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Comparative analysis of the simple additive weighting method and the deviation-based pairwise assessment ratio technique for material selection

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Abstract

Multi-criteria decision-making (MCDM) techniques are widely used to rank alternatives defined by multiple criteria. However, due to fundamental algorithmic differences, they often yield different results for the same problem. This study presents a comparative analysis of two MCDM approaches with distinct historical backgrounds: the simple additive weighting (SAW) method and the deviation-based pairwise assessment ratio technique (DEPART) method, a novel and recently introduced approach. The comparison assesses their effectiveness in material ranking within mechanical engineering. Two primary criteria guided this evaluation: the stability of alternative scores derived from each method and the degree of correlation between the rankings generated by SAW and DEPART relative to other well-established MCDM methods. Comprehensive sensitivity analyses show that the DEPART method outperforms the SAW method. The analysis was performed on two cases of material selection used for the production of gearbox housing and connecting rod, based on data from the literature. The comparison was conducted using two key performance metrics: the ranking similarity coefficient (r) and the stability coefficient (S), demonstrating DEPART's overall superior effectiveness.

1. Introduction

In manufacturing, appropriate material selection is crucial, as it prevents potential damage or failure of components and ensures optimal performance [1]. Material selection is widely regarded as the cornerstone of engineering design and applications [2], forming the essential foundation for effective product development [3]. Sustainable development and sustainable consumption-production patterns are directly related to material selection [4]. Since production engineering is a core industry that provides tools and parts to a diverse array of industries, material selection in this industry has great importance [5].

In production engineering, material selection affects important factors such as power consumption during machining, cutting tool wear and cost, machining time and many operating-related expenses. Furthermore, material selection is a critical step that determines not only the quality of the final product, but also production efficiency, user satisfaction and the product's recyclability after use [6]. Material evaluation in mechanical engineering can be conducted through a range of methodologies, including experimental investigations [7], the application of machine learning algorithms [8] and homogeneous computational strategies [9]. Additionally, multi-criteria decision-making (MCDM) techniques have gained widespread adoption in this domain [10], and have emerged as one of the most prominent approaches for material ranking, owing to their robust capability to manage the complexities of decision-making processes involving multiple, and often conflicting, criteria, objectives and stakeholder perspectives [11].

The simple additive weighting (SAW) method is recognised as the earliest developed MCDM method and serves as a foundational basis for the evolution of many subsequent techniques [12]. In contrast, the deviation-based pairwise assessment ratio technique (DEPART) method represents a recently introduced addition to the MCDM family [13].

This study aims to carry out a comparative analysis of the SAW, a widely used classical MCDM method, and the recently developed DEPART method. By comparing these two approaches, the study seeks to understand how well each method supports real-world decision-making processes in which optimal material selection requires balancing multiple technical and performance-related criteria. SAW was chosen because it is a widely used classical MCDM method, providing a simple and interpretable benchmark. Also, its transparent and straightforward computational process provides a reliable benchmark for comparison with the proposed DEPART method. DEPART was chosen as a modern ranking method that employs pairwise deviation-based evaluation, offering more consistent and sensitive performance compared to SAW.

This study makes three key contributions to the MCDM literature. First, it presents an early systematic evaluation of the recently introduced DEPART method using multiple engineering-focused material selection problems. Second, it provides a rigorous comparison with the well-established SAW method through two complementary performance metrics, ranking similarity (r) and stability (S), supported by extensive sensitivity analyses. Third, it demonstrates the robustness of DEPART under different weighting methods and decision scenarios, highlighting its potential as a reliable tool for complex engineering applications.

2. Literature review

In the context of decision-making, performance-based assessment methods are frequently used in various engineering problems. For example, Aher and Ghuge [14] compared various machine learning algorithms to predict the failure state of cone bearings. Bibliometric studies have also demonstrated the rapid development of MCDM methods in material selection. Sahoo et al. [15] identified the main trends in the field by analysing publications between 2010 and 2024. Więckowski and Sałabun [16] compared the comprehensive sensitivity analysis method and the one-at-a-time approach in composite material selection, emphasising the importance of sensitivity analysis. Furthermore, fuzzy MCDM approaches are common in decision-making problems involving uncertainty. Dan et al. [17] modelled criteria and alternative uncertainties with advanced fuzzy sets. Soft computing methods based on expert opinion are also used. Biswas et al. [18] evaluated nanotechnologies used in agriculture using an interval-valued p, q–quasirung orthopair fuzzy number-based hybrid MCDM model.

As aforementioned, numerous MCDM methods have been employed to rank materials in mechanical engineering. While some studies have adopted a comparative approach, others have focused on the application of a single method for specific tasks. However, existing studies indicate that material ranking outcomes can vary considerably depending on the specific MCDM method employed [19]. Hence, the literature suggests that, to achieve stronger and more reliable results in material selection, more than one MCDM method should be employed simultaneously for a specific application. This method is widely used, and numerous other review works have shown a growing trend of utilising multiple MCDM methods to solve the material ranking problem. All these works invariably confirm the effectiveness of the MCDM methods in material selection decisions [11,20].

It has been concluded by some researchers that some MCDM methods are somewhat equally good regarding materials' ranking in the area of mechanical engineering. For example, the complex proportional assessment (COPRAS) and weighted aggregated sum product assessment techniques showed similar performance in ranking coating materials [21]. It is known that the compromise ranking of alternatives from distance to ideal solution, measurement of alternatives and ranking according to compromise solution (MARCOS), additive ratio assessment and COPRAS methods have similar results in the insulation materials selection [22]. Additionally, the MARCOS, evaluation based on distance from average solution, combinative distance-based assessment, multi-attributive border approximation area comparison, and technique for order preference by similarity to ideal solution (TOPSIS) methods exhibited comparable effectiveness in ranking pulley materials [23], while MARCOS, TOPSIS, VIKOR (višekriterijumska optimizacija i kompromisno rešenje) and preference ranking organization method for enrichment evaluation (PROMETHEE) were found to perform similarly in the ranking of gear materials [24].

In contrast, several investigations have emphasised the significant rule of thumb performance differences among MCDM techniques for material ranking in mechanical engineering. Several examples illustrate this divergence, namely, the magnitude of the area for the ranking of alternatives method is best for ranking lubricants for two-stroke engines and the root assessment method is more suitable for selecting gear and worm shaft material [25]. In a comparative study involving ten methods for ranking flywheel materials, VIKOR outperformed nine other techniques, including SAW and the weighted product model [26]. VIKOR also demonstrated superior performance over TOPSIS and PROMETHEE in various applications such as material selection for cryogenic tanks, high-speed naval vessels, lightweight train car bodies, high-temperature products and flywheels [27]. In the same way, in the screening of six materials for a low-altitude aircraft part, the analytic hierarchy process (AHP), SAW, TOPSIS, elimination and choice translating reality and best-worst based simple additive weighting provided different results [28].

The aforementioned findings demonstrate why it is crucial to use more than one MCDM method when selecting materials for mechanical engineering applications. This practice enhances decision accuracy in identifying the most suitable material. Moreover, comparative analyses of MCDM methods within specific contexts offer valuable insights for engineers, helping them select the most appropriate method for similar decision-making scenarios. Aligning this research direction, this study contributes by comparing two MCDM methods of different conceptual underpinnings and historical evolution: the SAW and DEPART methods.

