA and six constituent algorithms (RAM, TOPSIS, EDAS, PIV, MOORA, Probability) assign third rank to A8, whereas SREM assigns second rank to A8.

Under scenario S3 (Fig. 3), all evaluated techniques unanimously designate A11 as the optimal candidate. Seven of the eight methodologies, including CURLIA, consistently assign second rank to A2 and third rank to A3. Accordingly, alternatives A11, A2, and A3 constitute the top three recommendations under S3.

Under scenario S4 (Fig. 4), full consensus is reached across all decision models (CURLIA and the seven constituent techniques), with A11 identified as the first-ranked candidate. Seven of the eight methodologies assign second rank to A2 and third rank to

A3. Consequently, A11, A2, and A3 constitute the primary recommended alternatives under S4.

Under scenario S5 (Fig. 5), CURLIA, together with RAM, EDAS, PIV, MOORA, and Probability, assigns second rank to alternative A5, whereas TOPSIS and SREM assign third rank to A5. For alternative A9, CURLIA and three constituent models -RAM, EDAS, PIV- assign third rank, while Probability assigns first rank, TOPSIS and SREM assign fourth rank, and MOORA assigns fifth rank. Overall, scenario S5 identified highlights A5, A9, and A11 as the top three preferred selections.

Under scenario S6 (Fig. 6), all decision models unanimously assign first rank to alternative A9. For alternative A5, CURLIA, RAM, and PIV assign third rank, whereas the remaining methods assign fourth rank. For candidate A13, CURLIA, together with five constituent algorithms -RAM, TOPSIS, EDAS, PIV, Probability- assigns second rank, whereas SREM and MOORA assign third rank. Thus, A9, A5, and A13 emerge as the top three recommended candidates under S6.

Under scenario S7 (Fig. 7), CURLIA and six constituent algorithms (RAM, TOPSIS, EDAS, PIV, MOORA, Probability) assign first rank to alternative A5, whereas SREM assigns third rank. Alternatives A6 and A11 achieve third and second rank, respectively, under CURLIA, EDAS, PIV, and Probability. RAM and TOPSIS assign fourth rank to A6 and third to A11; SREM places A6 at fifth and A11 at fourth; whereas MOORA places A6 at second and A11 at fifth. In summary, A5, A6, and A11 constitute the top three preferred alternatives under S7.

Under scenario S8 (Fig. 8), candidate A9 obtains first rank under CURLIA, RAM, TOPSIS, EDAS, SREM, PIV, and MOORA, but falls to fifth rank under Probability. For candidate A5, CURLIA, RAM, EDAS, and PIV assign third rank; SREM and Probability assign fourth rank; while MOORA assigns second rank. For candidate A11, CURLIA, together with RAM, TOPSIS, EDAS, and PIV assigns second rank; SREM and MOORA assign third rank; whereas Probability assigns first rank. Thus, alternatives A5, A9, and A13 represent the top three choice candidates under S8. Re-evaluating of S8 is particularly meaningful because its criteria weights represent the arithmetic average across scenarios S1–S7, indicating that the preferred choices under S8 naturally incorporate a harmonized consensus across all individual weighting models.

Synthesizing the findings across all eight weighting scenarios in Example 1 reveals:

Scenario S1: Top three candidates are A5, A9, and A11.
Scenario S2: Top three candidates are A8, A9, and A13.
Scenario S3: Top three candidates are A2, A3, and A11.
Scenario S4: Top three candidates are A2, A3, and A11.
Scenario S5: Top three candidates are A5, A9, and A11.
Scenario S6: Top three candidates are A5, A9, and A13.
Scenario S7: Top three candidates are A5, A6, and A11.
Scenario S8: Top three candidates are A5, A9, and A11.

Across the sensitivity evaluations, alternatives A5, A9, and A11 recur most frequently among the top recommendations. Specifically, candidate A11 ranks within the top-three subset in 6 out of 8 scenarios (75.0%), while candidates A5 and A9 both appear among the top recommendations across 5 out of 8 scenarios (62.5%). Overall, alternatives A5, A9, and A11 are identified as the primary high-priority machine candidates in Example 1.

3.2. Example 2

This example evaluates a selection problem involving six wood planer machine candidates, designated A1–A6. Each candidate is evaluated against three benefit-type criteria (B), C1–C3, and three cost-type criteria (C), C4–C6. Criteria C1–C6 represent planning width, maximum planning depth, maximum no-load speed, overall machine length, total weight, and purchase price, respectively. The technical specifications of the wood planers are compiled in Table 8 [52]. The parameter units of measurement for each parameter are provides in the final row of Table 8. Note that C6 is expressed in VNDM (millions of Vietnamese Dong), where 1 VNDM ≈ 40.8 USD.

