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Comparative Evaluation of SREM and ARAS Methods for Multi-Criteria Decision-Making in Mechanical Machining

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Abstract

The selection of machine tools, materials, and machining options in mechanical manufacturing involves complex multi-criteria decision-making (MCDM) problems, yet different MCDM methods often yield different rankings for the same data. This study compares SREM, a method proposed in 2026, with the established ARAS method. Both employ linear-sum normalization and weighted aggregation, but SREM additionally applies squaring and square-root transformations. A comprehensive comparative framework is developed, integrating decision matrices, criteria-weighting scenarios, alternative-removal scenarios, and eight benchmark MCDM methods (TOPSIS, EDAS, PIV, ROV, SAW, RAM, MARCOS, and MOORA). Six practical selection problems are examined, covering grinding machines, CNC lathes, cutting tool materials, pulley materials, turning options, and grinding options. Spearman's rank correlation coefficient is used to assess ranking agreement. Sensitivity analyses further evaluate the effects of criteria-weight variations and alternative removal. The results show that ARAS generally achieves higher ranking agreement with the benchmark methods. Notably, the grinding option selection case reveals that extreme data values combined with dominant criterion weights can amplify ranking distortions in SREM due to its additional mathematical transformations. Removing alternatives containing extreme values reduces data dispersion and improves SREM's ranking agreement. These findings indicate that the ARAS method is more capable than the SREM method of producing alternative rankings that are consistent with those obtained using existing methods. Thus, when multiple MCDM methods are compared, ARAS appears to provide more consistent rankings, particularly for datasets containing extreme values.

Keywords: MCDM; ARAS; SREM; machine tool selection; material selection; machining option; spearman correlation coefficient

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1. Introduction

Mechanical machining plays an important role in modern industry, serving as an indispensable link in the production chain and in social life. It not only manufactures everyday items to meet daily needs but also produces tools and production equipment that

support human labor [1]. In particular, mechanical machining provides machine components and precision parts for almost all other economic sectors, including transportation, energy, aviation, healthcare, and agriculture [2]. Mechanical production processes are influenced by numerous complex factors that require coordinated consideration to achieve high productivity and quality. Among these factors, machine tools, workpiece materials, and technological options are three decisive factors [3]. Therefore, the selection of appropriate machine tools, materials, and production options is of great importance.

Machine tools play an important role in production because they directly influence machining accuracy and productivity [4,5]. The selection of suitable machine tools is a crucial factor in enabling manufacturing enterprises to maintain high competitiveness in the market [6–8]. For specific machining tasks, multiple types of machine tools may satisfy the required technical specifications; therefore, factors such as cost, productivity, and profitability need to be considered when selecting an appropriate machine [8–10]. To select suitable machine tools, engineers and managers generally make decisions based on technical handbooks, textbooks, user manuals, and their professional experience, or rely on recommendations from suppliers and technical experts. However, engineers may face difficulties when selecting suitable machines due to a lack of necessary experience or knowledge. Consulting services are usually expensive, whereas advice from suppliers is generally provided free of charge. However, because suppliers aim to persuade customers to purchase their products, the reliability and objectivity of such advice for machine selection may be limited [11]. Due to the complexity of machine selection, which involves the simultaneous consideration of multiple criteria, MCDM methods have emerged as powerful tools for evaluating complex systems [12]. Practical applications have demonstrated that MCDM methods are effective tools for addressing machine selection problems [6,10,13].

Material selection is one of the most important yet challenging tasks faced by structural engineers because it directly affects the performance and efficiency of the overall manufacturing process [14,15]. Although material selection can be performed at any stage of the product life cycle, it is generally carried out during the initial design phase [16]. Currently, more than 100,000 types of materials are available worldwide, each with distinct properties and specific advantages and disadvantages. Selecting a material for a specific product requires comparing the characteristics of several candidate materials [17–19]. Consequently, material selection involves considering multiple, diverse, and often conflicting objectives. In this context, MCDM methods have proven to be effective tools [20,21]. Practical applications have shown that MCDM methods can streamline the material selection process, making it more systematic and transparent [22–24]. MCDM methods have become increasingly popular for addressing the complex trade-offs involved in material selection and reducing the need for labor-intensive experimental procedures [22,25].

After selecting the machine tool and workpiece material, choosing an appropriate production process for a specific machining task is also a complex endeavor for various reasons [26]. Each machining option may involve different technological parameters, such as cutting regime parameters, cutting tool parameters, lubrication and cooling conditions, and other relevant factors, resulting in different responses for each machining option [27,28]. The complexity of the responses associated with each machining option further complicates the decision-making process for selecting the appropriate machining option, thereby constituting an MCDM problem [29,30].

Thus, machine selection, material selection, and production option selection in mechanical machining can all be considered MCDM problems. MCDM techniques have been widely used to rank alternative options under multiple conflicting criteria across various fields [18]. However, the large number of available MCDM methods makes selecting an appropriate method a challenge in itself [31,32]. Practical applications have demonstrated

that, when applied to the same problem, different MCDM methods can produce different ranking results [33,34]. The approach to ranking alternatives in each MCDM method and the normalization method available in each MCDM method are two of the main reasons leading to this phenomenon.

For the first reason, several studies have compared MCDM methods with different approaches to ranking alternatives in specific applications. The SAW method uses a weighted sum, whereas WPM employs a weighted product. MAVT is based on multi-attribute value theory, TOPSIS on distances from ideal solutions, and VIKOR on compromise ranking. Additionally, PROME-THEE II uses criterion-specific preference functions and pairwise comparisons, while ELECTRE III employs an out-ranking relation with indifference, preference, and veto thresholds. All of these methods have been compared with each other when evaluating industrial energy system structures. The results showed that SAW, WPM, and TOPSIS yield highly stable recommendations that are less sensitive to weight changes, whereas VIKOR is more sensitive to weight perturbations [35]. The COMET method is based on characteristic objects and fuzzy logic; the SPOTIS method calculates normalized distances directly to the ideal solution point; and the MARCOS method simultaneously considers the ideal and anti-ideal solutions. These methods, along with VIKOR and TOPSIS, have been compared with each other in supplier selection. The results showed that VIKOR and COMET yield completely identical alternative ranking results; COMET, TOPSIS, and MARCOS exhibit high correlation, whereas the SPOTIS method shows the largest deviation from the remaining methods [36]. In [37], TOPSIS and PROMETHEE were compared with each other in city ranking. The results showed that the city rankings are very different when ranked using these two methods. The ARAS method is based on the value of the optimality function, the COPRAS method is based on complex proportional assessment, and the MOORA method is based on multi-objective optimization on the basis of ratio analysis; all three of these methods, along with SAW, VIKOR, and TOPSIS, have been used to evaluate commercial banks. The alternative ranking results vary significantly when they are simultaneously used to rank commercial banks [38]. It was reported in [39] that the TOPSIS, MOORA, COPRAS, and PROMETHEE methods produce different alternative rankings when ranking renewable energy alternatives.

The second reason for different ranking results of alternatives when using different MCDM methods is the normalization methods used in MCDM [40,41]. Even MCDM methods that employ the same type of data normalization can produce different ranking results when applied to the same problem [42].

SREM [43] and ARAS [44] are two MCDM methods that employ the same type of data normalization, namely linear sum normalization, in their calculation procedures. However, these two methods have different approaches to ranking alternatives. The SREM method is based on a non-linear approach that combines the square root and squaring transformations. Meanwhile, the ARAS method ranks alternatives based on the value of the optimality function. A comparison of these two methods, with their distinct approaches to ranking alternatives, has not been found in the existing literature. Details on the mathematical structures of these two methods will be presented in Section 2 of this paper. Normalization significantly influences the ranking of alternatives obtained using MCDM methods [45]. However, even when the same normalization method is applied, different MCDM methods may still produce different rankings of the evaluated alternatives [46]. This occurs because the ranking results depend not only on the normalization method but also on the specific algorithm used, the weights assigned to the criteria, and the data's inherent characteristics. Therefore, comparisons of MCDM methods should be conducted within specific application contexts [34]. Comparative evaluations of MCDM methods in context-specific conditions are essential, as some studies have indicated that all evaluated methods are suitable for a

particular decision-making problem, whereas others have demonstrated that certain methods are suitable while others are not. For example, the PIV, PSI, FUCA, and CURLI methods have all been shown to be suitable for ranking plastic injection molding machines [47]. In contrast, another study found that the RAM and MOORA methods were unsuitable for evaluating the financial performance of 30 banks in Vietnam, whereas the FUCA and CURLI methods were effective [48].

ARAS was proposed relatively early, in 2010, and has since been applied in numerous studies. During the period 2010–2020 alone, more than 95 studies applied ARAS to rank alternatives across various fields [49]. The method has been widely applied not only in mechanical engineering, such as for ranking gear manufacturing materials [50], robots [51], and conveyor types [11], but also in other fields, including the ranking of mineral exploitation areas [52], investment assets [53], recruitment candidates [54], sustainable materials in the construction industry [55], and evaluation criteria for transportation systems [56]. In contrast, because SREM was proposed only recently, in May 2026, studies applying this method remain very limited.

The similarity in the data normalization methods used by SREM and ARAS, along with differences in their approaches to ranking alternatives and in their development timelines, raises the question of the effectiveness of these two methods when applied to the same decision-making problem. This question motivates the present study, which aims to compare the performance of the two methods in mechanical machining. It should also be emphasized that the simultaneous application of these two methods to specific decision-making problems remains relatively limited in the published literature.

Section 2 presents the procedures for applying the SREM and ARAS methods to rank alternatives. The methodology for comparing these two methods is presented in Section 3. Six examples related to machine selection, material selection, and production option selection in mechanical engineering are presented in Section 4 to compare the performance of SREM and ARAS. The discussion of the obtained results and the conclusions of this study are presented in Sections 5 and 6, respectively.

2. SREM Method and ARAS Method

The procedure for ranking alternatives using the SREM method consists of the following steps [43]:

Step 1. Construct a decision matrix consisting of (m) rows and (n) columns, as shown in Equation (1), where (m) and (n) represent the number of alternatives to be ranked and the number of criteria used to evaluate the alternatives, respectively. Let (x_{ij}) denote the value of alternative (i) with respect to criterion (j), where $(i = 1,..., m)$ and $(j = 1,...,n)$.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & x_{ij} & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2. Normalize the values in the decision matrix according to Equations (2) and (3).