According to the literature review, numerous MCDM methods (e.g. TOPSIS, AHP, VIKOR, MARCOS, etc.) have been applied either individually or comparatively for material selection in the context of mechanical engineering. However, the innovative and relatively recent DEPART method has not yet been addressed in this context, and no systematic comparison with a classical method such as SAW has been conducted. This gap represents a significant shortcoming in evaluating the performance of the DEPART method and in revealing its advantages and limitations compared with traditional approaches.

3. Methodology

This section presents the methods used in the study in detail. Suppose there are *m* alternatives to be ranked, each defined by *n* criteria. Let w_j represent the weight of criterion *j* and x_{ij} denote the value of alternative *i* on criterion *j*, where *i* = 1 to *m* and *j* = 1 to *n*.

The steps of the SAW method are as follows [12].

Step 1: Establish the normalised decision matrix

- for beneficial criteria

$$r_{ij} = \frac{d_{ij}}{d_{ij}^{\max}}, \tag{1}$$

- for non-beneficial (cost) criteria

$$r_{ij} = \frac{d_{ij}^{\min}}{d_{ij}}, \tag{2}$$

where d_{ij} is the original value of alternative *i* for criterion *j* and $d_{ij}^{\max}$ and $d_{ij}^{\min}$ are the highest and lowest value of the criterion, respectively.

Step 2: Formulate the weighted normalised decision matrix

$$v_{ij} = r_{ij}\, w_j, \quad \sum_{j=1}^{n} w_j = 1 \tag{3}$$

where v_{ij} is the weighted normalised decision value, r_{ij} is the normalised value and w_j is the assigned weight of criterion *j*.

Step 3: Determine the score for each alternative

$$V_i = \sum_{j=1}^{n} v_{ij}\,. \tag{4}$$

The alternatives are ranked in descending order based on their V_i values.

The application of the DEPART method for ranking alternatives is performed as follows [13].

Step 1: Normalise the data

$$x'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \tag{5}$$

where x_{ij} is the original value of alternative *i* on criterion *j* and x'_{ij} is its normalised value.

Step 2: Calculate the positive deviations (dv_{ij}^{+}) and negative deviations (dv_{ij}^{-})

$$dv_{ij}^{+} = \left| x'_{ij} - t_j^{+} \right|, \tag{6}$$

$$dv_{ij}^{-} = \left| x'_{ij} - t_j^{-} \right|, \tag{7}$$

where t_j^{+} is the maximum value in terms of beneficial criteria and the minimum value in terms of cost criteria and t_j^{-} is the minimum value in terms of beneficial criteria and the maximum value in terms of cost criteria.

Step 3: Construct the pairwise positive deviation matrix elements (e_{kl}^{+}) and the pairwise negative deviation matrix elements (e_{kl}^{-}), where k = 1 to m and l = 1 to m

$$e_{kl}^{+} = \sum_{j=1}^{n} w_j \left(\frac{dv_{lj}^{+} + md^{+}}{dv_{kj}^{+} + md^{+}} \right), \tag{8}$$

$$e_{kl}^{-} = \sum_{j=1}^{n} w_j \left(\frac{dv_{kj}^{-} + md^{-}}{dv_{lj}^{-} + md^{-}} \right), \tag{9}$$

where md^{+} is the maximum of positive values and md^{-} is the maximum of negative values.

If $k = l$, then $e_{kl}^{+} = e_{kl}^{-} = 1$.

Step 4: Synthesise matrices with elements e_{kl}^{+} and e_{kl}^{-} (determined in Step 3) using the user-defined coefficient η. This coefficient is set to 0.5 according to the Keshavarz-Ghorabaee et al. [13]. Finally, the total deviation ratio for each alternative (e_l^{s}) is calculated

$$e_l^{s} = \sum_{k=1}^{m} \left[\eta e_{kl}^{+} + (1-\eta) e_{kl}^{-} \right]. \tag{10}$$

Step 5: Calculate the overall performance score (S_i) for each alternative

$$S_i = \frac{1}{n} \sum_{l=1}^{m} \frac{e_{il}}{e_l^{s}}. \tag{11}$$

The alternative with the largest score is ranked as 1, and the alternative with the smallest score is ranked as m.

To compare SAW and DEPART, two indicators were used: the ratio of the highest to lowest scores (coefficient r) [29] and Spearman's rank correlation coefficient (coefficient S) [30]. The coefficient r measures ranking robustness, while the coefficient S shows agreement with other MCDM methods. A method is considered superior if it yields a lower r and a higher S [29,30]. For the SAW and DEPART methods, the coefficient r is calculated using Equations (12) and (13), respectively.

$$r_i = \frac{\max(V_i)}{\min(V_i)}, \tag{12}$$

$$r_i = \frac{\max(S_i)}{\min(S_i)}, \tag{13}$$

The coefficient S is computed using the following formula.

$$S = 1 - \frac{6\sum_{i=1}^{m} D_i^2}{m(m^2-1)}, \tag{14}$$

where D_i is the difference in rank for alternative i when ranked by different MCDM methods and m is the number of alternatives.

The study proceeds through a structured, multi-stage workflow applied separately to each case study and to every weighting method. All diagnostics in stages 2 and 3 are first computed under equal criterion weights.

Stage 1. Baseline scoring and ranking. For each weighting set, scores are computed using SAW and DEPART, followed by multi-objective optimisation by ratio analysis (MOORA), proximity indexed value (PIV), measurement of alternatives and ranking according to compromise solution (MARCOS) and ranking of alternatives with weights of criterion (RAWEC) method. The resulting score vectors are then converted into rank orders.

Stage 2. Performance diagnostics for SAW. Calculation of the coefficient S – the average Spearman's rank correlation between SAW and the four benchmark methods (MOORA, PIV, MARCOS, RAWEC) and coefficient r – the SAW-specific robustness index, defined as the highest to lowest score ratio across all alternatives.

Stage 3. Performance diagnostics for DEPART. Calculation of the coefficient S – the average Spearman's rank correlation between DEPART and the four benchmark methods (MOORA, PIV, MARCOS, RAWEC) and the DEPART analogue of coefficient r, capturing the method's internal score dispersion.

Stage 4. Weighted analyses. Criterion weights are obtained using the entropy method, the method based on the removal effects of criteria (MEREC), the logarithmic percentage change-driven objective weighting (LOPCOW) method and the symmetry point of criterion (SPC) method. Stages 1, 2 and 3 are repeated for each weighting set to compare SAW and DEPART behaviour.

Stage 5. Sensitivity analysis. To assess robustness, all non-empty subsets of alternatives are generated to create reduced decision matrices. Stages 1 to 4 are rerun for each subset, producing a dataset to evaluate the consistency and significance of differences between SAW and DEPART.

4. Application

This section presents a comparative analysis of the SAW and DEPART methods based on the coefficients *r* and *S*, as previously defined. Two distinct case studies were conducted, applying both methods to rank mechanical engineering materials across two product categories: gearbox housing materials and connecting rod materials. Given that the primary objective of this research is to compare SAW and DEPART, datasets from recent literature were employed for each case study.