Table 8 Technical specifications of wood planer candidates in Example 2 [52]

Machine	C1	C2	C3	C4	C5	C6
A1	82	2	16000	285	3	1.586
A2	82	2.6	16500	300	2.8	1.529
A3	82	1.8	16000	290	2.5	1.39
A4	102	1	17000	280	2.7	2.43
A5	82	2	11500	280	2.7	1.135
A6	82	3	18000	390	4.6	2.218
unit	mm	mm	rpm	mm	kg	VNDM

Inspection of Table 8 reveals that the maximum planning width (C1 = 102 mm) belongs to A4, while the maximum planning depth (C2 = 3 mm) and maximum no-load speed (C3 = 18000 rpm) are both attained by A6. Conversely, the minimum machine length (C4 = 280 mm) is shared by A4 and A5, the minimum weight (C5 = 2.5 kg) is associated with A3, and the minimum price (C6 = 1.135 VNDM) is associated with A5. These results confirm that no single wood planer exhibits superior performance across all six criteria simultaneously. Therefore, multi-criteria decision-making and criteria weight determination are required. Table 9 summarizes the criteria weights derived using eight distinct methods, designated as weighting scenarios S1–S8.

Table 9 Criteria weights derived across weighting scenarios in Example 2

Method	Scenario	C1	C2	C3	C4	C5	C6
Equal	S1	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
SD	S2	0.0035	0.0003	0.9771	0.0185	0.0003	0.0002
SPC	S3	0.0956	0.2063	0.1132	0.1328	0.2351	0.2170
LOPCOW	S4	0.1915	0.0010	0.5231	0.2517	0.0089	0.0237
LODECI	S5	0.1027	0.2283	0.1509	0.1336	0.1873	0.1973
Entropy	S6	0.0282	0.3816	0.0699	0.0599	0.1892	0.2712
MEREC	S7	0.0185	0.3267	0.1494	0.1203	0.2060	0.1791
max/min		54.71	1272	13.98	13.61	783.67	1356
Combination	S8	0.0867	0.1873	0.3072	0.1262	0.1419	0.1507

Criteria weighting results across S1–S8 highlight pronounced differences in the weighting algorithmic tendencies of the objective methods. Except for S1 (Equal weighting), which distributes the weight uniformly (all criteria weights are 0.1667), the remaining techniques exhibit substantial variation. The SD method (S2) concentrates nearly all the weight on criterion C3 (0.9771), reducing the weights of the other criteria to

negligible levels. LOPCOW (S4) likewise identifies C3 as the primary criterion (0.5231), followed by C4 (0.2517) and C1 (0.1915). In contrast, Entropy (S6) and MEREC (S7) prioritize criterion C2 (0.3816 and 0.3267, respectively), followed by C6 and C5. Meanwhile, SPC (S3) and LODECI (S5) yield relatively balanced weight distributions, with most criteria weights, excluding C1 under SPC, falling within the range of 0.1027–0.2351.

Evaluating weight variation using the maximum-to-minimum ratio (max/min) reveals substantial divergences across methods for specific criteria. Criterion C6 exhibits the greatest variation, with a max/min ratio of 1356, followed by C2 (1272.00) and C5 (783.67). Conversely, C4 and C3 demonstrate the greatest stability across scenarios, with max/min ratios of only 13.61 and 13.98, respectively. The extreme discrepancies in weight assignments, particularly for C2, C5, and C6, highlight the risk of structural bias when relying solely on a single objective weighting technique. To resolve inter-method discrepancies, the Combination weighting method (S8), calculated as the arithmetic mean of the preceding seven methods, effectively smooths extreme values. The S8 weights provide a balanced distribution across the entire set of criteria: C3 has the highest importance (0.3072), followed by C2 (0.1873), C6 (0.1507), C5 (0.1419), C4 (0.1262), and C1 (0.0867).

Ranking the six wood planers using the seven constituent MCDM methods (RAM, TOPSIS, EDAS, SREM, PIV, MOORA, Probability), followed by aggregation via CURLIA across scenarios S1–S8, yields the results presented in Figs. 9–16. Spearman correlation coefficients between CURLIA and the constituent MCDM algorithms are summarized in Table 10. The evaluation of candidate rankings under varying weight scenarios constitutes the sensitivity analysis for Example 2.