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \ if\, j \in B \quad (2)$$

$$n_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m} \frac{1}{x_{ij}}}, \ if\, j \in C \quad (3)$$

Step 3. Obtain the transformed decision matrix by squaring each element of the normalized decision matrix according to Equation (4).

$$S_{ij} = \frac{{n_{ij}}^2}{\sum_{i=1}^{m} {n_{ij}}^2} \tag{4}$$

Step 4. Transform the normalized matrix by taking the square root of each element, with the matrix components calculated according to Equation (5).

$$R_{ij} = \frac{\sqrt{n_{ij}}}{\sum_{i=1}^{m} \sqrt{n_{ij}}} \tag{5}$$

Step 5. Construct a unified matrix with its components calculated according to Equation (6). Here, (α) ranges from $(0 - 1)$ and serves as the adjustment coefficient between the square-root and square transformations. If only the square transformation is considered, the coefficient is set to (1); conversely, if only the square-root transformation is considered, the coefficient is set to (0). If equal contributions from the square and square-root transformations are considered, the coefficient is set to (0.5). In the examples presented in the subsequent section of this study, the value of this coefficient is set to (0.5).

$$\alpha_{ij} = \alpha \cdot S_{ij} + (1 - \alpha) \cdot R_{ij} \tag{6}$$

Step 6. Construct a weighted unified matrix with its components calculated according to Equation (7), where (w_j) is the weight of criterion (j).

$$c_{ij} = w_j \cdot \alpha_{ij} \tag{7}$$

Step 7. Calculate the score of each alternative according to Equation (8). The alternative with the highest score is ranked first.

$$F_i = \sum_{j=1}^{n} c_{ij} \tag{8}$$

The procedure for ranking alternatives using the ARAS method consists of the following steps [44]:

Step 1: Similar to Step 1 of the SREM method.

Step 2: Construct a decision matrix including the ideal alternative, as shown in Equation (9), where (x_{0j}) is the optimal value of criterion (j) among all alternatives.

$$\mathrm{X} = \begin{bmatrix} x_{01} & x_{02} & \cdots & x_{0n} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ \cdots & \cdots & x_{ij} & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{9}$$

Step 3: Similar to Step 2 of the SREM method. This represents a common feature of SREM and ARAS, as both methods employ the linear sum normalization type, as shown in Equations (2) and (3).

Step 4: Calculate the normalized values considering the weights of the criteria, as shown in Equation (10), where (w_j) is the weight of criterion (j).

$$v_{ij} = w_j \cdot n_{ij} \tag{10}$$

Step 5: Calculate the optimal function value for each alternative according to Equation (11).

$$S_i = \sum_{j=1}^{n} v_{ij} \tag{11}$$

Step 6: Calculate the score of each alternative according to Equation (12), where (S_0) is the optimal function value for the ideal alternative. The alternative with the highest score is ranked first.

$$Q_i = \frac{S_i}{S_0} \tag{12}$$

It can be observed that, although the two methods employ the same data normalization, as shown in Equations (2) and (3), their approaches to ranking alternatives are substantially different. SREM addresses the problem through the nonlinear transformation of the data matrix using a combination of squaring and square-root operations [43]. In contrast, ARAS addresses the problem based on an ideal optimal alternative. In ARAS, the score of each alternative is calculated as the optimal function value for that alternative divided by the optimal function value for the ideal alternative [44]. Therefore, this research addresses how these two methods perform when applied to a specific field, such as mechanical production.

3. Procedure for Comparing SREM and ARAS

To compare SREM and ARAS in ranking key categories of mechanical production, including machine tools, materials, and machining options, it is necessary to clarify the comparison criteria and establish a specific methodological framework.

Although numerous MCDM methods are available, it should be noted that no method is perfect [57]. Every MCDM technique, regardless of its popularity, has certain limitations. Practical applications have shown that no standard procedure or model has been established for selecting specific MCDM methods [58]. It has been suggested that solutions based on multiple methods can increase the reliability of decision-making [59,60]. When multiple methods are employed to rank alternatives for the same decision-making problem, a method that produces rankings highly consistent with those obtained using other ranking methods can be considered suitable for the problem under consideration. A higher degree of ranking consistency indicates greater suitability of the method for the given problem [61]. From this perspective, comparing SREM and ARAS requires comparing the rankings of alternatives generated by these two methods with those obtained using other MCDM methods [62]. To evaluate the relative performance and ranking consistency of SREM and ARAS, eight multi-criteria decision-making (MCDM) methods were selected, including TOPSIS, EDAS, PIV, ROV, SAW, RAM, MARCOS, and MOORA. The selection of these methods was based on four main criteria:

First: Algorithmic diversity in normalization schemes. The selected methods cover a comprehensive range of data normalization techniques, including vector normalization (TOPSIS [63], PIV [64], MOORA [65]), max-min/proportional linear normalization (EDAS [66], ROV [67], SAW [68], MARCOS [69]), and linear sum normalization (RAM [70]). This ensures that the comparative evaluation process is not biased toward a single normalization mathematical structure.

Second: Diversity in aggregation principles. These methods encompass fundamental operational concepts in decision theory: logic based on distance to ideal solutions (TOPSIS [63], EDAS [66], MARCOS [69]), additive linear weighting (SAW [68]), pairwise dominance comparison (PIV [64]), value operation within bound ranges (ROV [67]), radical-based utility scoring (RAM [70]), and utility ratio aggregation (MOORA [65]).

Third: Maturity and widespread acceptance. These eight methods represent a balanced mix of classical algorithms well-proven in extensive literature (TOPSIS, SAW, MOORA) and recently applied advanced methods (MARCOS, RAM, PIV).

Fourth: Methodological objectivity. By evaluating SREM and ARAS against a structurally diverse yet broadly validated set of methods, the comparative results between the two methods ensure the necessary objectivity.

The similarity between alternative rankings obtained using different methods can be evaluated using metrics such as Spearman's rank correlation coefficient (hereafter referred to as the Spearman coefficient) [71], the Ties-Adjusted Spearman Rank Correlation Coefficient [72], the rank similarity coefficient (RS), or the weighted Spearman rank correlation coefficient (WSRE) [73]. While RS and WSRE assign greater weights to higher-ranked alternatives and place less emphasis on lower-ranked alternatives, the Spearman coefficient assigns equal weight to all ranking positions [74,75]. To ensure a comprehensive comparison between SREM and ARAS, that is, an evaluation based on the complete ranking of alternatives rather than solely on the top-ranked alternative, this study employs the Spearman coefficient. The coefficient is calculated according to Equation (13), where (D_i) represents the rank difference for alternative (i) between the rankings obtained using different methods [76].

$$S = 1 - \frac{6\sum_{i=1}^{m} D_i^2}{m(m^2 - 1)} \tag{13}$$

If $0 \leq S \leq 0.19$, the similarity level is classified as "Very Weak". If $0.2 \leq S \leq 0.39$, it is classified as "Weak". If $0.4 \leq S \leq 0.59$, it is classified as "Moderate". If $0.6 \leq S \leq 0.79$, it is classified as "Strong". Finally, if $0.8 \leq S \leq 1$, it is classified as "Very Strong" [77].

In manufacturing processes in general, and mechanical engineering in particular, decision-makers, such as production managers, process engineers, and technical directors, often have different preference structures depending on specific operational objectives. For example, in finishing operations, technical criteria such as machining accuracy, surface roughness, and material mechanical properties of are given high priority. In contrast, in mass production or budget-constrained environments, economic factors such as machine cost, cutting tool expenses, and operational costs tend to receive greater emphasis. To adequately reflect these practical differences in decision-maker preferences, sensitivity analysis involving variations in criteria weights is essential. Although the generation of different scenarios for sensitivity analysis can be carried out in ways such as changing the weights of criteria, altering (adding or removing) the number of alternatives to be ranked, generating extreme values, changing the criterion type from the larger-the-better to the smaller-the-better and vice versa, etc. [77,78]. This study employs two approaches: varying the weights of the criteria and removing alternatives from the list of alternatives to be ranked in order to generate different scenarios. Varying the weights of the criteria is considered the most common method, while also reflecting the differences in perspectives among decision-makers regarding the importance of the criteria [79]. Removing an alternative from the list of alternatives to be ranked also somewhat reflects practical conditions, such as the scarcity of a certain alternative in reality—for example, the unavailability of a specific type of machine or material, or instances where a previously planned production alternative cannot be implemented for some reason.

Accordingly, different weighting scenarios are considered to evaluate the robustness of the alternative rankings. Based on the above analysis, the procedure for comparing SREM and ARAS is illustrated in the flowchart shown in Figure 1.

As described in Figure 1, for each specific case, data on the alternatives, criteria, and criterion values for each alternative are collected to construct the decision matrix. Subsequently, the criteria weights are determined under different weighting scenarios. For each weighting scenario, SREM, ARAS, and eight other methods, TOPSIS, EDAS, PIV, ROV, SAW, RAM, MARCOS, and MOORA, are employed to rank the alternatives. The Spearman correlation coefficients are then calculated between the rankings obtained using SREM and ARAS and those obtained using the eight other methods. Based on the calculated Spearman coefficients, the rankings obtained using SREM and ARAS are compared. This procedure is repeated for each criterion-weighting scenario, thereby serving as a sensitivity analysis

to evaluate the robustness of the results. For each example, after comparing SREM and ARAS across all weighting scenarios, a comparative conclusion is drawn. All calculations performed in this study were carried out using Microsoft Excel software. In the subsequent section, this procedure is applied to specific applications in the mechanical field, as outlined within the scope of this research.

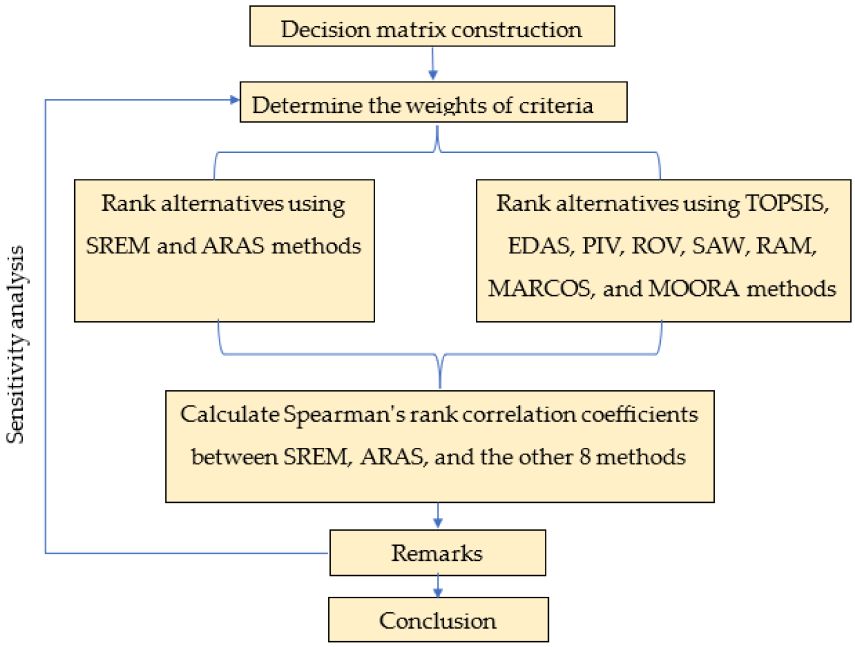


Figure 1. Block diagram of the SREM–ARAS comparison process.