4.1 Case study 1: Gearbox housing

In this case study, the SAW and DEPART methods are compared in the context of ranking nine types of cast iron used in the production of gearbox housings. These materials are identified as alternatives A1 through A9. Each alternative is evaluated based on five criteria (CR1 to CR5). All five criteria are classified as beneficial, meaning that higher values are preferred. The data corresponding to these nine materials are presented in Table 1.

The weight (w_i) for each of the five criteria was assigned equally and set to 0.2. Using Equation (3), the V_i scores for each alternative were computed using the SAW method. Similarly, the S_i scores for each alternative were determined using the DEPART method, using Equation (11). The results of these calculations are summarised in Table 2, which also presents the corresponding rankings of the alternatives derived from their V_i and S_i scores for SAW and DEPART, respectively.

Table 2. Scores and ranks of alternatives

Alternative	SAW method		DEPART method	
	V_i	rank	S_i	rank
A1	0.6088	3	0.1221	2
A2	0.5151	4	0.1125	4
A3	0.4264	8	0.1030	7
A4	0.3989	9	0.0994	9
A5	0.4308	7	0.1017	8
A6	0.4926	6	0.1071	6
A7	0.5090	5	0.1080	5
A8	0.6693	2	0.1206	3
A9	0.7471	1	0.1268	1

Based on the data presented in Table 2 and using Equations (12) and (13), the coefficient *r* was calculated as 1.8728 for the SAW method and 1.2762 for the DEPART method. These results indicate that, in terms of the coefficient *r*, the DEPART method exhibits a clear advantage over the SAW method, suggesting greater stability in its ranking performance.

To enable comparison of the SAW and DEPART methods using the coefficient *S*, this paper also considers four other MCDM methods: MOORA, PIV, MARCOS, and RAWEC (Table 3). The coefficient *S* values representing the rank correlation between methods were computed and are also presented in the lower part of Table 3.

Table 1. Mechanical properties of cast irons used for gearbox housing production; adapted from Trung et al. [31], licensed under CC BY-NC-ND 4.0

Alternative	Tensile strength (CR1), kg/mm^2	Yield strength (CR2), kg/mm^2	Elongation (CR3), %	Impact toughness (CR4), kg/cm^2	Hardness HB (CR5)
GC38-17 (A1)	38	24	17	6	170
GC42-12 (A2)	42	28	12	4	200
GC45-05 (A3)	45	33	5	3	220
GC50-02 (A4)	50	38	2	2	260
GC60-02 (A5)	60	40	2	2	280
GC70-03 (A6)	70	40	3	3	280
GC80-03 (A7)	80	50	3	2	300
GC100-04 (A8)	100	70	4	3	369
GC120-04 (A9)	120	90	4	3	369

Table 3. Alternative rankings for different MCDM methods (case study 1)

Alternative	SAW	DEPART	MOORA	PIV	MARCOS	RAWEC
A1	3	2	2	2	3	3
A2	4	4	4	4	4	6
A3	8	7	7	7	8	7
A4	9	9	9	9	9	9
A5	7	8	8	8	7	8
A6	6	6	6	6	6	4
A7	5	5	5	5	5	5
A8	2	3	3	3	2	2
A9	1	1	1	1	1	1
Coefficient *S*						
SAW	–	0.9667	0.9667	0.9667	1.0000	0.9167
DEPART	0.9667	–	1.0000	1.0000	0.9667	0.9167

The results show that alternative rankings are stable across methods, with consistently high *S* values, indicating that both SAW and DEPART are suitable. DEPART rankings align more with MOORA and PIV, while SAW aligns more with MARCOS and RAWEC. Thus, *S* values alone do not clearly indicate which method performs better. The average coefficient *S* between SAW and the four reference methods (MOORA, PIV, MARCOS and RAWEC) is 0.9626, calculated as the average of four values (0.9667, 0.9667, 1.0000 and 0.9167). Similarly, the average coefficient *S* between DEPART and the same methods is 0.9708, computed as the average of four values (1.0000, 1.0000, 0.9667 and 0.9167). The results suggest that SAW and DEPART perform similarly with respect to the coefficient *S*. However, DEPART shows superior performance in the coefficient *r*, indicating more stable rankings. Considering both *S* and *r*, DEPART is the more favourable method, assuming equal criterion weighting.

To evaluate robustness under varying criteria weights, four weighting methods were tested: Entropy, MEREC, LOPCOW and SPC. These widely used methods offer methodological diversity, and their computed weights are summarised in Table 4.

Table 4. Criteria weights (case study 1)

Weighting method	CR1	CR2	CR3	CR4	CR5
Entropy	0.1348	0.1585	0.5335	0.1205	0.0526
MEREC	0.1850	0.2116	0.2984	0.1391	0.1659
LOPCOW	0.2247	0.1948	0.1215	0.1571	0.3019
SPC	0.1979	0.1632	0.0737	0.1770	0.3882

Table 5. Alternative scores for different weighting methods (case study 1)

Alternative	Entropy		MEREC		LOPCOW		SPC	
	V_i	S_i	V_i	S_i	V_i	S_i	V_i	S_i
A1	0.7632	0.1263	0.6289	0.1254	0.5408	0.1095	0.5357	0.1426
A2	0.5819	0.1123	0.5239	0.1127	0.4934	0.1049	0.5005	0.1216
A3	0.3572	0.1028	0.4032	0.1020	0.4500	0.1009	0.4757	0.1029
A4	0.2631	0.0993	0.3648	0.0992	0.4553	0.1018	0.4926	0.0963
A5	0.2807	0.1013	0.3939	0.1012	0.4947	0.1046	0.5337	0.0976
A6	0.3434	0.1064	0.4501	0.1052	0.5467	0.1076	0.5840	0.1023
A7	0.3550	0.1066	0.4748	0.1074	0.5773	0.1115	0.6102	0.1033
A8	0.4740	0.1190	0.6244	0.1194	0.7478	0.1248	0.7859	0.1134
A9	0.5317	0.1261	0.7023	0.1275	0.8285	0.1344	0.8551	0.1198
	Coefficient *r*							
	SAW	DEPART	SAW	DEPART	SAW	DEPART	SAW	DEPART
	2.9008	1.2715	1.9252	1.2859	1.8411	1.3316	1.7977	1.4809

Table 4 shows that weighting methods yield significantly different criterion priorities. Under entropy (0.5335) and MEREC (0.2984), CR3 weighs high but low under LOPCOW (0.1215) and SPC (0.0737). CR5 is highest for LOPCOW (0.3019) and SPC (0.3882). CR1 and CR2 vary moderately between these extremes. Thus, these results indicate that the choice of weighting method can influence the perception of criterion importance. The V_i scores for the alternatives calculated using the SAW method, the S_i scores computed using the DEPART method and the coefficient r were also determined for these scenarios. The results are summarised in Table 5.

It can be seen that the coefficient r in the DEPART method is always lower than that in the SAW method in all four weighting methods (entropy, MEREC, LOPCOW and SPC). This advantage stems from DEPART's unique method for ranking alternatives through binary evaluations based on deviations [20]. Consequently, when considering the coefficient r alone, the DEPART method consistently demonstrates superior performance compared to SAW across all tested methods.

Alternative MCDM rankings were generated using four weighting methods (entropy, MEREC, LOPCOW, SPC) to compare the coefficients S of SAW and DEPART. The results are presented in Table 6.