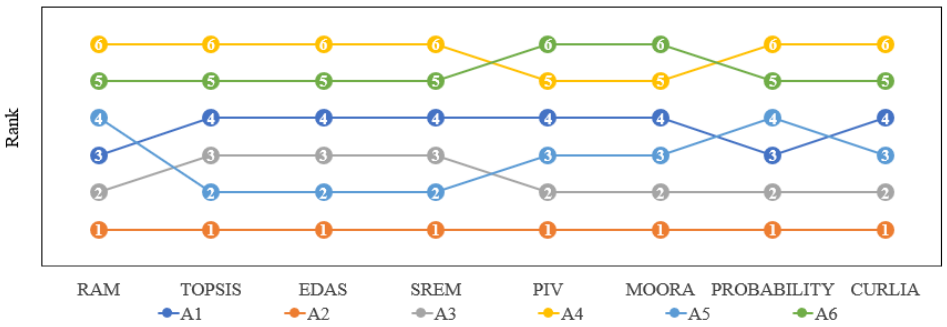

Fig. 9 Candidate alternative rankings in Example 2 under scenario S1

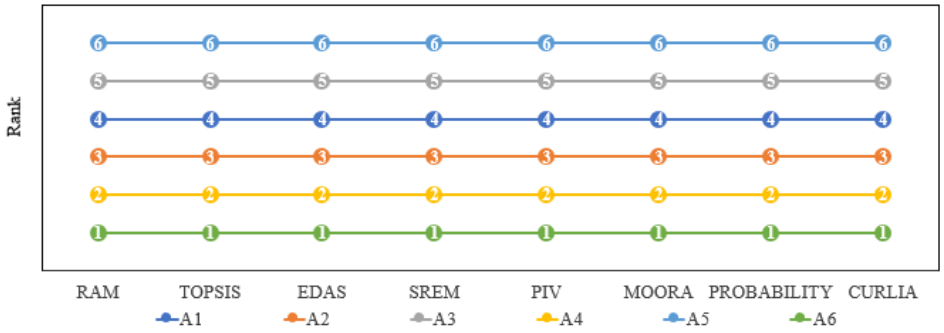

Fig. 10 Candidate alternative rankings in Example 2 under scenario S2

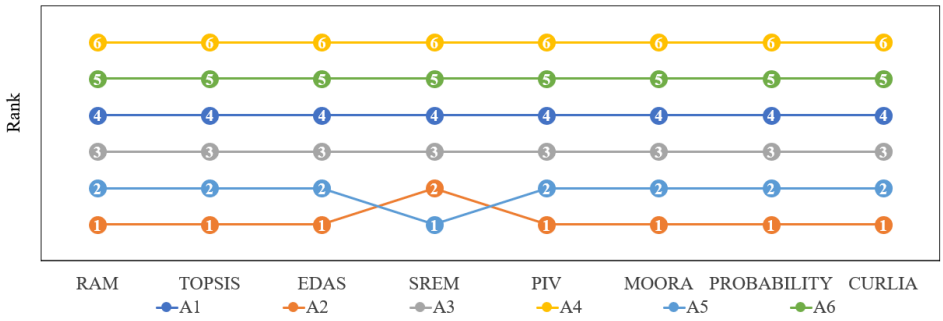

Fig. 11 Candidate alternative rankings in Example 2 under scenario S3

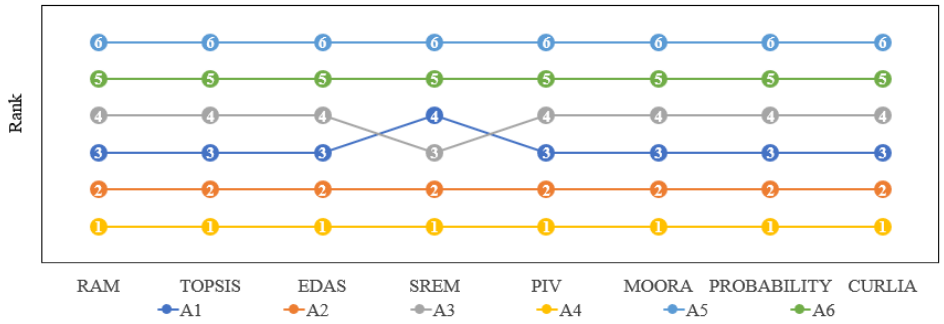

Fig. 12 Candidate alternative rankings in Example 2 under scenario S4

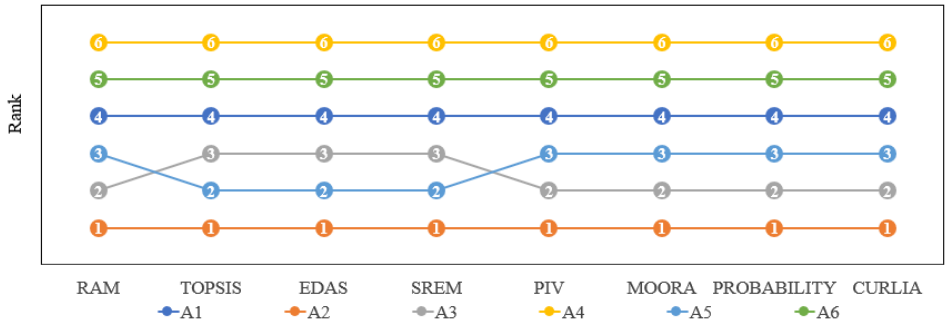

Fig. 13 Candidate alternative rankings in Example 2 under scenario S5

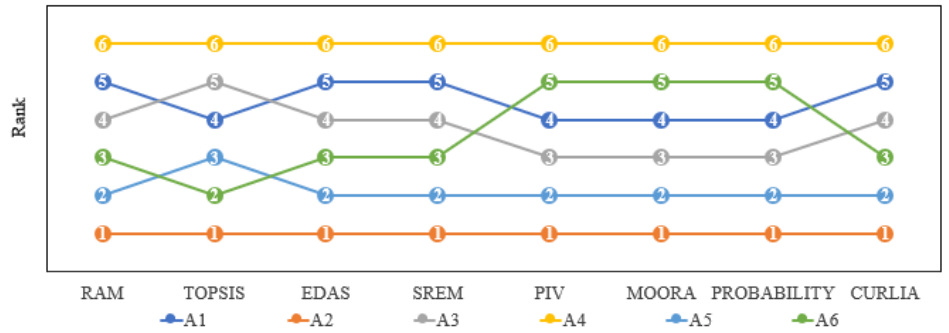

Fig. 14 Candidate alternative rankings in Example 2 under scenario S6

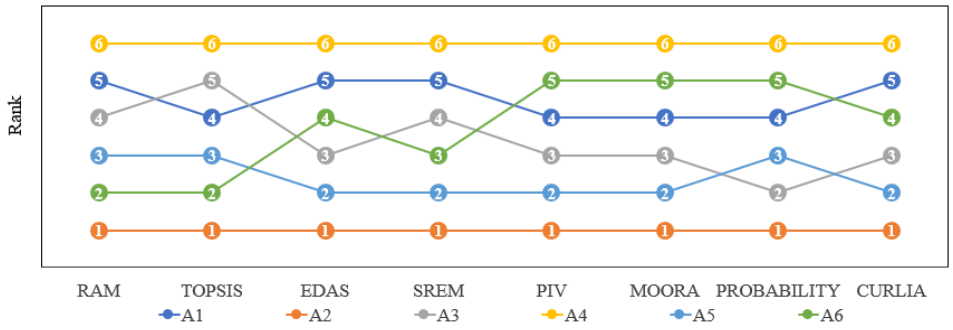

Fig. 15 Candidate alternative rankings in Example 2 under scenario S7

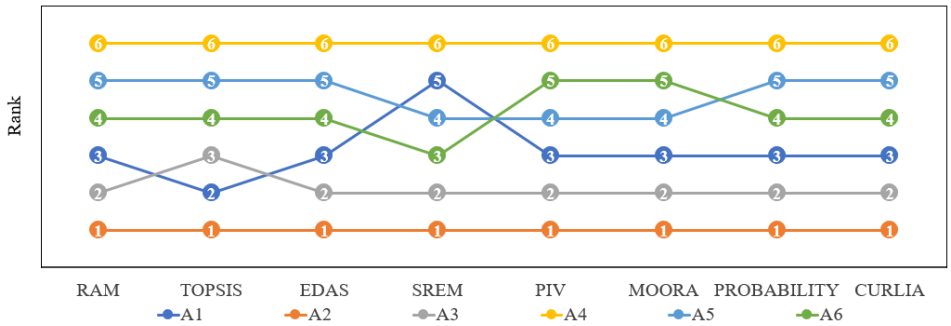

Fig. 16 Candidate alternative rankings in Example 2 under scenario S8

Table 10 Spearman correlation coefficients between CURLIA and constituent MCDM algorithms in Example 2

Scenario	MCDM methods							Average
	RAM	TOPSIS	EDAS	SREM	PIV	MOORA	Probability	
S1	0.9429	0.9429	0.9429	0.9429	0.9429	0.9429	0.9429	0.9429
S2	1	1	1	1	1	1	1	1
S3	1	1	1	0.9429	1	1	1	0.9918
S4	1	1	1.0000	0.9429	1	1	1	0.9918
S5	1	0.9429	0.9429	0.9429	1	1	1	0.9755
S6	1	0.8857	1	1	0.8286	0.8286	0.8286	0.9103
S7	0.8286	0.7143	1	0.9429	0.9429	0.9429	0.8857	0.8939
S8	1	0.9429	1	0.8286	0.9429	0.9429	1	0.9510

Across all scenarios presented in Table 10, the Spearman correlation coefficients between CURLIA and the individual constituent MCDM algorithms remain high. The lowest observed correlation is 0.7143, corresponding to TOPSIS under S7, while the next-lowest value is 0.8286, observed for PIV, MOORA, and Probability under S6. In all other scenarios, the Spearman