4. Results of Comparing SREM and ARAS

The purpose of this research is to compare two MCDM methods that employ the same type of data normalization, namely SREM and ARAS, for ranking alternatives associated with key components in the field of mechanical manufacturing. Therefore, the data used in the examples presented in this study were obtained from the existing literature. This approach is based on two main reasons. First, the study does not focus on constructing experimental setups or collecting primary data; instead, it focuses entirely on comparing the SREM and ARAS methods. Second, the use of datasets reported in published literature and subjected to rigorous peer review in reputable journals enhances the reliability and objectivity of the comparative results obtained for SREM and ARAS.

To objectively evaluate the applicability of the SREM and ARAS methods to various decision-making problems in the field of mechanical manufacturing, a comprehensive sensitivity analysis was conducted in each case study. The weighting scenarios were not generated randomly but were systematically designed to reflect different industrial management priorities. Specifically, the first scenario in the case study assigned equal weights to all criteria, representing a balanced weighting scheme. In the subsequent scenarios, each criterion was sequentially assigned a dominant weight, while the weights of the remaining criteria were adjusted accordingly to ensure that the sum of all criteria weights remained equal to one. This systematic and deterministic approach to weight variation simulates changes in decision-makers' preferences under practical conditions, thereby enabling a comprehensive evaluation of the comparative performance of SREM and ARAS under different operating conditions.

The decision to vary the criteria weights by up to 300% (in Examples 1 and 4) and 400% (in Examples 2, 3, 5, and 6) serves a dual practical purpose. Methodologically, this wide range

acts as a numerical stress test to determine whether the ranking order remains stable under severe preference fluctuations. Industrially, these variation ranges directly simulate real-world shifts in manufacturing objectives: for instance, heavy rough machining operations strongly prioritize power capacity, cutting forces, and material removal rates, whereas precision finishing operations shift primary focus entirely toward strict geometric tolerances, low surface roughness, and tool life. Therefore, this systematic and deterministic approach to weight variation realistically captures the spectrum of decision-makers' operational preferences, enabling a rigorous evaluation of the comparative performance and consensus between SREM and ARAS. In addition, Example 6 also performs a sensitivity analysis by generating scenarios in which one alternative is removed from the list of alternatives to be ranked in each scenario. Generating scenarios in this manner also reflects real-world conditions that may occur, such as the potential scarcity of a certain alternative in practice.

4.1. Example 1—Selection of Grinding Machines

In this example, the comparison between ARAS and SREM was conducted by ranking (12) grinding machines, designated as alternatives (A1) through (A12), as shown in Table 1. Eight criteria were used to evaluate each machine, including maximum table travel along the X-axis (C1), maximum table travel along the Y-axis (C2), maximum table travel along the Z-axis (C3), maximum grinding wheel diameter that can be mounted on the machine (C4), maximum grinding wheel speed (C5), machine power (C6), machine accuracy (C7), and year of manufacture (C8). Among these criteria, C7 is a Cost (C) criterion, whereas the remaining seven criteria are Benefit (B) criteria [80]. C1 specifies the maximum workpiece length, directly affecting productivity when machining long surfaces, while C2 defines the maximum component width that can be ground in a single setup. C3 determines the vertical workspace clearance required for machining thick workpieces, whereas C4 specifies the maximum grinding wheel size, which affects both the cutting depth and tool life. Furthermore, C5 determines the cutting speed, directly influencing surface roughness and material removal rate, while C6 reflects the equipment's load capacity, which determines its roughing performance and cutting stability. Finally, C7 is a key criterion for evaluating geometric accuracy and surface flatness, whereas C8 reflects technological advancement and overall operational reliability of the equipment.

Table 1. Types of Grinding Machines [80].

Machine	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
unit	mm	mm	mm	mm	m/s	kW	mm	year

It can be observed that alternative (A11) has the highest values for criteria (C1–C5) and (C6). The lowest value for criterion (C7), (0.002), is shared by alternatives (A6), (A9), (A10), and (A11). The highest value for criterion (C8), (2018), belongs to alternative (A10). Thus, it is clear that no single machine has optimal values for all eight criteria compared to the other alternatives. This implies that ranking the machines first requires calculating the criterion weights. Initially, all criteria are considered equally important, with each criterion assigned a weight of (1/8); this is designated as weighting scenario (S1). When the criterion weights change, different scenarios arise. Using different weighting scenarios to rank the machines constitutes the sensitivity analysis phase for evaluating the stability of the results from the comparison between SREM and ARAS. Corresponding to scenario (S1), Table 2 summarizes the rankings of the grinding machines obtained using different methods.

Table 2. Rankings of grinding machines in Scenario S1.

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

According to the data presented in Table 2, the rankings of the grinding machines show a very high degree of similarity across the different ranking methods. A comparison between SREM and ARAS shows that (9) out of (12) grinding machines have consistent rankings under these two methods. For the three remaining alternatives whose rankings differ between the two methods, the differences are also very small. Specifically, (A6) is ranked 7th using SREM, whereas it is ranked 9th using ARAS; (A8) is ranked 9th using SREM, whereas it is ranked 8th using ARAS. Finally, (A12) is ranked 8th using SREM, whereas it is ranked 7th using ARAS.

As also shown in Table 2, all ten methods produce machine rankings with a very high degree of mutual similarity. All ten methods consistently identify (A11) as the 1st-ranked alternative and (A9) as the 2nd-ranked alternative. For the other rank positions, the ranking results across the ten methods are also highly similar. For instance, regarding alternative (A1), (9) out of (10) methods indicate that it is ranked 11th, whereas only one method, MARCOS, ranks it 9th. Considering another example, for (A5), (9) out of (10) methods consistently indicate that this alternative is the worst, i.e., ranked 12th, whereas only the MARCOS method shows a slight difference by ranking this alternative 11th, which differs only marginally from the rankings obtained using the other methods.

Examining the other alternatives reveals a similar pattern, with the machine rankings showing a high degree of similarity across the ten different methods. Thus, based on a visual assessment of the data in Table 2, the SREM and ARAS methods yield machine rankings equivalent to those obtained using the other methods. The machine rankings

generated by these two methods are also highly similar. Overall, the SREM and ARAS methods can be considered equivalent to each other and to the other methods. However, to quantify these observations, the Spearman coefficients between the two methods were calculated, and the results are summarized in Table 3.

Table 3. Spearman Correlation Coefficients for SREM, ARAS, and Other Methods in Scenario (S1).

	TOPSIS	EDAS	PIV	ROV	SAW	RAM	MARCOS	MOORA	Average (AS)
SREM	1.000	0.958	0.958	0.846	1.000	0.958	0.671	0.958	0.919
ARAS	0.979	0.993	0.993	0.867	0.979	0.993	0.748	0.895	0.931

According to the results presented in Table 3, it can be seen that the Spearman correlation coefficients between the rankings generated by SREM, ARAS and those obtained using the seven methods (TOPSIS, EDAS, PIV, ROV, SAW, RAM, and MOORA) are consistently high, with most values exceeding 0.9. These values are substantially higher than the threshold of 0.8, which indicates a "Very Strong" level of ranking similarity among the MCDM methods [76].

For the MARCOS method, the Spearman correlation coefficients between MARCOS and SREM or ARAS do not reach the (0.8) threshold. This can be attributed to the significant differences in the rankings of the alternatives produced by MARCOS compared with those obtained using SREM and ARAS. Specifically, MARCOS determines the rankings based on the compromise distance from two reference points simultaneously: the ideal solution and the anti-ideal solution. In contrast, ARAS calculates utility scores based on the overall performance relative to a single optimal point, whereas SREM combines nonlinear transformations (squaring and square root) with a compromise coefficient (α coefficient) between these two transformations.

The average Spearman correlation coefficient (AS) between SREM, ARAS, and the eight remaining methods is also presented in the last column of Table 3, with values of (0.919) for SREM and (0.931) for ARAS. This indicates that, overall, the ARAS method generates grinding machine rankings with a higher degree of similarity to those obtained using the eight other methods (TOPSIS, EDAS, PIV, ROV, SAW, RAM, MARCOS, and MOORA) than the SREM method.

Varying the criterion weights to further compare SREM and ARAS across different weighting scenarios constitutes a sensitivity analysis, which is an important step in MCDM problems [81]. Eight additional scenarios were generated, with each scenario assigning one criterion a weight three times higher than those of the remaining criteria, while the other criteria were assigned equal weights. For example, in Scenario (S2), criterion (C1) is assigned a weight of 0.3, while each of the remaining seven criteria is assigned a weight of 0.1. Similarly, in Scenario S3, criterion C2 is assigned a weight of 0.3, while each of the remaining seven criteria is assigned a weight of 0.1. Figure 2 illustrates the weights of the criteria for Example 1 across all nine scenarios. Accordingly, considering all nine scenarios, the weight of each criterion varies from 0.1 to 0.3 across these scenarios, representing a 300% variation.

For the eight scenarios (S2–S9), the grinding machines were ranked using different methods, and the Spearman correlation coefficients between SREM, ARAS, and the other eight methods were also calculated. Table 4 summarizes the average Spearman correlation coefficient (AS) between SREM, ARAS, and the other methods across the eight newly defined scenarios (S2–S9), as well as for Scenario S1, which was considered previously.

According to the data presented in Table 4, the (AS) values for both SREM and ARAS are very high, with the lowest value being (0.816), which exceeds the threshold of (0.8).

This indicates that the rankings of the grinding machines generated by SREM and ARAS are highly similar to those obtained using the other methods.