Table 6. Correlation through the coefficients *S* of different MCDM methods under four weighting methods (case study 1)

MCDM method	SAW	DEPART	MOORA	PIV	MARCOS	RAWEC
Entropy						
SAW	–	0.9667	0.9833	0.9833	1.0000	0.9833
DEPART	0.9667	–	0.9833	0.9833	0.9667	0.9833
MOORA	0.9833	0.9833	–	1.0000	0.9833	0.9500
PIV	0.9833	0.9833	1.0000	–	0.9833	0.9500
MARCOS	1.0000	0.9667	0.9833	0.9833	–	0.9833
RAWEC	0.9833	0.9833	0.9500	0.9500	0.9833	–
MEREC						
SAW	–	1.0000	0.9833	0.9833	1.0000	0.9833
DEPART	1.0000	–	0.9833	0.9833	1.0000	0.9833
MOORA	0.9833	0.9833	–	1.0000	0.9833	0.9500
PIV	0.9833	0.9833	1.0000	–	0.9833	0.9500
MARCOS	1.0000	1.0000	0.9833	0.9833	–	0.9833
RAWEC	0.9833	0.9833	0.9500	0.9500	0.9833	–
LOPCOW						
SAW	–	0.9667	0.9667	0.9667	1.0000	0.7833
DEPART	0.9667	–	1.0000	1.0000	0.9667	0.6667
MOORA	0.9667	1.0000	–	1.0000	0.9667	0.6667
PIV	0.9667	1.0000	1.0000	–	0.9667	0.6667
MARCOS	1.0000	0.9667	0.9667	0.9667	–	0.7833
RAWEC	0.7833	0.6667	0.6667	0.6667	0.7833	–
SPC						
SAW	–	1.0000	0.9833	0.9833	1.0000	1.0000
DEPART	1.0000	–	0.9833	0.9833	1.0000	1.0000
MOORA	0.9833	0.9833	–	1.0000	0.9833	0.9833
PIV	0.9833	0.9833	1.0000	–	0.9833	0.9833
MARCOS	1.0000	1.0000	0.9833	0.9833	–	1.0000
RAWEC	1.0000	1.0000	0.9833	0.9833	1.0000	–

The coefficients *S* of SAW and DEPART show high agreement with those of other MCDM methods, confirming the reliability of both methods. Under entropy, the *S* values are similar for most methods. MEREC and SPC achieve high agreement with all methods. Under LOPCOW, DEPART shows higher agreement with MOORA and PIV, and SAW with MARCOS and RAWEC. Overall, the average coefficients *S*, shown in Table 7, indicate that the differences between SAW and DEPART are quite small.

Table 7. Average coefficients *S* for different weighting methods (case study 1)

MCDM method	Equal	Entropy	MEREC	LOPCOW	SPC
SAW	0.9626	0.9875	0.9875	0.9292	0.9916
DEPART	0.9708	0.9791	0.9875	0.9083	0.9916

SAW and DEPART show comparable coefficients *S* with MEREC and SPC weights, while SAW performs slightly better under entropy and LOPCOW. Conversely, DEPART consistently achieves lower coefficients *r* with all methods. Thus, SAW has a slight advantage in *S*, whereas DEPART performs better in *r*, and no clear overall superiority emerges between the two methods.

4.2 Case study 2: Connecting rod

In this case study, the SAW and DEPART methods were used to rank four steel alternatives (A1 to A4) for connecting rod production. Fifteen different criteria (CR1 to CR15) were used to evaluate these materials. Only CR3 (elongation at break) and CR11 (coefficient of linear thermal expansion) were considered as cost criteria. Data for these alternatives are presented in Table 8.

The coefficients *r* and *S* were calculated following the same procedures as in case study 1. The results are presented in Table 9. An examination of the coefficient *r* under five weighting methods indicates that DEPART consistently achieves lower values than SAW, reflecting its stronger performance. Regarding coefficient *S*, the two methods yield comparable results across all weighting methods. Taken together, the results for *r* and *S* demonstrate that DEPART is the more effective method overall. Moreover, the high coefficients *S* among SAW, DEPART and other MCDM methods, showing strong similarities in their rankings, indicate that SAW and DEPART methods are robust and suitable for finding the best option.

Table 9. Coefficients *r* and average coefficients *S* for different weighting methods (case study 2)

MCDM method	Weighting method	Coefficient *r*	Average coefficient *S*
SAW	equal	12.566	1.0000
	entropy	12.510	1.0000
	MEREC	14.868	0.9500
	LOPCOW	13.109	0.9500
	SPC	14.810	0.9500
DEPART	equal	12.116	1.0000
	entropy	12.067	1.0000
	MEREC	13.343	0.9500
	LOPCOW	12.566	0.9500
	SPC	13.334	0.9500

5. Sensitivity analysis

This section aims to statistically support the superior performance of the DEPART method by presenting a comprehensive subset-based analysis and comparing it with the SAW method.

Table 8. Physical and mechanical properties of steels used for connecting rod production; adapted from Nguyen et al. [32], licensed under CC BY 4.0

Alternative	CR1, MPa	CR2, MPa	CR3, %	CR4, GPa	CR5, GPa	CR6	CR7	CR8	CR9, %	CR10, GPa	CR11, 1/K	CR12, W/mK	CR13, J/kgK	CR14, °C	CR15, kg/m^3
1080 (A1)	440	205	15.0	140	80	0.290	126	71	70	205	8.0	52.0	440	820	7800
18CrMo4 (A2)	517	365	33.0	140	80	0.285	137	75	60	210	14.0	20.0	440	760	7850
4130 (A3)	560	460	21.5	140	80	0.285	217	95	70	200	22.3	42.7	420	460	7800
S48C (A4)	765	625	16.5	200	65	0.300	186	80	65	275	10.0	25.0	460	1480	7700

CR1 – tensile strength; CR2 – yield strength; CR3 – elongation at break; CR4 – bulk modulus; CR5 – shear modulus; CR6 – Poisson's ratio; CR7 – Brinell hardness; CR8 – Rockwell hardness; CR9 – machinability; CR10 – modulus of elasticity; CR11 – coefficient of linear thermal expansion × 10^{-6}; CR12 – thermal conductivity; CR13 – specific heat capacity; CR14 – melting temperature; CR15 – density

5.1 Comparative performance analysis of DEPART and SAW methods using subset-based evaluation

In two case studies, DEPART consistently outperformed SAW across multiple weighting methods. To test DEPART's superiority across different conditions, the analysis was repeated on all significant subsets of alternatives in the decision matrix (502 subsets in case study 1) and experiments were conducted across various weighting methods. This comprehensive subset analysis assesses the stability and generalisability of DEPART's superior performance, increasing the reliability of the comparative results.

Table 10 shows the descriptive statistics of the coefficient *S* calculated for SAW and DEPART across different subset sizes (ranging from 2 to 9). DEPART exhibits generally higher or similar average S values and lower standard deviations than SAW across all subsets, demonstrating greater stability and consistency. Most values cluster near the upper limit (close to 1), indicating a positive trend.

As a first step, all possible combinations of alternatives were evaluated under the assumption of equal weights for all criteria. To statistically assess whether the DEPART method performs better than the SAW method, a nonparametric hypothesis test was conducted.

The following hypotheses were tested using the Mann-Whitney *U* test, a nonparametric method that assesses differences between two independent samples [33].