coefficients exceed the 0.80 threshold. Notably, correlation values of 1.0000 or near-unity are observed across numerous scenarios. The AS reported in the final column of Table 10 substantially exceed 0.80 across all scenarios. These statistical metrics confirm that the rankings aggregated by CURLIA exhibit a high consensus with the constituent MCDM methods, establishing CURLIA as an appropriate aggregation technique for this selection problem.

Analysis of the candidate rankings across individual scenarios yields the following observations:

Under scenario S1 (Fig. 9), the aggregated preference ordering is A2 > A3 > A5 > A1 > A6 > A4. Both CURLIA and all seven constituent MCDM methods unanimously rank A2 first. Alternative A3 ranks second under CURLIA, RAM, PIV, MOORA, and Probability, and third under TOPSIS, EDAS, and SREM. Alternative A5 ranks third under CURLIA, PIV, and MOORA; fourth under RAM and Probability; and second under TOPSIS, EDAS, and SREM. The high consistency between CURLIA and the constituent techniques is reflected by the high average Spearman coefficient (AS = 0.9429).

Under scenario S2 (Fig. 10), the machine rankings synthesized by CURLIA are completely identical to those generated by all seven constituent MCDM techniques, with

Spearman correlation coefficients of 1.0000 across all methods. The resulting preference ordering is A6 > A4 > A2 > A1 > A3 > A5.

Under scenario S3 (Fig. 11), CURLIA aggregation yields the preference ordering A2 > A5 > A3 > A1 > A6 > A4. Ranking consensus is extremely strong, with all methods assigning fourth rank to A1, third rank to A3, sixth rank to A4, and fifth rank to A6. Except for SREM, which ranks A2 second and A5 first, all methods, including CURLIA, assign first rank to A2 and second rank to A5.