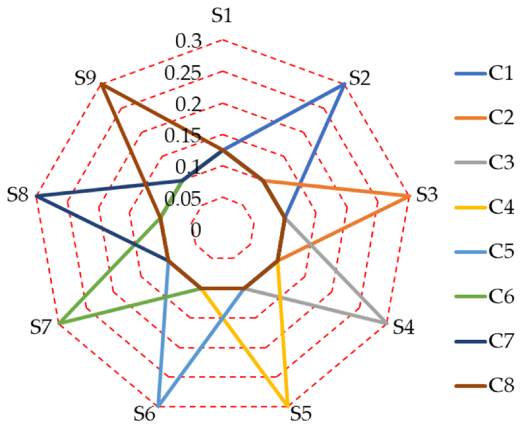


Figure 2. Criterion Weights in Example 1.

Table 4. (AS) for SREM and ARAS Compared with other Methods in Example 1.

	S1	S2	S3	S4	S5	S6	S7	S8	S9
SREM	0.919	0.944	0.953	0.909	0.940	0.816	0.944	0.923	0.898
ARAS	0.931	0.944	0.953	0.944	0.945	0.816	0.944	0.923	0.910

More specifically, across the five scenarios S2, S3, S6, S7, and S8, the (AS) values for SREM and ARAS are equal, indicating that the two methods yield equivalent results. In the four scenarios S1, S4, S5 and S9, the (AS) value for ARAS is higher than that for SREM. This implies that, in these three scenarios, the machine rankings generated by ARAS exhibit a higher degree of similarity to those obtained with the other methods than those generated by SREM.

Overall, across all evaluated scenarios in this example, the ARAS method produces alternative rankings that exhibit a higher degree of similarity to those obtained using existing methods than the SREM method.

4.2. Example 2—Selection of CNC Lathes

In this example, the two methods, SREM and ARAS, are compared for ranking eight CNC lathes, denoted (A1–A8), as summarized in Table 5 [82]. Seven criteria are used to characterize each machine: price, spindle speed, maximum processable workpiece diameter, X-axis rapid traverse rate, Z-axis rapid traverse rate, center height, and maximum processable workpiece length, denoted as criteria C1 through C7, respectively. Among these criteria, C1 is a cost (C) criterion, whereas the remaining six criteria are benefit (B) criteria. C1 represents the initial investment cost, which directly affects economic efficiency and the enterprise's payback period, while C2 determines the cutting speed, which strongly influences machining productivity and component surface roughness. C3 defines the radial machining limit, determining the machine's capability to process large-diameter rotational workpieces, whereas C4 represents the horizontal tool positioning speed, which helps reduce auxiliary operating time. Additionally, C5 determines the longitudinal travel speed of the tool slide, directly affecting the non-cutting time of the machining cycle, while C6 specifies the clearance between the spindle center and the guideways, thereby determining the maximum permissible workpiece diameter. Finally, C7 determines the maximum workpiece length, directly affecting the machine's capability to process long shaft-type components.

Table 5. CNC Lathes and Their Characteristics [82].

Machine	C1	C2	C3	C4	C5	C6	C7
A1	2,737,600	4000	400	10	30	250	200
A2	1,365,000	4000	480	15	15	200	350
A3	1,565,000	4000	600	15	15	200	550
A4	2,350,000	3500	600	25	25	300	550
A5	2,550,000	3500	1000	25	25	300	950
A6	1,650,000	2000	700	20	20	200	625
A7	1,050,000	2000	700	24	20	250	600
A8	6,000,000	2500	425	16	21	235	530
unit	INR	rpm	mm	m/min	m/min	mm	mm

To rank the machines presented in Table 5, the criterion weights must first be determined. Accordingly, fifteen scenarios, (S1–S15), were generated by varying the criterion weights. In S1, all criteria are assigned equal weights of (1/7). For scenarios S2 through S8, one criterion is assigned a weight of (0.1), while each of the remaining six criteria is assigned a weight of (0.15). For example, in Scenario S2, criterion C1 is assigned a weight of (0.1), while each of the remaining six criteria is assigned a weight of (0.15). In Scenario S3, criterion C2 is assigned a weight of 0.1, while each of the remaining six criteria is assigned a weight of 0.15, and so on.

For scenarios S9 through S15, one criterion is assigned a weight of 0.4, while each of the remaining six criteria is assigned a weight of 0.1. For example, in Scenario S9, criterion C1 is assigned a weight of 0.4, while each of the remaining six criteria is assigned a weight of 0.1. In Scenario S10, criterion C2 is assigned a weight of 0.4, while each of the remaining six criteria is assigned a weight of 0.1, and so on. Figure 3 illustrates the criteria weights across all 15 scenarios described above. Across these scenarios, the weight of each criterion varies from 0.1 to 0.4, representing a 400% variation.

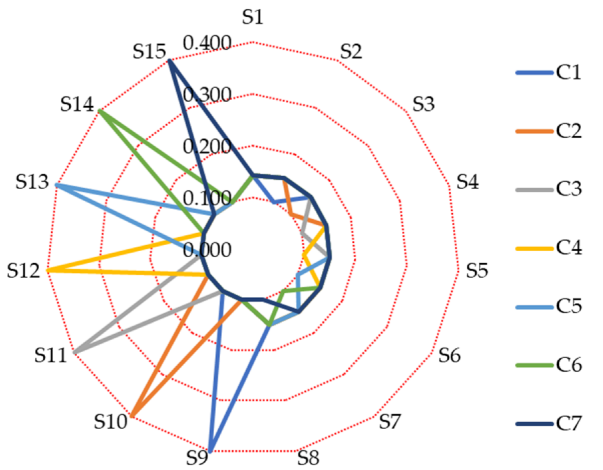


Figure 3. Criterion Weights in Example 2.

Similar to Example 1, in this example, the lathes were ranked using different methods across all fifteen scenarios, and the Spearman correlation coefficients between SREM, ARAS, and the eight other methods were calculated. Figure 4 illustrates the (AS) values for SREM and ARAS compared with the other methods across all fifteen scenarios.

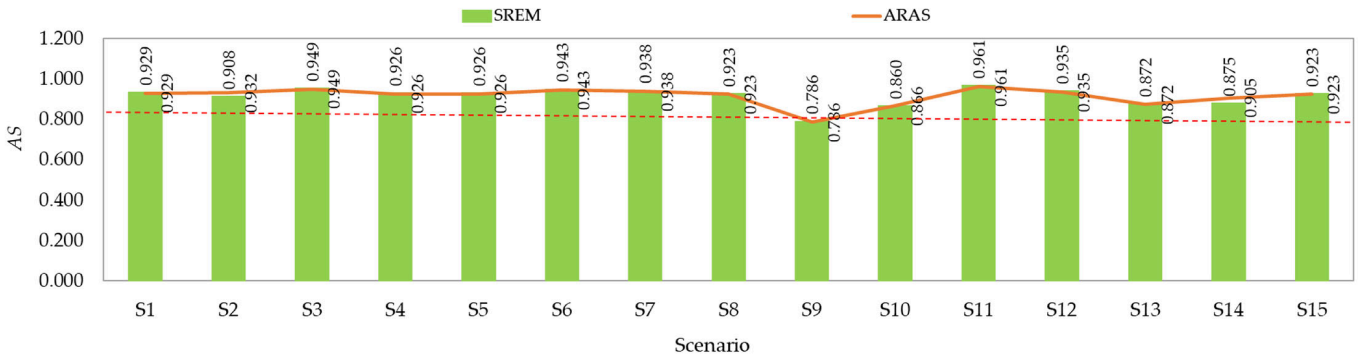


Figure 4. (AS) for SREM and ARAS Compared with Other Methods in Example 2.

An examination of Figure 4 reveals that, except for Scenario S9, the (AS) values of both SREM and ARAS exceed the 0.8 threshold in all other scenarios, with many values exceeding 0.9. This indicates that the lathe rankings generated by SREM and ARAS are highly similar to those obtained with the other methods. In Scenario S9, the (AS) values for both SREM and ARAS are 0.786, which, although slightly below the 0.8 threshold, represents only a negligible deviation from the threshold. This further demonstrates that, even in this scenario, SREM and ARAS yield lathe rankings that are relatively similar to those obtained using the other methods.

In 12 scenarios, namely S1, S3, S4–S9, S11, S12, S13, and S15, the (AS) values for SREM and ARAS are equal. This indicates that, across these twelve scenarios, the CNC lathe rankings generated by the SREM method exhibit the same degree of similarity to those obtained using the other methods as the rankings generated by the ARAS method. In other words, SREM and ARAS yield equivalent results in these twelve scenarios.

In the remaining three scenarios (S2, S10, and S14), the (AS) values for ARAS are 0.932, 0.866, and 0.905, respectively, whereas those for SREM are 0.908, 0.860, and 0.875, respectively. Thus, in all three scenarios, the (AS) value for ARAS is consistently higher than that for SREM. This implies that, in these scenarios, the lathe rankings generated by ARAS exhibit a higher degree of similarity to those obtained using the other methods than the rankings generated by SREM.

In summary, across all fifteen evaluated scenarios in this example, the results indicate that the ARAS method produces alternative rankings that exhibit a higher degree of similarity to those obtained using existing methods than the SREM method. The two preceding examples, which focused on grinding machine and lathe selection, demonstrate that using ARAS is more capable than SREM of generating machine rankings that are highly consistent with those produced by other MCDM methods. The comparison between SREM and ARAS is subsequently extended to the selection of other components involved in mechanical manufacturing operations, beginning with material selection in examples 3 and 4.

4.3. Example 3—Selection of Cutting Tool Materials

Table 6 summarizes information on 12 types of cutting tool materials, designated as alternatives (A1) through (A12) [83]. Seven criteria are used to characterize each alternative: hardness, Young's modulus, elastic recovery, coefficient of friction, load-bearing capacity, resistance to plastic deformation index of the coating, and abrasive wear resistance index of the coating, denoted as criteria (C1–C7), respectively. Among these criteria, C4 is a cost criterion, whereas the remaining six criteria are benefit criteria. C1 represents wear resistance and resistance to plastic deformation, helping maintain a sharp cutting edge at elevated temperatures. C2 indicates stiffness, reflecting the material's ability to resist bending and elastic deformation under high cutting forces, thereby ensuring machining

accuracy. C3 represents the material's ability to recover its original surface condition after deformation, thereby minimizing surface damage and impact-induced cracks. C4 reflects the ability to reduce friction between chips and the cutting tool, thereby lowering cutting temperatures and preventing chip adhesion. C5 indicates the material's ability to resist chipping or fracture under high loads. C6 represents resistance to plastic deformation under high pressure. Finally, C7 indicates toughness and crack resistance, contributing to extended tool life severe operating conditions.

