Applied Engineering Letters **Vol.11, No.2, 55-70 (2026)** **e-ISSN: 2466-4847**

Application of the Depart Method in Ranking Alternatives for Mechanical Machining and Chemical Extraction Processes

UDC:519.816:658.511.3

Original scientific paper https://doi.org/10.46793/aeletters.2026.11.2.1

Do Duc Trung[1*], Bui Thi Thu Trang[1], Branislav Dudić[2]

[1]Hanoi University of Industry, Hanoi, Vietnam

[2]Comenius University Bratislava, Faculty of Management, Bratislava, Slovakia

Abstract:
Ranking manufacturing processes has significant technical and economic importance in production operations. However, this task is intricate due to the inherent diversity of technical and economic parameters in different manufacturing processes. This complexity makes the ranking of manufacturing processes a Multi-Criteria Decision-Making (MCDM) problem. This study evaluated the application of the recently proposed method, named Deviation-Based Pairwise Assessment Ratio Technique (DEPART), to rank production processes across three distinct scenarios, including ranking nine alternatives in metal grinding using slotted grinding wheels, ranking nine metal turning processes, and ranking six extraction processes in the chemical field. In each example, the process ranking results obtained via the DEPART method were compared to those generated by six other MCDM methods, including Simple Additive Weighting (SAW), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Multiobjective Optimization On the basis of Ratio Analysis (MOORA), COmplex PRroportional Assessment (COPRAS), Root Assessment Method (RAM), and probability method. The findings indicated that the DEPART method is suitable for ranking production alternatives. However, upon reviewing all utilized MCDM techniques, the probability method emerged as the most appropriate method for ranking production alternatives within the analyzed problems.

ARTICLE HISTORY
Received: 24 May 2025
Revised: 22 January 2026
Accepted: 25 February 2026
Published: 29 June 2026

KEYWORDS
MCDM, DEPART method, Metal grinding, Metal turning, Extraction processes

1. INTRODUCTION

Within the manufacturing sector, selecting an appropriate alternative among multiple available technological processes represents a significant challenge. Manufacturing processes can be classified into multiple groups, such as additive manufacturing methods like Fused Deposition Modeling (FDM), Stereolithography (SLA), and Selective Laser Sintering (SLS) [1,2]; mechanical machining techniques [3,4], natural product extraction processes [5], etc. Each process possesses its own characteristics in materials compatibility, precision, productivity, and operational cost, resulting in different performance outcomes under practical production conditions. Consequently, establishing a systematic ranking of manufacturing alternatives is necessary for decision-making aimed not only at optimizing production efficiency but also ensuring agreement with technical and economic requirements [6-8]. However, in the real manufacturing environments, due to the presence of trade-offs among process capacity, production scale, precision, cost-related constraints, etc., decision-making is rarely straightforward [9]. To address this issue, numerous decision-support approaches have been proposed, including the use of IoT decision trees [10] or computational models [11], etc. Among these, MCDM methods have been increasingly adopted for manufacturing-related applications because of

*CONTACT: Do Duc Trung, e-mail: doductrung@haui.edu.vn

their ability to simultaneously incorporate multiple, and often heterogeneous, evaluation criteria [12-15]. Statistics from ScienceDirect for the 2012–2022 period show a sharp increase, with over 10,000 publications on MCDM applications [16]. The growth of literature reflects the expanding use of MCDM techniques across diverse industrial sectors, highlighting their relevance for complex decision problems involving competing objectives and constraints [16,17].

The rapid development of MCDM techniques also introduces new challenges for decision-makers. Owing to differences in some properties, such as mathematical structures, data-handling strategies, and aggregation mechanisms, variations in method behavior may arise when these techniques are applied to manufacturing problems characterized by diverse data distributions and operational conditions [18]. Therefore, understanding how a given MCDM approach performs across various manufacturing scenarios is necessary to ensure reliable and interpretable ranking results. Also, the novel MCDM methods recently developed need to be further investigated when applied to manufacturing decision problems involving multiple processes and criteria. To contribute to understanding a novel MCDM method recently developed, the DEPART method [19], this study was carried out and focused on examining the applicability of the DEPART technique for ranking production alternatives across different manufacturing sectors. By analyzing multiple manufacturing scenarios and comparing the ranking results with those of other MCDM techniques, this research will provide managers, such as production line supervisors or technological engineers, with a basis for deciding whether to use the DEPART method to rank alternatives in manufacturing operations. The remainder of this report is organized as follows. Section 2 presents a brief overview of various applications of MCDM methods in evaluating production processes across multiple fields. Section 3 describes the selected manufacturing cases in diverse sectors, the associated data sets, and the analytical procedures adopted for ranking alternatives, including the implementation of the DEPART method alongside several well-known MCDM techniques. Section 4 presents and discusses the results of the comparative analyses. Finally, Section 5 is the conclusion, which summarizes the study's main findings and outlines potential directions for future work.