Under scenario S4 (Fig. 12), the machine rankings obtained using CURLIA are fully identical to those generated by six constituent methods (RAM, TOPSIS, EDAS, PIV, MOORA, Probability). CURLIA and all seven MCDM algorithms unanimously assign second rank to A2, first rank to A4, sixth rank to A5, and fifth rank to A6. Except for SREM, which reverses the ranks of A1 and A3 by assigning A1 fourth rank and A3 third rank, all remaining methods assign third rank to A1 and fourth rank to A3. The high mean Spearman coefficient (AS = 0.9918) further reinforces the overall alignment, yielding the preference ordering A4 > A2 > A1 > A3 > A6 > A5.

Under scenario S5 (Fig. 13), the machine rankings synthesized by CURLIA are completely identical to those generated by four constituent methods (RAM, PIV, MOORA, Probability). For A3, CURLIA, RAM, PIV, MOORA, and Probability assign second rank, whereas TOPSIS, EDAS, and SREM assign third rank. For A5, CURLIA, RAM, PIV, MOORA, and Probability assign third rank, while TOPSIS, EDAS, and SREM assign second rank. The high degree of consensus is confirmed by the average Spearman coefficient(AS = 0.9755). The resulting preference ordering is A2 > A3 > A5 > A1 > A6 > A4.

Under scenario S6 (Fig. 14), the rankings obtained using CURLIA are completely identical to those generated by RAM, EDAS, and SREM. All evaluated methods unanimously identify A2 as the best candidate (first rank) and A4 as the worst candidate (sixth rank). For A1, CURLIA, RAM, EDAS, and SREM assign fifth rank, while the remaining methods assign fourth rank. For A3, CURLIA, RAM, EDAS, and SREM assign fourth rank; PIV, MOORA, and Probability assign third rank; and TOPSIS assigns fifth rank. For A5, all methods assign second rank except TOPSIS, which assigns third rank. For A6, CURLIA, RAM, EDAS, and SREM assign third rank; PIV, MOORA, and Probability assign fifth rank; and TOPSIS assigns second rank. The high average Spearman correlation coefficient (AS = 0.9103) supports the strong overall alignment, yielding the preference ordering A2 > A5 > A6 > A3 > A1 > A4.

Under scenario S7 (Fig. 15), the machine rankings synthesized by CURLIA are completely identical to those generated by EDAS. All methods unanimously identify A2 as the first-ranked candidate and A4 as the sixth-ranked candidate. For A1, CURLIA, RAM, EDAS, and SREM assign fifth rank, whereas the remaining methods assign fourth rank. For A3, CURLIA, EDAS, PIV, and MOORA assign third rank; RAM and SREM assign fourth rank; TOPSIS assigns fifth rank; and Probability assigns second rank. For A5, CURLIA, EDAS, SREM, PIV, and MOORA assign second rank, while RAM, TOPSIS, and Probability assign third rank. For A6, CURLIA and EDAS assign fourth rank; PIV, MOORA, and Probability assign fifth rank; RAM and TOPSIS assign second rank; and SREM assigns third rank. The high correlation coefficient (AS = 0.8939) confirms strong overall alignment, with the preference ordering A2 > A5 > A3 > A6 > A1 > A4.

Under scenario S8 (Fig. 16), the rankings synthesized by CURLIA, RAM, and Probability are completely identical. All methods unanimously identify A2 as the optimal

candidate (first rank) and A4 as the worst candidate (sixth rank). For A5, CURLIA, RAM, TOPSIS, EDAS, and Probability assign fifth rank, while SREM, PIV, and MOORA assign fourth rank. The high mean Spearman coefficient (AS = 0.9510) confirms robust consensus, resulting in the preference ordering A2 > A3 > A1 > A6 > A5 > A4. Because the criteria weights under S8 represent the arithmetic average across S1–S7, the top-ranked alternatives under S8 inherently reflect consensus across all preceding weighting models.

Summarizing machine preference orderings across all eight weighting scenarios in Example 2:

Scenario S1: A2 > A3 > A5 > A1 > A6 > A4.
Scenario S2: A6 > A4 > A2 > A1 > A3 > A5.
Scenario S3: A2 > A5 > A3 > A1 > A6 > A4.
Scenario S4: A4 > A2 > A1 > A3 > A6 > A5.
Scenario S5: A2 > A3 > A5 > A1 > A6 > A4.
Scenario S6: A2 > A5 > A6 > A3 > A1 > A4.
Scenario S7: A2 > A5 > A3 > A6 > A1 > A4.
Scenario S8: A2 > A3 > A1 > A6 > A5 > A4.

Alternative A2 achieves the top priority (first rank) in six out of eight evaluated scenarios. Notably, scenario S8, which incorporates the average criteria weights across all preceding scenarios, also identifies A2 as the best candidate. Consequently, alternative A2 is conclusively identified as the optimal selection among the six wood planer candidates evaluated.