- null hypothesis (H_0): median performance of the SAW method is greater than or equal to that of the DEPART method;
- alternative hypothesis (H_1): median performance of the SAW method is less than that of the DEPART method.

This test allows for a robust comparison of the two methods without assuming normality in the data distribution, making it well-suited for the type of performance scores generated from multiple subset evaluations under equal weighting. The results of the test provide empirical support for evaluating whether DEPART statistically outperforms SAW across the full set of alternative combinations.

Figure 1 presents the histogram and box plot of the coefficient *S*. A box plot is a graphical summary that shows the median, quartiles and possible outliers of the data distribution. The test under equal weights confirms the superiority of DEPART over SAW ($p = 0.0036$, $z = -2.6872$, signed rank = 1744). The null hypothesis is rejected, and it is concluded that DEPART outperforms all significant alternative subsets.

Table 10. Descriptive statistical profile of the coefficients *S* across different subset sizes (case study 1)

Size	MCDM method	Number of cases	Minimum	Maximum	Average	25 %	Median (50 %)	75 %	Standard deviation	Skewness	Kurtosis
2	SAW	36	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	–	–
	DEPART	36	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	–	–
3	SAW	84	0.7000	1.0000	0.9643	1.0000	1.0000	1.0000	0.0816	−1.9384	5.1151
	DEPART	84	0.7000	1.0000	0.9536	1.0000	1.0000	1.0000	0.0870	−1.3780	3.0682
4	SAW	126	0.6800	1.0000	0.9543	0.9200	1.0000	1.0000	0.0691	−1.6078	5.2945
	DEPART	126	0.7600	1.0000	0.9548	0.9200	1.0000	1.0000	0.0641	−1.3958	4.4207
5	SAW	126	0.8000	1.0000	0.9543	0.9400	0.9600	1.0000	0.0483	−1.1478	3.9902
	DEPART	126	0.7900	1.0000	0.9563	0.9400	0.9600	1.0000	0.0463	−1.3420	4.8650
6	SAW	84	0.8629	1.0000	0.9573	0.9314	0.9657	0.9771	0.0317	−0.7304	2.9742
	DEPART	84	0.8571	1.0000	0.9588	0.9429	0.9657	0.9771	0.0317	−0.8784	3.3855
7	SAW	36	0.8643	1.0000	0.9577	0.9500	0.9571	0.9679	0.0246	−1.5121	7.1229
	DEPART	36	0.8679	1.0000	0.9586	0.9464	0.9643	0.9714	0.0241	−1.4746	6.8371
8	SAW	9	0.9333	0.9762	0.9561	0.9476	0.9571	0.9643	0.0134	−0.0801	2.1860
	DEPART	9	0.9381	0.9810	0.9587	0.9476	0.9595	0.9673	0.0134	0.0707	2.0686
9	SAW	1	0.9533	0.9533	0.9533	0.9533	0.9533	0.9533	0.0000	–	–
	DEPART	1	0.9567	0.9567	0.9567	0.9567	0.9567	0.9567	0.0000	–	–

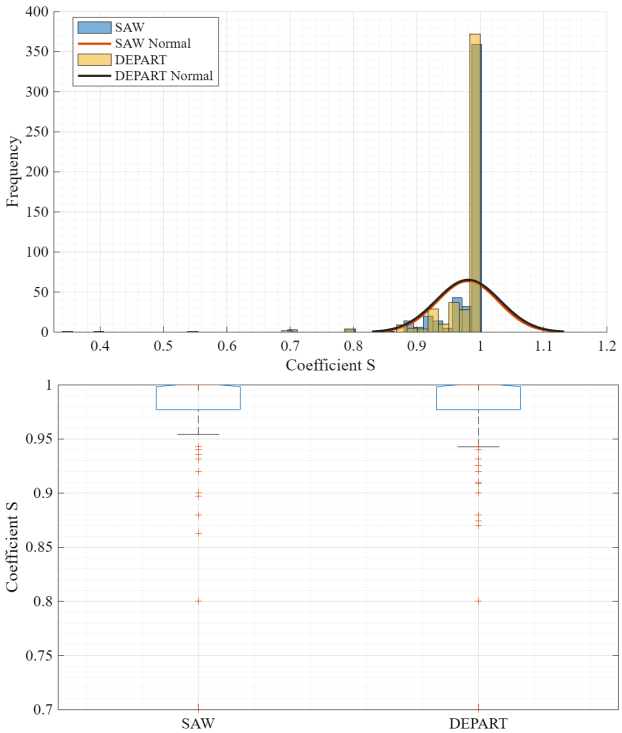

Figure 1. Histogram and the box plot of the coefficient *S*

The coefficients *r* calculated for each alternative were compared between SAW and DEPART. Lower *r* values indicate higher consistency. Hypothesis testing was conducted as H_0: median SAW ≥ median DEPART and H_1: median SAW < median DEPART.

The Mann-Whitney *U* test showed a definitive rejection of the null hypothesis with $p = 5.44 \times 10^{-71}$ ($p < 0.001$) and $z = 17.78$. Accordingly, DEPART produces significantly lower coefficients *r* compared to SAW. This result confirms the significant superiority of DEPART in terms of consistency and reliability, with higher *S* and lower *r* values, and demonstrates that the method is a more robust option in decision-making processes.

5.2 Scatter plot matrix analysis and method performance

Figure 2 illustrates the distributions of the coefficients *S* and *r* obtained through entropy-based weighting. The right-skewness noticed in the histograms confirms the superior performance of the DEPART method.

The histograms located on the main diagonal of the scatter plot matrix (i.e. the univariate distributions of CR1 to CR5) show asymmetric and variable patterns, indicating that the entropy-based weights assign different levels of importance to each criterion. The off-diagonal scatter plots show negative correlations, particularly between CR1 to CR3 and the other criteria, suggesting compensatory behaviour. SAW-S and DEPART-S exhibit right-skewed distributions, while DEPART-R is left-skewed, indicating that DEPART offers more stable and reliable performance with higher *S* values and lower *r* values.

The scatter plots between *S* and *r* values for both methods show clear separation and concentrated clustering for DEPART, reinforcing that this method provides both higher *S* values and lower *r* values across a wide range of entropy weight configurations.

Figure 3 presents a scatter plot matrix showing the distributions and relationships between the MEREC-based criterion weights and the *S* and *r* performance metrics of the SAW and DEPART methods for the 502 subsets created within the scope of the sensitivity analysis.

Unlike entropy, MEREC weights are distributed more broadly and variably, while CR5 remains lower and more focused, demonstrating a compensatory relationship between the criteria. DEPART-S has dense and high values, reflecting robust performance, while SAW-S is more dispersed. DEPART-R left-skewed distribution indicates better and more consistent results. Consequently, DEPART produces more robust and reliable outputs regardless of the scoring function used.

Figure 4 is a scatter plot matrix showing the distributions and relationships of the criteria weights obtained by the LOPCOW method with the *S* and *r* performance indicators of the SAW and DEPART methods for the 502 subsets used in the sensitivity analysis. This figure complements earlier analyses conducted using entropy and MEREC, allowing a comparative perspective on the behaviour of different objective weighting methods.