Table 6. Cutting Tool Materials Considered in the Analysis [83].

Material	C1	C2	C3	C4	C5	C6	C7
A1	34	380	60	0.6	30	0.089	0.272
A2	31	380	59	0.49	50	0.082	0.206
A3	20	280	49	0.45	41	0.071	0.102
A4	23	300	46	0.45	46	0.077	0.135
A5	19	270	45	0.45	46	0.07	0.094
A6	30	370	53	0.52	22	0.081	0.197
A7	19	270	43	0.51	47	0.07	0.094
A8	25	340	47	0.45	90	0.074	0.135
A9	17	280	40	0.5	67	0.061	0.063
A10	23	300	48	0.52	54	0.077	0.135
A11	20	260	46	0.43	37	0.077	0.118
A12	19	280	44	0.45	41	0.068	0.087
unit	GPa	GPa	%	-	N	GPa	-

To rank the cutting tool materials, fifteen different criterion-weighting scenarios, designated (S1–S15), were defined, as illustrated in Figure 5. In scenario S1, each criterion is assigned an equal weight of 1/7.

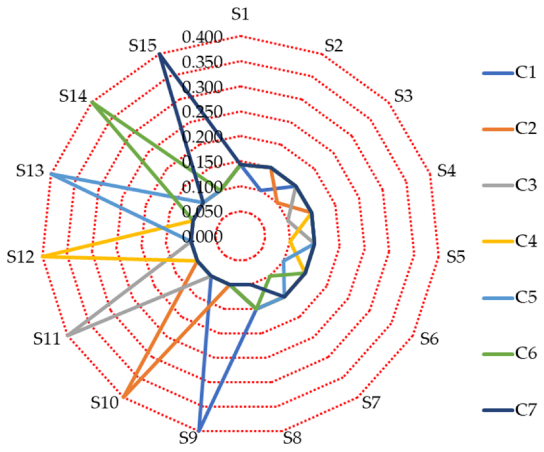


Figure 5. Criterion Weights in Example 3.

In scenarios S2–S8, each scenario assigns one criterion a weight of 0.1, while the remaining six criteria are each assigned a weight of 0.15. In scenarios S9–S15, each scenario assigns one criterion a weight of 0.4, while the remaining six criteria are each assigned a weight of 0.1. Accordingly, considering all fifteen scenarios, the weight of each criterion varies from 0.1 to 0.4, corresponding to a variation of up to 400%.

Following the same procedure as in Examples 1 and 2, the cutting tool materials were ranked using ten different methods for each weighting scenario. Subsequently, Spearman correlation coefficients were calculated between SREM and ARAS and each of the remaining eight methods (TOPSIS, EDAS, PIV, ROV, SAW, RAM, MARCOS, and MOORA). The (AS) values for SREM and ARAS were then calculated, and the results are illustrated in Figure 6.

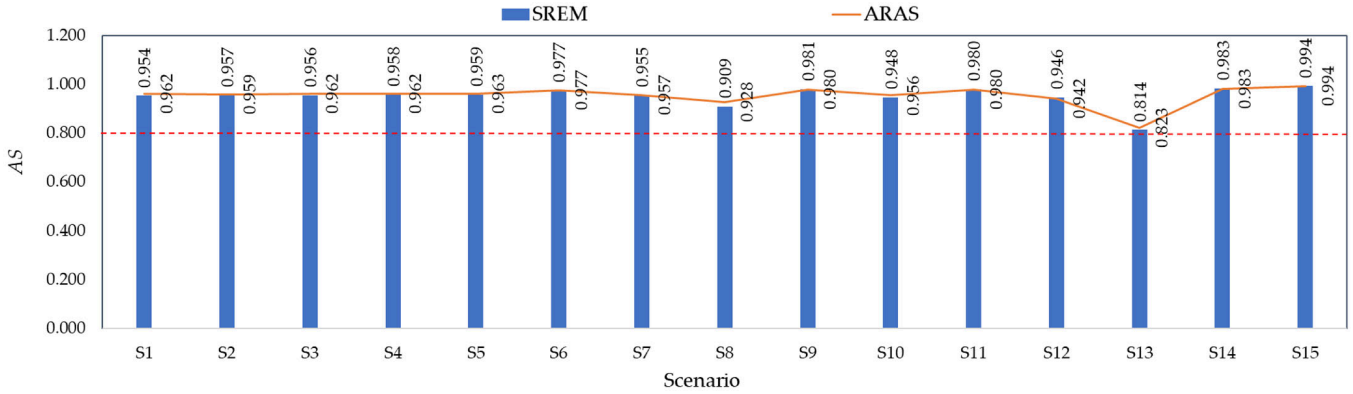


Figure 6. (AS) for SREM and ARAS Compared with Other Methods in Example 3.

Observation of Figure 6 reveals that all (AS) values across the fifteen scenarios are very high, with the lowest value being 0.814 for SREM in scenario S13. This indicates that, in all scenarios considered in this example, the rankings of the cutting tool materials generated by SREM and ARAS exhibit a high degree of similarity to those obtained using the other methods.

When comparing SREM and ARAS, we find that in scenarios S9, and S12, the AS value of SREM is higher than that of ARAS, but the difference is very small. In scenarios S6, S11, S14, and S15, the AS values of SREM and ARAS are equal. Specifically, for both SREM and ARAS, the AS in scenario S6 is 0.977, in scenario S11 is 0.980, in scenario S14 is 0.983, and in scenario S15 is 0.994. In the remaining 9 scenarios, the AS of ARAS is always higher than that of SREM. However, the difference is also very small, such as in scenario S1 where the AS of ARAS is 0.962 while that of SREM is 0.954, or in scenario S2 where the AS of ARAS is 0.959 while that of SREM is 0.957. Thus, across all fifteen scenarios analyzed in this example, the rankings of cutting tool material types generated by the SREM method show a high degree of similarity with the results from the ARAS method.

In conclusion, in this example, both SREM and ARAS generate highly consistent alternative rankings, with a high degree of similarity between their results and those obtained using existing methods.

4.4. Example 4—Selection of Pulley Materials

In this example, SREM and ARAS are compared for ranking ten materials used to manufacture sintered automotive pulleys, designated as alternatives (A1) through (A10), as shown in Table 7 [84]. Ten criteria are used to evaluate each alternative: yield strength, tensile strength, modulus of elasticity in tension, hardness, density, compressive strength, coefficient of thermal expansion, thermal conductivity, Poisson's ratio, and cost, denoted as criteria (C1–C10), respectively. Among these criteria, the first six are benefit criteria, whereas the remaining four are cost criteria. C1 represents the ability to resist permanent deformation under heavy load. C2 reflects the material's resistance to fracture under tensile stress. C3 indicates structural rigidity and resistance to bending. C4 represents wear resistance against friction from the belt. C5 determines the pulley weight and rotational inertia. C6 reflects the ability to withstand compressive forces. C7 represents dimensional

stability under temperature variations. C8 indicates thermal conductivity. C9 reflects the ability to minimize lateral strain during stress. Finally, C10 represents manufacturing cost efficiency.

Table 7. Materials Considered for Pulley Manufacturing [84].

Material	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	550	700	210	357	7850	600	12.5	50	0.27	61
A2	261	359	210	220	8400	400	15	385	0.30	350
A3	760	689	200	240	8050	1000	15	50	0.30	1999
A4	590	1100	210	600	8050	1500	14	45	0.28	90
A5	500	1000	220	700	7800	1200	15	48	0.30	55
A6	1000	2000	210	300	8050	2000	17	45	0.30	180
A7	220	450	105	120	8600	300	20	120	0.33	600
A8	350	500	115	100	8600	350	20	120	0.34	480
A9	300	550	120	150	8600	380	18	25	0.34	1500
A10	500	600	79	70	2700	280	24	250	0.35	210
unit	MPa	MPa	GPa	HB	kg/m^3	Mpa	µm/m°C	W/m°C	-	Rs/kg

In this example, the criterion weights were defined across eleven different scenarios, designated (S1–S11), as illustrated in Figure 7. In scenario S1, each criterion is assigned an equal weight of 1/10. In scenarios S2 through S11, one criterion in each scenario is assigned a weight three times that of each of the remaining criteria. For example, in scenario S2, C1 is assigned a weight of 3/12 (as 0.250), while each of the remaining criteria is assigned a weight of 1/12 (as 0.083). In scenario S3, C2 is assigned a weight of 3/12, while each of the remaining criteria is assigned a weight of 1/12. Likewise, in scenario S11, C10 is assigned a weight of 3/12, while each of the remaining criteria is assigned a weight of 1/12. Accordingly, across all scenarios, the weight of each criterion varied up to 300%.

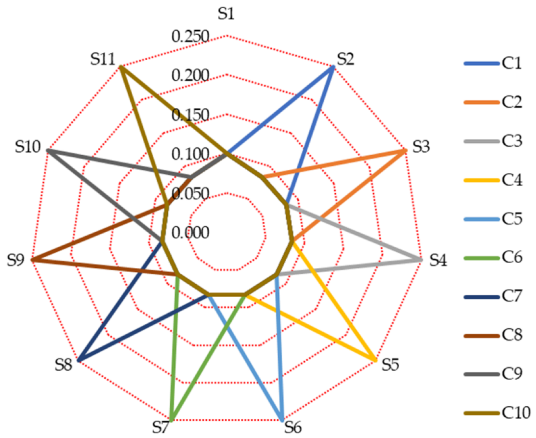


Figure 7. Criterion Weights in Example 4.

Following the same procedure as in the previous examples, the pulley materials were ranked using ten different methods for each weighting scenario. Subsequently, Spearman correlation coefficients were calculated between SREM and ARAS and each of the eight remaining methods (TOPSIS, EDAS, PIV, ROV, SAW, RAM, MARCOS, and MOORA). The (AS) values for SREM and ARAS were then calculated, and the results are presented in Figure 8.