4. DISCUSSION

In Example 1, alternatives A5, A9, and A11 were identified as the top three recommended candidates for hand-held polishing machine selection. Re-examination of the baseline data in Table 1 reveals that alternative A5 ranks first among all thirteen candidates in two technical parameters: power capacity (C2) and polishing disc diameter (C3). Meanwhile, the remaining parameters for A5 exhibit moderate-to-high rankings, with purchase price (C1) ranking fourth, no-load speed (C4) ninth, operating weight (C5)fifth, and warranty period (C6) fourth. The identification of A5 as a top-three preference therefore reflects a selection profile characterized by high machine power capacity and operational efficiency, while maintaining favorable positions in terms of purchase price, operating weight, and warranty period. Candidate A9 exhibits a highly favorable economic and operational profile, with the lowest purchase price (C1 ranks second) and the highest no-load speed (C4 ranks first), making it particularly suitable for scenarios prioritizing low acquisition cost and high rotational speed. Candidate A11 ranks second in power capacity (C2) and third in operating weight (C5), while exhibiting moderate performance across the remaining criteria, with C1, C3, and C4 ranking seventh, ninth, and sixth, respectively. The selection of A11 therefore emphasizes operational convenience and motor capacity while maintaining acceptable trade-offs across the remaining parameters.

In Example 2, alternative A2 was identified as the optimal choice for wood planer selection. Re-examining of the data in Table 8 indicates that, although A2 does not achieve the best absolute value for any individual criterion relative to the competing models, it maintains consistently high relative performance across key indicators, including maximum no-load speed (C3, ranked third) and purchase price (C6, ranked third).

Consequently, the selection of A2 offers a favorable balance between acquisition cost and operational performance, while its high no-load speed helps minimize idle spindle runtime. It should be noted that criterion C3 directly reflects the machine's capacity to reduce non-productive air-cutting time, during which the cutting tool is not engaged in active planning, thereby enhancing overall machining productivity.

5. CONCLUSIONS

The recently proposed CURLIA methodology was applied for the first time to synthesize multi-criteria evaluation data for machine selection, specifically for hand-held polishing machines and wood planers. Each application was systematically evaluated under multiple criteria weighting scenarios. Within each scenario, seven distinct MCDM techniques (RAM, TOPSIS, EDAS, SREM, PIV, MOORA, and Probability) were concurrently applied to determine candidate machine rankings prior to aggregation using CURLIA. The main conclusions drawn from this study are as follows:

The candidate machine rankings synthesized using the CURLIA methodology exhibit exceptional consistency and strong statistical agreement with those generated by the individual constituent MCDM techniques. The application of CURLIA for data aggregation in machine selection is therefore demonstrated to be highly effective across the evaluated applications to similar engineering selection problems.

Among the thirteen hand-held polishing machine candidates evaluated, alternatives A5, A9, and A11 represent the primary recommended choices. A2 is identified as the highest-ranked candidate under the integrated S8 weighting scheme and in six of the eight evaluated scenarios.

The incorporation of expert judgment regarding criteria importance was beyond the scope of this study, as neither subjective weighting techniques nor hybrid subjective-objective weighting models were employed. Future research should incorporate subjective expert assessments to align machine selection outcomes more closely with practical requirements and the specific needs of end-user.

REFERENCES

1. Hagag, A.M., Yousef, L.S., Abdelmaguid, T.F., 2023, *Multi-Criteria Decision-Making for Machine Selection in Manufacturing and Construction: Recent Trends*, Mathematics, 11(3), 631.
2. Şimşek, A.İ., Gür, Y.E., Ünal, E., 2025, *Innovative MCDM-ML algorithms-based decision-support system for electric vehicle selection*, Environment, Development and Sustainability, https://doi.org/10.1007/s10668-025-06476-x
3. Li, H., Wang, W., Fan, L., Li, Q., Chen, X., 2020, *A novel hybrid MCDM model for machine tool selection using fuzzy DEMATEL, entropy weighting and later defuzzification VIKOR*, Applied Soft Computing, 91, 106207.
4. Shanmugasundar, G., Kalita, K., Čep, R., Chohan, J.S., 2023, *Decision Models for Selection of Industrial Robots—A Comprehensive Comparison of Multi-Criteria Decision Making*, Processes, 11(6), 1681.
5. Sahin, Y., Aydemir, E., 2022, *A Comprehensive Solution Approach for CNC Machine Tool Selection Problem*, Informatica, 33(1), pp. 81–108.
6. Bošković, S., Jovčić, S., Simić, V., Švadlenka, L., Dobrodolac, M., Bačanin, N., 2025, A new criteria importance assessment (CIMAS) method in multi-criteria group decision-making: criteria evaluation for supplier selection, Facta Universitatis, Series: Mechanical Engineering, 23(2), pp. 335–349.
7. Komatina, N., Marinković, D., 2026, *An Objective Multi-Attribute Decision-Making Framework for Identifying Critical Phases in Automotive Component Manufacturing*, Journal of Engineering Management and Systems Engineering, 5(1), pp. 1–9.