Diagonal histograms show that LOPCOW produces broader and more dispersed weight distributions than MEREC and entropy for CR1, CR3 and CR5. This suggests that LOPCOW adjusts criterion importance more dynamically based on percentage variability and is sensitive to cross-criterion dispersion. Scatter plots, however, show strong negative correlations, confirming that as some criteria gain importance, others systematically decrease.

DEPART-S values exhibit dense and consistent performance near the upper limit, despite the high variation introduced by LOPCOW. SAW-S shows greater dispersion, with some low values, thereby proving DEPART's superiority in maximising *S*. DEPART-R is left-skewed, with low values prevalent. SAW-R is more diffuse and right-skewed, indicating variability and inconsistent performance.

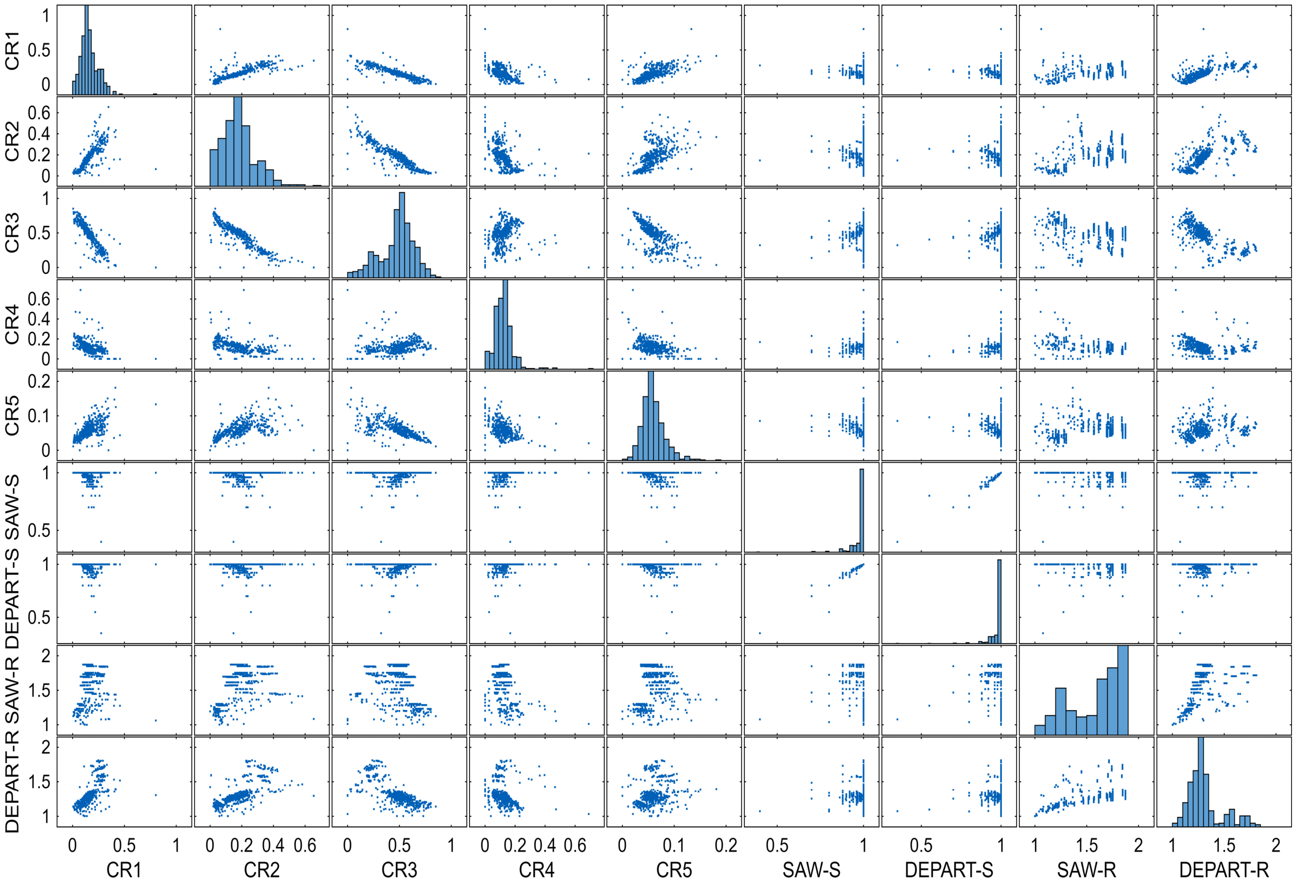

Figure 2. Entropy criteria weights and performance indicators

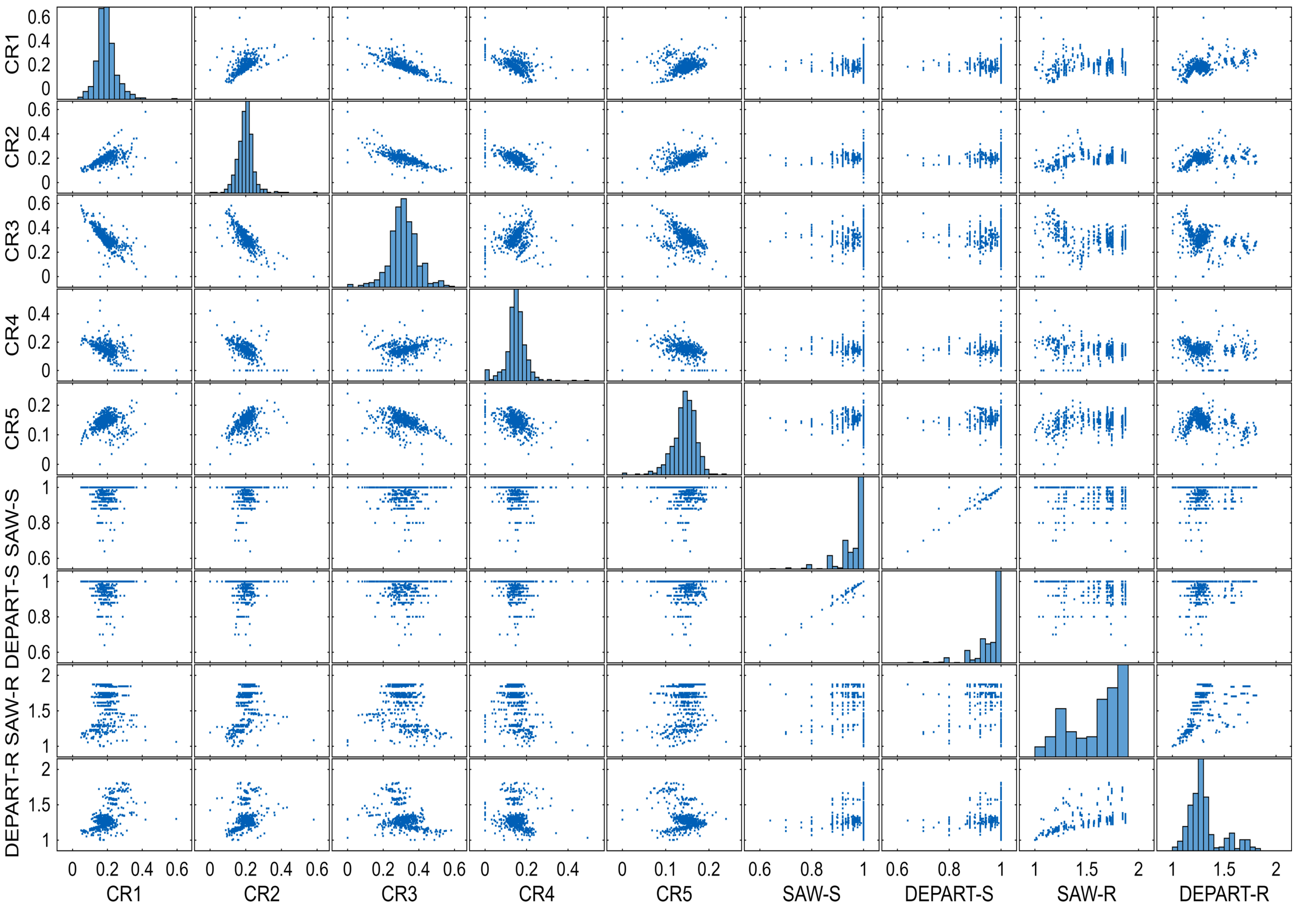

Figure 3. MEREC criteria weights and performance indicators

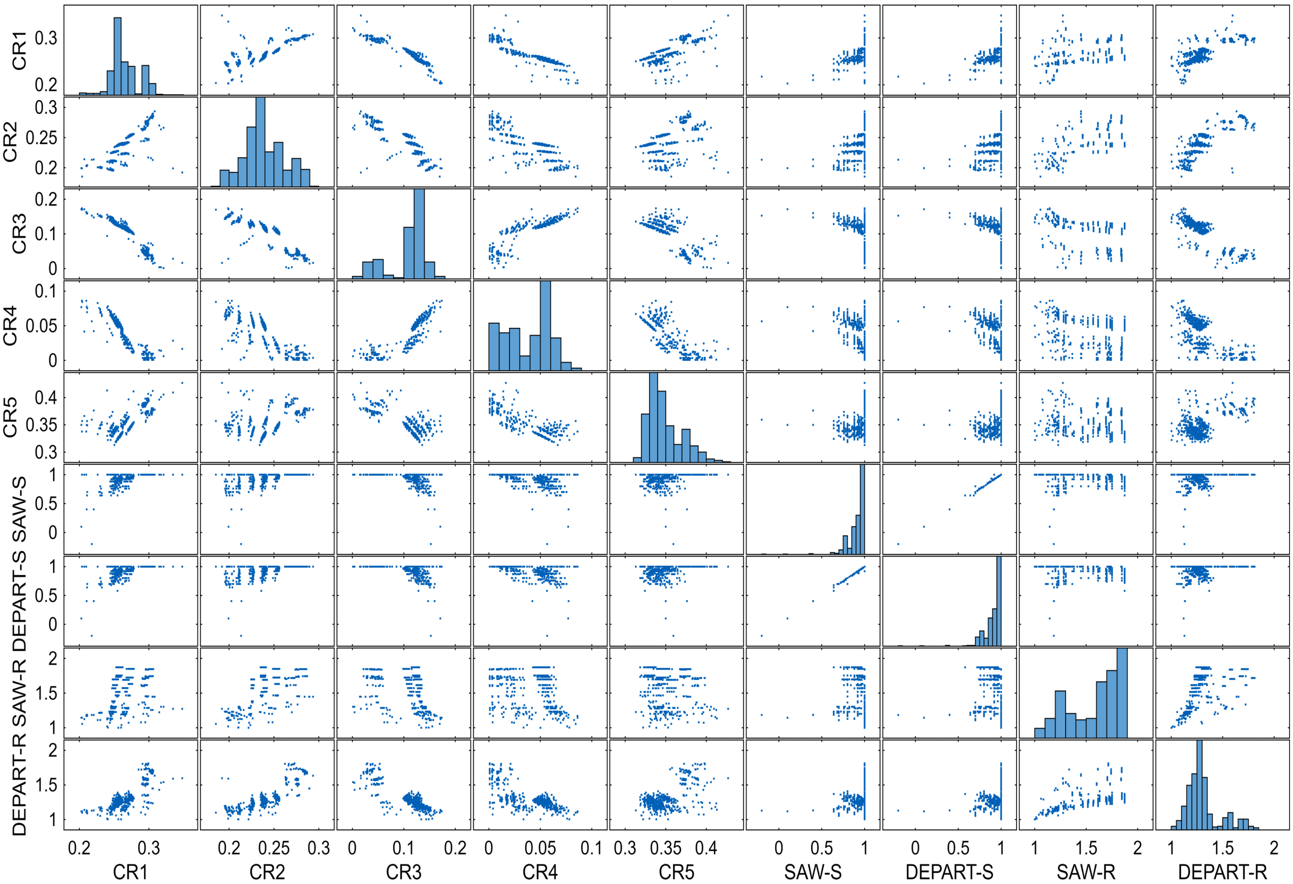

Figure 4. LOPCOW criteria weights and performance indicators

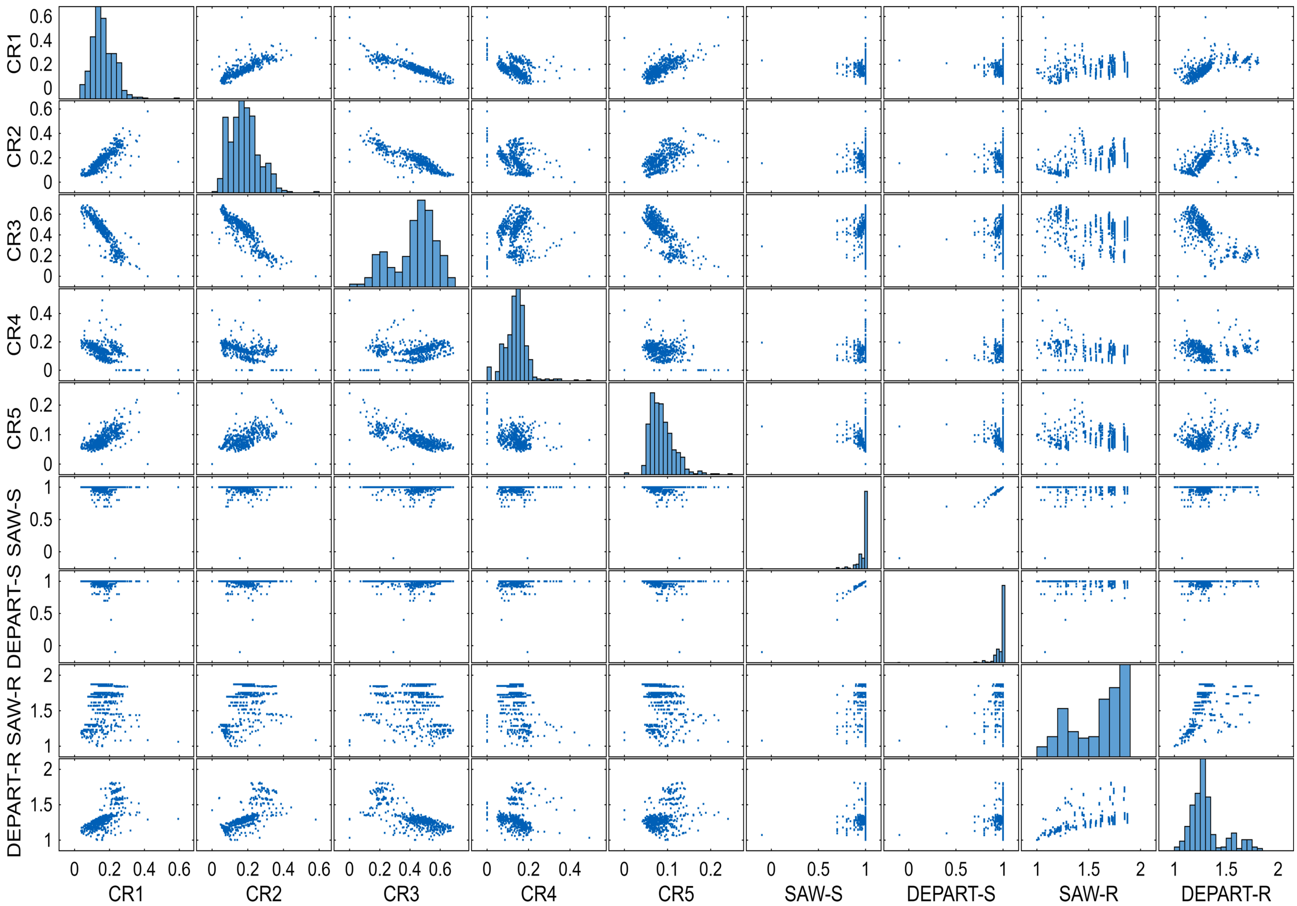

Figure 5. SPC criteria weights and performance indicators

Figure 5 is a scatter plot matrix showing the distributions and relationships between the criteria weights calculated with the SPC method and the *S* and *r* performance indicators of the SAW and DEPART methods for the 502 subsets evaluated in the sensitivity analysis. The SPC method emphasises the relative dispersion (standard deviation) of criteria, assigning greater weights to those with higher variability.

Diagonal histograms show that SPC produces wide and right-skewed weight distributions for CR2 and CR3, and tight and left-skewed weight distributions for CR5. Scatter plots show strong negative correlations, confirming that increasing the importance of one criterion decreases the importance of the others. DEPART-S remains close to the upper bound and right-skewed despite weight variability, while SAW-S is more scattered and may underperform. This supports the robustness and consistency of DEPART.

DEPART-S values remain dense near the upper bound despite the high variation induced by LOPCOW. In contrast, SAW-S shows greater dispersion with lower values, confirming DEPART's superiority in maximising *S*. DEPART-R exhibits a left-skewed distribution dominated by low values. At the same time, SAW-R is more dispersed and right-skewed, indicating higher variability and less consistent performance.

While entropy and MEREC produce balanced weight distributions, LOPCOW and SPC are more sensitive to outliers. However, DEPART outperforms SAW across all weighting methods, providing higher *S* and lower *r* values. This demonstrates that DEPART is a consistent and reliable method that is less sensitive to criterion fluctuations.