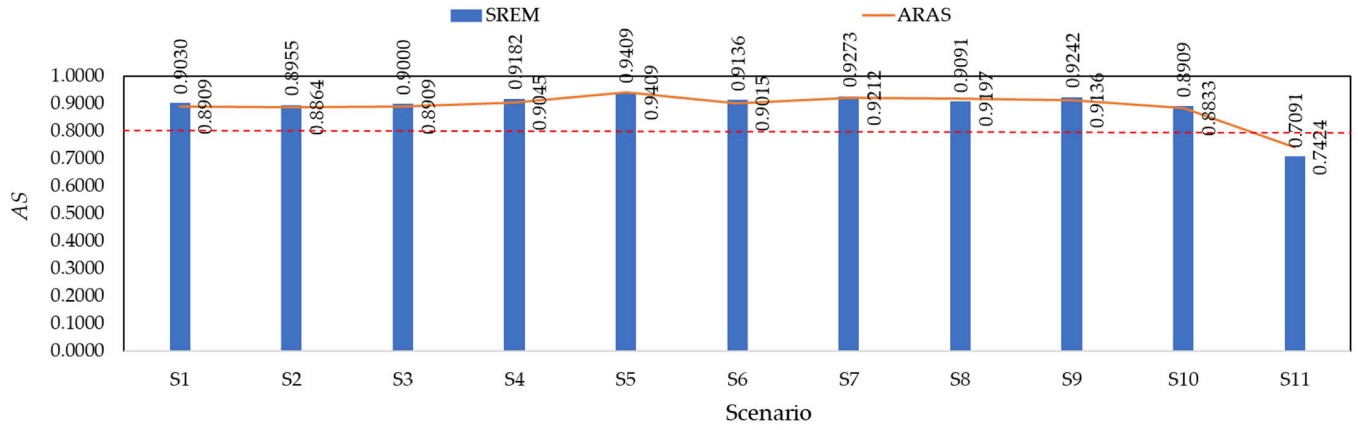


Figure 8. (AS) for SREM and ARAS Compared with Other Methods in Example 4.

In this example, it is also observed that, except for scenario S11, the (AS) values of SREM and ARAS in the remaining ten scenarios all exceed the 0.8 threshold, with some values exceeding 0.9. This indicates that in these ten scenarios, the rankings of the pulley materials generated by SREM and ARAS are highly similar to those obtained with the other methods. Although the (AS) values of SREM and ARAS in scenario S11 are 0.7091 and 0.7424, respectively, the average (AS) values across all eleven scenarios are 0.8939 for SREM and 0.8905 for ARAS, respectively, both of which remain above the 0.8 threshold. Therefore, when considering all eleven scenarios collectively, the pulley material rankings generated by SREM and ARAS exhibit a relatively high degree of similarity to those obtained using the other methods.

Observation A detailed examination of each scenario shows that, in S5, the AS values of SREM and ARAS is equal, in eight scenarios (S1, S2, S3, S4, S6, S7, S9, and S10), the (AS) value of SREM is higher than that of ARAS, whereas in the remaining two scenarios, S8 and S11, the (AS) value of ARAS is higher than that of SREM. However, in each scenario, the difference between the (AS) values of SREM and ARAS is very small. For example, in scenario S1, the (AS) values of SREM and ARAS are 0.9030 and 0.8909, respectively, indicating only a small difference between the two methods. Similarly, in scenario S3, the (AS) values of SREM and ARAS are 0.9000 and 0.8909, respectively. The (AS) values of SREM and ARAS are likewise very close across the remaining scenarios. Thus, across all scenarios, the pulley material rankings generated by SREM and ARAS are highly similar.

In summary, the results of this example indicate that both the SREM and ARAS methods can generate alternative rankings that are highly consistent with one another and with those obtained using existing MCDM methods. In Examples 1 and 2, which involve machine selection (grinding machines and lathes), the ARAS method produces alternative rankings that are more consistent with those obtained using existing methods than the SREM method. Conversely, in Examples 3 and 4, which involve material selection (cutting tool material and pulley manufacturing material), SREM and ARAS both produce rankings of alternatives similar to those obtained using other methods. Therefore, to provide a more objective comparison of the two methods for ranking key alternatives in mechanical manufacturing, Examples 5 and 6 evaluate and rank alternatives in mechanical manufacturing processes.

4.5. Example 5—Selection of Turning Process Options

Table 8 summarizes nine metal turning options, designated as alternatives (A1) through (A9). To generate these options, the values of the cutting parameters, including cutting speed, feed rate, and depth of cut, were varied [85]. Three cutting force components along the (X), (Y), and (Z) axes and cutting productivity are used as the four criteria to

characterize each option, denoted as criteria (C1–C4), respectively. Among these criteria, (C4) is a benefit criterion, whereas the remaining three criteria are cost criteria. C1 represents the cutting force in the X direction, for which lower values are preferred to reduce tool wear and machine vibration. C2 and C3 represent the cutting forces in the Y and Z directions, respectively, with lower values indicating improved machining stability and reduced energy consumption. Finally, C4 represents cutting productivity, for which higher values are preferred, indicating greater production efficiency and higher material removal rates.

Table 8. Metal Turning Options [85].

Exp.	C1	C2	C3	C4
A1	59.844	187.437	44.165	11.561
A2	87.943	199.762	99.125	49.062
A3	78.913	127.456	69.874	109.108
A4	54.816	172.714	60.19	28.588
A5	63.117	180.361	68.869	99.039
A6	68.79	113.951	70.694	61.669
A7	46.654	116.88	92.222	57.177
A8	44.989	162.337	63.25	55.462
A9	54.846	167.837	74.165	151.09
unit	N	N	N	mm^3/s

To rank the turning process options, nine criterion-weighting scenarios (S1–S9) were defined, as shown in Figure 9. In scenario S1, each criterion is assigned an equal weight of 0.25. In scenarios S2 through S5, one criterion in each scenario is assigned a weight twice that of each of the remaining criteria. For example, in scenario S2, C1 is assigned a weight of 0.4, while each of the remaining criteria is assigned a weight of 0.2. In scenarios S6 through S9, one criterion in each scenario is assigned a weight of one-third (1/3) that of each of the remaining criteria. For example, in scenario S6, C1 is assigned a weight of 0.1, while each of the remaining criteria is assigned a weight of 0.3. Across all scenarios, the weight of each criterion varies from 0.1 to 0.4, corresponding to a variation up to 400%.

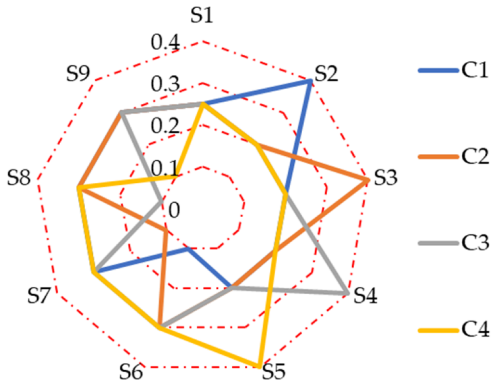


Figure 9. Criterion Weights in Example 5.

Following the same procedure as in the previous examples, the (AS) values of SREM and ARAS were calculated for all nine weighting scenarios, and the results are illustrated in Figure 10.

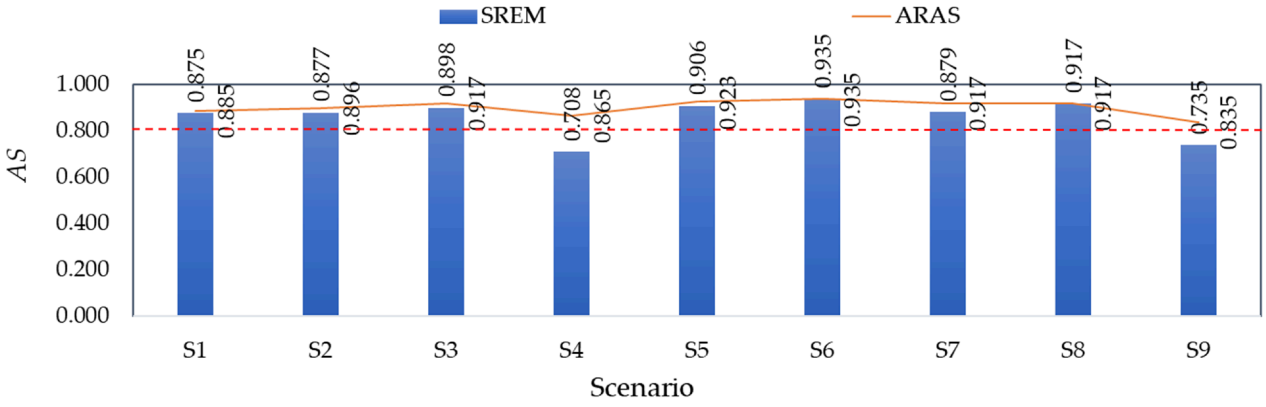


Figure 10. (AS) for SREM and ARAS Compared with Other Methods in Example 5.

Observation of Figure 10 reveals that almost all (AS) values exceed the 0.8 threshold, indicating that the rankings of the metal turning options generated by SREM and ARAS exhibit a high degree of similarity to those obtained using the other methods.

In two scenarios, S6 and S8, the (AS) values for SREM and ARAS are equal at 0.935 and 0.917, respectively. In all remaining scenarios, the (AS) value of ARAS is consistently higher than that of SREM. Notably, in some scenarios, the difference between the (AS) values of the two methods is relatively large. For example, in scenario S4, the (AS) values of SREM and ARAS are 0.708 and 0.865, respectively. Similarly, in scenario S9, the (AS) values of SREM and ARAS are 0.735 and 0.835, respectively. These results indicate that, in most scenarios, the rankings of the metal turning options generated by ARAS are more similar to those obtained using the other ranking methods than those generated by SREM.

In summary, the results of this example indicate that the ARAS method produces alternative rankings that are more consistent with those obtained using other MCDM methods than the SREM method.

4.6. Example 6—Selection of Grinding Process Options

Table 9 summarizes nine metal grinding options, designated as alternatives (A1) through (A9). These alternatives were generated by varying the grinding process parameters, including depth of cut, feed rate, workpiece speed, and coolant flow rate and pressure [86]. Four criteria are used to characterize each option: surface roughness and three cutting force components along the (X), (Y), and (Z) axes, denoted as criteria (C1–C4), respectively. All four criteria are cost criteria. C1 represents surface roughness; lower values are preferred to achieve higher surface quality and machining precision. C2, C3, and C4 represent the cutting forces along the X, Y, and Z directions, respectively. For all three force components, lower values are desirable to minimize grinding wheel wear, reduce heat generation, and prevent structural deflection during surface grinding.