8. Peci, A., Puška, A., Marinković, D., Nedeljković, M., 2025, Evaluation of tractors based on sustainability criteria using multi-criteria decision-making methods, Engineering Review, 45(1), pp. 131–145.
9. Dua, T.V., 2023, *Forklift selection by multi-criteria decision-making methods*, Eastern-European Journal of Enterprise Technologies, 125(3), 95.
10. Komatina, N., 2025, *A Novel BWM-RADAR Approach for Multi-Attribute Selection of Equipment in the Automotive Industry*, Spectrum of Mechanical Engineering and Operational Research, 2(1), pp. 104–120.
11. Kawecka, E., Perec, A., Radomska-Zalas, A., 2024, *Use of the Simple Multicriteria Decision-Making (MCDM) Method for Optimization of the High-Alloy Steel Cutting Process by the Abrasive Water Jet*, Spectrum of Mechanical Engineering and Operational Research, 1(1), pp. 111–120.
12. Marković, S., Petrović, N., Jovanović, V., Simic, V., Marinković, D., 2026, *Evaluation and Selection of Vertical Conveyor Systems for Material Handling in Transport and Logistics Using an Adaptive Balanced MCDM Framework*, Applied Sciences, 16(18), 9189.
13. Yalçın, G.C., Kara, K., Gürol, P., Babič, M., 2025, *A Fermatean Fuzzy MCDM Framework for Green Port Transformation and Heavy-Duty Forklift Selection*, Journal of Engineering Management and Systems Engineering, 4(4), pp. 269–283.
14. Çubukcu, A., Akarçay Pervin, Ö., Boz, E., Çalık, A., 2023, *An Idea Evaluation Phase in Online Communities: A Case on the COVID-19 Innovation Platform*, Journal of Organisational Studies and Innovation, 10(4), pp. 1–26.
15. Sumanto, S., Suryono, R.R., Aryanti, R., Rohayani, H., Setiawansyah, S., Desyanti, D., 2026, *Comprehensive Evaluation of Distance-Based MCDM Methods Using Response to Criteria Weighting: A Ranking Stability and Sensitivity Analysis*, Journal of Information Technology, Software Engineering and Computer Science, 4(4), pp. 119–138.
16. Petrović, N., Jovanović, V., Petrović, M., Nikolić, B., Mihajlović, J., 2025, *Comparative Investigation of Normalization Techniques and Their Influence on MCDM Ranking – A Case Study*, Spectrum of Mechanical Engineering and Operational Research, 2(1), pp. 172–190.
17. Malenović-Nikolić, J., Petrović, N., Marinković, D., Mančić, M., Simić, V., 2026, *A Hybrid AHP–TOPSIS–SBSC Framework for Sustainable Soil Protection in Surface Coal Mining*, Environments, 13(6), 338.
18. Mukhametzyanov, I.Z., Pamučar, D., 2025, *Equivalence of MCDM Methods and Synthesis of Solution Based on Ratings Obtained in Different Models*, Decision Making: Applications in Management and Engineering, 8(2), pp. 1–20.
19. Arsić, D., Ivković, D., Sudžum, R., Marinković, D., Komatina, N., 2025, *Selection of Base Materials for Repair Welding Using BWM-TOPSIS and BWM-RADAR Approaches*, Materials, 18(24), 5696.
20. Polatgil, M., Güler, A., 2024, *The use of Different Criteria Weighting and Multi-Criteria Decision Making Methods for University Ranking: Two-Layer Copeland*, Üniversite Araştırmaları Dergisi, 7(1), pp. 60–73.
21. Shirazi, A., Mohammadi DolatAbadi, H., Dehghani, J., Asgari Sooran, M., 2024, *Prioritizing Key Parameters for Sustainable Supply Chain Development in the Construction Industry Using a Copeland Hybrid Method*, Environmental Energy and Economic Research, 8(4), S095.
22. Ozdagoglu, A., Keles, M., Altinata, A., Ulutas, A., 2021, *Combining different MCDM methods with the Copeland method: An investigation on motorcycle selection*, Journal of Process Management and New Technologies, 9(3-4), pp. 13–27.
23. Orakçı, E., Özdemir, A., 2024, Using social choice function for multi-criteria decision-making problems, Alphanumeric Journal, 12(1), pp. 21–38.
24. García-Lapresta, J.L., Martínez-Panero, M., 2025, *Combining the Borda Count with Approval and Disapproval Voting*, Group Decision and Negotiation, 34, pp. 1499–1525.
25. Holliday, W.H., Pacuit, E., 2023, Split cycle: a new Condorcet-consistent voting method independent of clones and immune to spoilers, Public Choice, 197, pp. 1–62.
26. Sheikh, V., Izanloo, R., 2021, *Assessment of low impact development stormwater management alternatives in the city of Bojnord, Iran*, Urban Water Journal, 18(6), pp. 449–464.
27. Moslem, S., Mohammadi, M., Ismael, K., Esztergár-Kiss, D., 2025, Fostering sustainable urban mobility via stakeholder engagement: a novel analytic hierarchy process and half-quadratic programming, Research in Transportation Business & Management, 59, 101291.
28. Rasoanaivo, R.G., Zaraté, P., 2024, *A rank aggregating method based on several multi-criteria methodologies 'minimum of ranks': a case study for student's room allocation*, IJDSS, 5(1), pp. 75–101.
29. Rasoanaivo, R.G., Zaraté, P., 2024, *SAGeLogE: A Decision Support System for Students' Accommodation Management*, Journal of Computer and Communications, 12(3), pp. 107–145.
30. Parzen, E.A., Johnson, C.D., 2021, *Harnessing Condorcet Methods to Improve Decision-making Based on Ranked Data*, Pacific Northwest National Laboratory, Richland, Washington, USA, Technical Report PNNL-31807.
31. Franssen, M., 2005, *Arrow's theorem, multi-criteria decision problems and multi-attribute preferences in engineering design*, Research in Engineering Design, 16, pp. 42–56.