5.3 Summary of hypothesis testing of coefficients *S* under varying weighting methods

The Wilcoxon signed-rank test [34] was employed to compare the coefficient *S* obtained from the SAW and DEPART methods under different weighting methods (Table 11). Table 11 reports only the results for case study 1, as case study 2 was excluded from the Wilcoxon signed-rank test due to the limited number of alternatives. As a nonparametric paired test, the Wilcoxon procedure is particularly suitable for evaluating median differences without assuming normality of the underlying data. The analysis was conducted using the *signrank* function with a left-tailed alternative hypothesis (H_1: median SAW < median DEPART), explicitly designed to examine whether the DEPART method yields statistically larger coefficient values than the SAW method.

The results indicate that the DEPART method significantly outperforms the SAW method under several weighting methods. In case study 1, statistically significant differences in favour of DEPART are noticed for the equal weighting ($p = 0.0036$, $z = -2.6872$) and SPC weighting ($p = 4.7809 \times 10^{-6}$, $z = -4.4269$) method. The negative z-statistics and corresponding low p-values lead to rejection of the null hypothesis at the 5 % significance level, providing strong evidence that the median coefficient *S* produced by the DEPART method exceeds that of the SAW method. The results confirm DEPART dominance, with low p-values and negative z-statistics indicating higher median *S* values than SAW.

Table 11. Wilcoxon signed-rank test results for coefficient *S* (SAW vs. DEPART) under alternative weighting methods

Weighting method	Case study 1
Equal	$p = 0.0036$ $z = -2.6872$ signed rank = 1744
Entropy	$p = 0.0090$ $z = -2.3671$ signed rank = 488
MEREC	$p = 0.9193$ $z = 1.4003$ signed rank = 1175.5
LOPCOW	$p = 1.0000$ $z = 6.6081$ signed rank = 4283.5
SPC	$p = 4.7809 \times 10^{-6}$ $z = -4.4269$ signed rank = 314.5

6. Conclusion

Material selection in mechanical engineering plays a critical role in determining both production costs and the technical performance of final products. Given the multitude of available alternatives, identifying the most suitable material for a specific application represents a complex decision-making challenge. MCDM techniques are the most popular approach to address this issue by systematically prioritising material selections. Therefore, this paper compares two MCDM techniques that differ significantly in their historical development: the classical SAW method and the newly proposed DEPART method. The comparison is made for different situations in mechanical engineering, considering two important evaluation criteria: the ranking similarity coefficient *r* and the stability coefficient *S*.