In this example, scenarios are first generated by varying the weights of the criteria. Accordingly, nine weighting scenarios (denoted S1–S9) were identified by varying the weights of the criteria. In scenario S1, each criterion is assigned an equal weight of 0.25. In scenarios (S2–S5), one criterion in each scenario is assigned a weight twice that of each of the remaining criteria. For example, in scenario S2, criterion C1 is assigned a weight of 0.4, while each of the remaining three criteria is assigned a weight of 0.2. In scenarios (S6–S9), three criteria in each scenario are assigned equal weights that are three times that of the remaining criterion. For example, in scenario S6, criteria (C2–C4) are each assigned a weight of 0.3, while C1 is assigned a weight of 0.1. Figure 11 illustrates the criterion weights across all scenarios, with each criterion's weight ranging from 0.1 to 0.4, representing a variation of up to 400%.

Table 9. Metal Grinding Options [86].

Exp.	C1	C2	C3	C4
A1	0.828	244.184	58.624	281.011
A2	0.894	212.825	38.87	135.12
A3	1.758	110.96	32.219	19.911
A4	1.396	13.038	94.41	28.897
A5	1.173	66.954	21.38	25.067
A6	0.901	233.08	46.393	7.39
A7	1.513	156.288	101.603	19.617
A8	1.053	14.113	22.929	17.991
A9	1.305	83.036	35.502	61.019
unit	μm	N	N	N

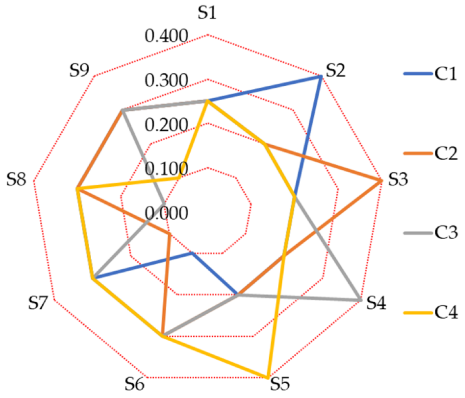


Figure 11. Criterion Weights in Example 6.

Following the same procedure as in the five previous examples, the (AS) values of SREM and ARAS were calculated for all scenarios, and the results are illustrated in Figure 12.

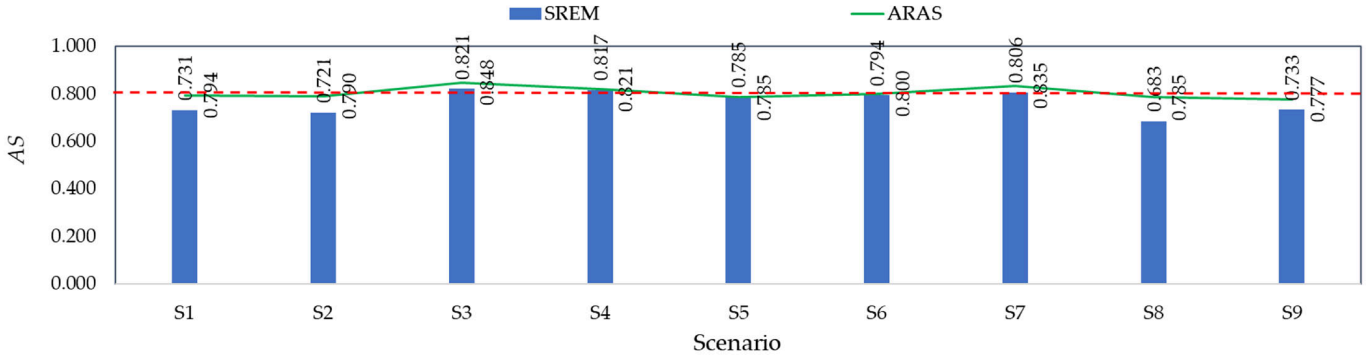


Figure 12. (AS) for SREM and ARAS Compared with Other Methods in Example 6.

It can be seen that, except for scenario S5 where the appraisal score (AS) values of SREM and ARAS are equal, in all remaining scenarios, the AS value of ARAS is higher than that of SREM. This is explained by the fact that in the decision-making matrix in Table 9, criteria C2, C3, and C4 all contain alternatives with values that are very small compared to the remaining alternatives. For example, regarding criterion C2, its values for A4 at 13.038 N and A8 at 14.113 N are much smaller than those of the remaining alternatives. Regarding

criterion C3, its values for A5 at 21.38 N and A8 at 22.929 N are also much smaller than those of the other alternatives. Regarding C3, its value for A6 at 7.39 N is also very small compared to the remaining alternatives. These values can be considered outliers for each criterion. The appearance of outlier values causes the normalized value of that alternative to be much larger than those of the remaining alternatives. Assuming the normalized values for the alternatives under criterion C4 are calculated by applying Formula (3), the results are as follows:

$$n_{41} = \frac{\frac{1}{281.011}}{\frac{1}{281.011} + \frac{1}{135.12} + \frac{1}{19.911} + \frac{1}{28.897} + \frac{1}{25.067} + \frac{1}{7.39} + \frac{1}{19.617} + \frac{1}{17.991} + \frac{1}{61.019}} = 0.0090$$

$$n_{42} = \frac{\frac{1}{135.12}}{\frac{1}{281.011} + \frac{1}{135.12} + \frac{1}{19.911} + \frac{1}{28.897} + \frac{1}{25.067} + \frac{1}{7.39} + \frac{1}{19.617} + \frac{1}{17.991} + \frac{1}{61.019}} = 0.0188$$

$$n_{43} = \frac{\frac{1}{19.911}}{\frac{1}{281.011} + \frac{1}{135.12} + \frac{1}{19.911} + \frac{1}{28.897} + \frac{1}{25.067} + \frac{1}{7.39} + \frac{1}{19.617} + \frac{1}{17.991} + \frac{1}{61.019}} = 0.1275$$

$$n_{44} = \frac{\frac{1}{28.897}}{\frac{1}{281.011} + \frac{1}{135.12} + \frac{1}{19.911} + \frac{1}{28.897} + \frac{1}{25.067} + \frac{1}{7.39} + \frac{1}{19.617} + \frac{1}{17.991} + \frac{1}{61.019}} = 0.0878$$

$$n_{45} = \frac{\frac{1}{25.067}}{\frac{1}{281.011} + \frac{1}{135.12} + \frac{1}{19.911} + \frac{1}{28.897} + \frac{1}{25.067} + \frac{1}{7.39} + \frac{1}{19.617} + \frac{1}{17.991} + \frac{1}{61.019}} = 0.1013$$

$$n_{46} = \frac{\frac{1}{7.39}}{\frac{1}{281.011} + \frac{1}{135.12} + \frac{1}{19.911} + \frac{1}{28.897} + \frac{1}{25.067} + \frac{1}{7.39} + \frac{1}{19.617} + \frac{1}{17.991} + \frac{1}{61.019}} = 0.3435$$

$$n_{47} = \frac{\frac{1}{19.617}}{\frac{1}{281.011} + \frac{1}{135.12} + \frac{1}{19.911} + \frac{1}{28.897} + \frac{1}{25.067} + \frac{1}{7.39} + \frac{1}{19.617} + \frac{1}{17.991} + \frac{1}{61.019}} = 0.1294$$

$$n_{48} = \frac{\frac{1}{17.991}}{\frac{1}{281.011} + \frac{1}{135.12} + \frac{1}{19.911} + \frac{1}{28.897} + \frac{1}{25.067} + \frac{1}{7.39} + \frac{1}{19.617} + \frac{1}{17.991} + \frac{1}{61.019}} = 0.1411$$

$$n_{49} = \frac{\frac{1}{61.019}}{\frac{1}{281.011} + \frac{1}{135.12} + \frac{1}{19.911} + \frac{1}{28.897} + \frac{1}{25.067} + \frac{1}{7.39} + \frac{1}{19.617} + \frac{1}{17.991} + \frac{1}{61.019}} = 0.0416$$

The normalized value of criterion C4 for alternative A6 is 0.3435, which is significantly larger than that of the second-ranked alternative, A8 (0.1411). The large difference in the normalized value of C4 for A6 compared to other alternatives dominated the ranking results. This is explained by the fact that, in such cases, the mathematical structure of SREM—with squaring and square-root operations—significantly alters the score gaps between alternatives. Specifically, for each criterion, the squaring operation pushes good alternatives distinctly higher while pulling poor values even lower; meanwhile, the square root operation narrows the gaps between values. The combination of squaring and square-root operations in SREM produces a nonlinear score distribution function, which significantly changes the relative distances between alternatives compared to the initial matrix. Considering outlier values for criteria C2 and C3 leads to arguments similar to those for criterion C4. Conversely, ARAS and other reference methods such as TOPSIS, EDAS, PIV, and ROV calculate scores for alternatives by measuring the distance from those alternatives to the ideal and anti-ideal solutions (or the average solution); therefore, the rankings of alternatives generated by ARAS are similar to the results from these methods.

Overall, across all scenarios generated by varying the weights of the criteria in this example, the ARAS method produces rankings of metal grinding alternatives that are more similar to the results of other multi-criteria decision-making (MCDM) methods than the

SREM method. Subsequently, the sensitivity analysis is further conducted by generating scenarios in which one alternative is removed from the list of alternatives to be ranked. Accordingly, nine scenarios from S10 to S18 were generated: A1 was removed from the list in S10, A2 in S11, and so on, with A9 removed in S18. Each of these scenarios was then implemented alongside the criteria weight-varying scenarios performed above. More specifically, each scenario from S10 to S18 was evaluated under the nine criteria weight-varying scenarios (S1 to S9). Table 10 summarizes the AS values of Spearman's rank correlation coefficient for the SREM, ARAS, and other MCDM methods in each scenario. The average AS values across each scenario from S10 to S18 are also summarized in the last column of this table.

Table 10. AS values of SREM and ARAS compared to other methods across the scenarios.