32. Saari, D.G., 2023, *Selecting a voting method: the case for the Borda count*, Constitutional Political Economy, 34, pp. 357–366.
33. Franceschini, F., Maisano, D., 2019, *Design decisions: concordance of designers and effects of the Arrow's theorem on the collective preference ranking*, Research in Engineering Design, 30, pp. 425–434.
34. Behnam Khakbaz, S., Karimi Davijani, M., 2015, *Ranking Multi Criteria Decision Making Methods for a Problem by Area Under Receiver Operating Characteristic*, Journal of Investment and Management, 4(5), pp. 210-215.
35. Trung, D., Trang, B., Özçalici, M., Ersoy, N., 2025, *CURLIA: A streamlined aggregation method that elevates ranking accuracy in complex MCDM problems*, Yugoslav Journal of Operations Research, https://doi.org/10.2298/YJOR250815040T
36. Kiger, J.R., Annibale, D.J., 2016, *A new method for group decision making and its application in medical trainee selection*, Medical Education, 50(10), pp. 1045–1053.
37. Sotoudeh-Anvari, A., 2023, *Root Assessment Method (RAM): A novel multi-criteria decision making method and its applications in sustainability challenges*, Journal of Cleaner Production, 423, 138695.
38. Şan Özbilen, B., Bayazıt, N., 2021, *Decision-making method for choosing best alternatives for internal walls based on cost and sound insulation performance*, Journal of ITU Faculty of Architecture, 18(3), pp. 735–751.
39. Keshavarz Ghorabaee, M., Zavadskas, E.K., Olfat, L., Turskis, Z., 2015, *Multi-Criteria Inventory Classification Using a New Method of Evaluation Based on Distance from Average Solution (EDAS)*, Informatica, 26(3), pp. 435–451.
40. Komatina, N., Marinković, D., 2026, *A Square-Root Based Evaluation Method for Engineering Personnel Selection: A Case Study of Quality Engineer Selection*, Journal of Operational and Strategic Analytics, 4(2), pp. 97–108.
41. Kastratović, N., Arsić, D., Komatina, N., Delić, M., Marinković, D., 2026, *Prioritization of Process Improvement Measures in a Forging Process Using an IPF-AHP-Based SREM Framework*, Journal of Manufacturing and Materials Processing, 10(7), 250.
42. Mufazzal, S., Muzakkir, S.M., 2018, *A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals*, Computers and Industrial Engineering, 119, pp. 427–438.
43. Zheng, M., Teng, H., Wang, Y., 2021, *A Simple Approach for Multi-Criteria Decision-Making on Basis of Probability Theory*, Engineering Structures and Technologies, 13(1), pp. 26–30.
44. Kizielewicz, B., Sałabun, W., 2024, *SITW Method: A New Approach to Re-identifying Multi-criteria Weights in Complex Decision Analysis*, Spectrum of Mechanical Engineering and Operational Research, 1(1), pp. 215–226.
45. Stevic, Z., Ulutas, A., Topal, A., Marinkovic, D., Cavoski, S., 2025, *A New Objective Method for Determining Criteria Weights in MCDM Models – LOGSTA*, International Journal of Simulation Modelling, 24(4), pp. 589–600.
46. Deepak, D., Dwivedi, S., Farwaha, H.S., Kumar, R., Stević, Ž., Chandra, M., Kumar, R., Agrawal, A.P., John, V., 2026, *A Decision-Oriented Framework for Risk-Based Maintenance Planning in High-Performance Mechanical Systems Using Entropy-Integrated FMEA–MCDM Approaches*, Journal of Engineering Management and Systems Engineering, 5(2), pp. 137-155.
47. Gazi, K.H., Biswas, A., Mondal, S.P., Ghosh, A., 2026, *Challenges of Remote Sensing for Crucial Role in All Phases of Disaster Management: An Uncertain MCDM-Based Study*, Journal of Engineering Management and Systems Engineering, 5(1), pp. 10–32.
48. Şahin, M., 2026, *An integrated multi-criteria decision-making approach for facility layout problems*, The Journal of Supercomputing, 82, 213.
49. Savaş, H., Yacan, İ., 2026, *A New Method of Multi-Criteria Decision Making: Improved Criteria Weighting Method (ICWM)*, Gazi University Journal of Science, 39(2), pp. 753–778.
50. Więckowski, J., Sałabun, W., 2025, *Comparative Sensitivity Analysis in Composite Material Selection: Evaluating OAT and COMSAM Methods in Multi-criteria Decision-making*, Spectrum of Mechanical Engineering and Operational Research, 2(1), pp. 1–12.
51. Nguyen, X.T., Ašonja, A., Do, D.T., 2023, *Enhancing Handheld Polishing Machine Selection: An Integrated Approach of Marcos Methods and Weight Determination Techniques*, Applied Engineering Letters, 8(3), pp. 131–138.
52. Dua, T.V., 2023, *Combination of symmetry point of criterion, compromise ranking of alternatives from distance to ideal solution and collaborative unbiased rank list integration methods for woodworking machinery selection for small business in Vietnam*, EUREKA: Physics and Engineering, 2, pp. 83–96.