Analysis across two case studies in the context of material selection shows that DEPART has greater stability across alternative rankings and is better correlated with other classical MCDM methods. Sensitivity analyses also demonstrated that DEPART significantly outperforms SAW. Therefore, DEPART can be considered an accurate and efficient methodology for complex, multi-criteria decision problems, making it well-suited for engineering applications, particularly in mechanical engineering.

Robustness was further tested across all material subsets, confirming DEPART has a statistically significant advantage over SAW even with reduced decision sets. Wilcoxon tests under equal and SPC weighting methods show higher median scores for DEPART in case study 1, indicating that its superiority is robust across weighting methods. The results statistically confirm the superiority of DEPART over SAW. In case study 1, DEPART produced significantly higher coefficient *S* under three weighting methods ($p = 0.0036$, 0.0090 and 4.78×10^{-6}), and in case study 2 under four schemes ($p = 4.11 \times 10^{-20}$, 5.54×10^{-7}, 9.07×10^{-9} and 0.7635). Additionally, its lower deviation of the coefficient *S* value and lower rank similarity coefficients *r* indicate greater stability and consistency.

This study has several limitations. First, the analysis is based on two specific mechanical engineering case studies, which may limit the generalisability of the findings to other application areas. Second, the study covers a limited number of material alternatives and weighting methods. The performance of DEPART in larger or more diverse decision universes has not yet been investigated. Finally, computational efficiency and scalability on very large datasets have not been evaluated.

Future research could explore the practical validity of the DEPART method by applying it to real-world decision-making problems across various sectors, such as component selection in the automotive industry or equipment evaluation in the energy sector. Additionally, the datasets used in this study were obtained from secondary sources. Key aspects relevant to practical implementation, including the method's scalability to large datasets combined with machine learning techniques and its computational efficiency, warrant further investigation. Integrating DEPART with other decision-making techniques, such as TOPSIS, may also prove beneficial for developing more flexible and robust decision support systems.

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