Scenario	Method	AS									Average
		S1	S2	S3	S4	S5	S6	S7	S8	S9	
S10	SREM	0.711	0.750	0.801	0.729	0.768	0.735	0.768	0.774	0.685	0.747
	ARAS	0.753	0.750	0.801	0.839	0.821	0.768	0.768	0.836	0.765	0.789
S11	SREM	0.723	0.717	0.780	0.780	0.759	0.714	0.839	0.676	0.789	0.753
	ARAS	0.735	0.735	0.798	0.836	0.818	0.723	0.887	0.774	0.789	0.788
S12	SREM	0.762	0.762	0.857	0.860	0.798	0.830	0.795	0.708	0.813	0.798
	ARAS	0.824	0.818	0.863	0.866	0.798	0.839	0.824	0.824	0.848	0.834
S13	SREM	0.845	0.744	0.845	0.860	0.893	0.875	0.866	0.699	0.854	0.831
	ARAS	0.848	0.827	0.836	0.923	0.893	0.875	0.935	0.738	0.890	0.863
S14	SREM	0.741	0.699	0.842	0.789	0.815	0.827	0.801	0.637	0.685	0.760
	ARAS	0.827	0.795	0.875	0.789	0.815	0.848	0.854	0.777	0.747	0.814
S15	SREM	0.774	0.670	0.905	0.899	0.872	0.845	0.810	0.801	0.789	0.818
	ARAS	0.833	0.818	0.952	0.899	0.872	0.845	0.851	0.914	0.824	0.868
S16	SREM	0.658	0.592	0.792	0.744	0.756	0.724	0.735	0.586	0.622	0.690
	ARAS	0.711	0.685	0.792	0.744	0.756	0.723	0.807	0.798	0.688	0.745
S17	SREM	0.685	0.604	0.762	0.604	0.753	0.714	0.753	0.670	0.622	0.685
	ARAS	0.705	0.693	0.795	0.667	0.753	0.714	0.801	0.696	0.723	0.727
S18	SREM	0.821	0.851	0.833	0.875	0.801	0.824	0.839	0.830	0.830	0.834
	ARAS	0.830	0.884	0.866	0.914	0.857	0.830	0.878	0.851	0.848	0.862

It can be observed that, among the 81 comparison positions in Table 10, there are only two positions where the AS value of SREM is greater than that of ARAS: namely, scenario S13 corresponding to weighting scenario S3 (referred to as position S13-S3) and scenario S16 corresponding to weighting scenario S6 (referred to as position S16-S6). Specifically, at position S13-S3, the AS value of SREM is 0.845 while that of ARAS is 0.836; at position S16-S6, the AS value of SREM is 0.724 while that of ARAS is 0.723. Nevertheless, this difference is very small. Among the remaining 79 positions, there are 17 positions where the AS value of SREM equals that of ARAS, while in the other 62 positions, the AS value of ARAS is always greater than that of SREM. Within these 62 positions, there are many instances where the AS value of ARAS significantly exceeds that of SREM. For example, at position S16-S8, the AS value of ARAS is 0.798 whereas that of SREM is only 0.586; at position S15-S2, the AS value of ARAS is 0.818 while that of SREM is only 0.670; or, as another example, at position S14-S8, the AS value of ARAS is 0.777 while that of SREM is only 0.637. Furthermore, when including the last column, all nine average AS values of SREM are lower than those of ARAS. These results are sufficient to show that using the ARAS method to rank alternatives consistently yields a higher degree of ranking similarity with other methods compared to the SREM method. This can be explained similarly to the previous analysis by the presence of outlier values in criteria C2, C3, and C4. For instance, considering position S16-S8—where the AS values of ARAS and SREM differ the most—the AS of ARAS is 0.798, and that of SREM is 0.586, representing a difference of up to 0.212. This

corresponds to the case where alternative A7 is removed from the list of alternatives to be ranked, and the weights of criteria C1, C2, C3, and C4 are 0.3, 0.3, 0.1, and 0.3, respectively. Because criterion C2 still contains two values considered as outliers at A4 and A8, and criterion C4 has an outlier at A6 after removing A7, combined with the fact that both of these criteria are assigned large weights (both equal to 0.3), the distortion amplification effect of SREM reaches its maximum level. This causes the ranking results of SREM to deviate significantly from most of the other methods. The average AS value of SREM in this scenario is only 0.690, reflecting that the alternative rankings generated by SREM only achieve a "Strong" level of similarity compared to other methods. This indicates that when an outlier appears in a criterion, and that criterion is assigned a larger weight, the alternative rankings produced by the SREM method deviate more substantially from those obtained using other methods. To substantiate this observation, we examine the opposite case. For instance, consider scenario S13, in which alternative A4 is removed from the list of alternatives to be ranked. Note that in Table 9, criterion C2 of A4 is the smallest among the nine alternatives and is naturally considered an outlier for C2. Eliminating this outlier from the list narrows the data dispersion range among the alternatives. As a result, in scenario S13, as many as 7 out of the 9 sub-scenarios achieve AS values exceeding the 0.8 threshold (namely cells S13-S1, S13-S3, S13-S4, S13-S5, S13-S6, S13-S7, and S13-S9). Across all nine cells of scenario S13, the average AS value is 0.831, reflecting that the alternative rankings generated by the SREM method achieve a "Very Strong" level of similarity compared to other methods.

From the sensitivity analysis results in Example 6, it can be concluded that the ARAS method exhibits superior stability and greater capability to generate alternative rankings with a higher degree of similarity to other standard MCDM methods than the SREM method. While SREM is prone to distortion due to outlier amplification under the influence of large weights, ARAS relies on an optimality function relative to an ideal solution, thereby maintaining greater robustness and significantly higher reliability.

5. Discussion

Six examples were implemented, covering three main topics in mechanical manufacturing: machine tool selection (Examples 1 and 2), material selection (Examples 3 and 4), and machining process option selection (Examples 5 and 6). Through comprehensive sensitivity analyses varying criterion weights by 300–400%, the robustness and ranking consistency of both SREM and ARAS were rigorously evaluated against eight established benchmark methods.

The comparative results indicate clear performance variations across different application domains. In machine selection (Examples 1 and 2), the ARAS method consistently generated alternative rankings with a higher degree of similarity and consensus to those obtained using the benchmark methods compared to SREM. In material selection contexts (Examples 3 and 4), both SREM and ARAS demonstrated comparable performance, yielding highly consistent rankings across the evaluated scenarios. However, in the process option selection problems (Examples 5 and 6), distinct methodological divergences emerged.

A critical finding from Example 6 (grinding process option selection) reveals that when extreme data values (outliers) coincide, the mathematical structure of the SREM method exhibits limited sensitivity and struggles to maintain ranking consensus with benchmark methods (resulting in a mean Spearman correlation coefficient below the 0.8 threshold). In contrast, under the same conditions, the ARAS method proves to be significantly more robust and stable. The reason is that SREM combines squaring and square root operations, which can significantly alter the distances between scores while disproportionately amplifying or compressing the impact of specific data distributions when the criteria contain outliers. Meanwhile, ARAS relies on an additive optimality function relative to an ideal reference

point, preserving better stability. Furthermore, the additional sensitivity analysis results across scenarios S10 to S18 in Example 6 further substantiate that the presence of outlier values in the decision matrix substantially compromises the ranking consistency of SREM, particularly when those outlier-containing criteria are assigned high weights. Specifically, when an alternative-removal scenario retains extreme outliers alongside dominant criterion weights (such as in cell S16-S8), SREM's nonlinear distortion reaches its peak, driving its ranking similarity down to a mere " Moderate" level (mean AS = 0.586) and creating a wide gap compared to ARAS. Conversely, when an alternative containing a primary outlier is eliminated from the candidate set (such as removing A4 in scenario S13), data dispersion is narrowed, allowing SREM's ranking consensus to immediately recover to a "Very Strong" level (mean AS = 0.831). This bidirectional evidence confirms that while ARAS remains consistently resilient regardless of structural perturbations in the decision matrix, SREM's stability is heavily contingent upon the absence of extreme data values.

Overall, across all six case studies, the ARAS method demonstrates a higher degree of consensus with existing MCDM methods than the SREM method. These findings provide crucial practical implications for production managers and mechanical engineers: when multiple MCDM methods are employed simultaneously to enhance decision-making reliability in mechanical manufacturing, ARAS should be preferred over SREM as a more stable and consistent tool.

Despite these insightful comparative findings, several limitations of this study should be acknowledged. First, the evaluation is constrained to six specific deterministic datasets within mechanical manufacturing; hence, these empirical conclusions cannot be generalized universally to all MCDM domains without further verification. Second, the current study relies strictly on crisp quantitative data. The applicability and behavior of SREM versus ARAS under uncertain, fuzzy, or qualitative decision-making environments remain important areas for future exploration.

6. Conclusions

This study systematically compares two MCDM methods, SREM and ARAS, which share the same linear-sum normalization scheme, across six representative decision-making problems in mechanical manufacturing. The robustness and ranking consistency of both methods are examined through comprehensive sensitivity analyses, including variations in criterion weights of 300–400% and alternative removal scenarios. Their performance is further evaluated against eight established benchmark methods: TOPSIS, EDAS, PIV, ROV, SAW, RAM, MARCOS, and MOORA. The empirical results indicate that, across the evaluated mechanical production contexts, the ARAS method generally yields alternative rankings with a higher degree of similarity and consensus than those obtained using existing benchmark methods, including the SREM method. The selection of the grinding process option reveals a clear difference between the two methods, as further supported by the alternative removal sensitivity analysis for scenarios S10 to S18. Extreme data values (outliers) can strongly affect the results when they are associated with dominant criterion weights. In SREM, the combination of squaring and square root transformations can amplify the influence of these extreme values. This limits SREM's sensitivity and causes it to struggle to maintain ranking consensus with benchmark methods (with mean Spearman coefficients dropping significantly when outliers are present), whereas ARAS proves substantially more robust, stable, and resilient to data dispersion and structural perturbations. Conversely, eliminating alternatives containing primary outliers narrows the data dispersion and helps restore SREM's consensus. As a result, ARAS is suggested as a more reliable and consistent option when several MCDM techniques are used concurrently to select machine, material, or machining options, particularly in datasets with outliers.

However, these conclusions are strictly bounded by the scope of deterministic mechanical machining datasets investigated in this study. To overcome the limitations of the current work, future research directions will focus on several promising avenues: (1) extending the comparative framework into uncertain and fuzzy environments by incorporating Fuzzy, Neutrosophic, Rough sets, or group decision-making frameworks to handle subjective human evaluations and linguistic variables; (2) integrating SREM and ARAS with advanced metaheuristic optimization algorithms (such as Genetic Algorithms and Particle Swarm Optimization) or experimental optimization techniques (such as Response Surface Methodology) to validate selected alternatives against optimized solutions; and (3) developing novel hybrid MCDM frameworks that combine the structural advantages of both linear-sum and nonlinear transformation models to enhance decision-making reliability across broader industrial sectors.

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