2. LITERATURE REVIEW

Previous studies have extensively applied MCDM to solve ranking problems in manufacturing. Initially, many authors focused on using individual methods. For instance, TOPSIS was utilized in gear grinding [20], Fuzzy TOPSIS was applied to renewable energy in Vietnam [21], and the AHP (Analytic Hierarchy Process) method was used for additive manufacturing and shipbuilding [22,23]. However, relying on a single method reveals a major limitation as multiple reports indicate that the ranking of alternatives can change significantly depending on the computational technique utilized [24,25]. Therefore, the simultaneous application of multiple methods to enhance reliability has been recommended [26,27]. Empirical studies have confirmed these discrepancies. In building energy optimization, CRADIS (Compromise Ranking of Alternatives from Distance to Ideal Solution), MARCOS (Measurement Alternatives and Ranking according to COmpromise Solution), and ARAS (Additive Ratio ASsessment) demonstrated superiority over COPRAS (COmplex PRroportional ASsessment) [28].

Practical evidence shows that, even when different methods identify the same best alternative, the rankings of the remaining options are often inconsistent, as seen in the cases of MAIRCA (MultiAtributive Ideal-Real Comparative Analysis), SPOTIS (Stable Preference Ordering Towards Ideal Solution), and COMET (Characteristic Objects METhod) in the energy sector [29], as well as in the comparison among WSM (Weighted Product Model), WASPAS (Weighted Aggregates Sum Product ASsessment), and PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) in EDM machining [30]. Beyond ranking results, methods also differ in complexity and flexibility. For example, VIKOR (VIsekriterijumska optimizacija I KOmpromisno Resenje) is considered less computationally complex than AHP and more flexible when the number of alternatives changes [31]. Furthermore, in certain applications, such as ranking production lines or FACTS system placement, methods like ELECTRE (Elimination Et Choice Transiting Reality), VIKOR, or GRA (Grey Relational Analysis) can yield entirely different ranking sets without a clear conclusion on which method is superior [32].

In summary, the effectiveness of MCDM methods depends heavily on the specific application. This indicates an urgent need for comprehensive evaluation studies for each new technique. With the recent emergence of the DEPART method [19], a knowledge gap exists regarding its adaptability in manufacturing practice, which is the central issue that this research focuses on addressing.

3. MATERIALS AND METHODS

3.1. Selected Manufacturing Processes

The primary objective of this study is to investigate the suitability of the DEPART method for ranking production alternatives. This research did not delve deeply into the production alternatives themselves but instead used data on production options from documents published in recent years. Three datasets within three distinct manufacturing sectors, including metal grinding with slotted grinding wheels, mechanical turning, and chemical extraction, were employed in this research. The number of alternatives and the number of criteria per alternative in the examples were intentionally set to differ, with the aim of achieving the most objective conclusions.

The first case involves nine metal-grinding alternatives using slotted grinding wheels, designated respectively from A1 to A9. The distinctions used to generate these alternatives lie in the adjustment of grinding machine parameters during machining. Five criteria were used to characterize each alternative: surface roughness, the X-direction vibration component of the grinding spindle, the Y-direction vibration component of the grinding spindle, the Z-direction vibration component of the grinding spindle, and the material removal rate, designated C1 to C5, respectively. Among these, the first four criteria are desired to have small values representing cost-type criteria, while the last criterion is desired to have a large value representing benefit-type criteria. Table 1 summarizes the information regarding the nine alternatives as described [12]. The objective of applying MCDM methods is to rank the alternatives from A1 to A9 to identify high-ranking options, i.e., those that simultaneously achieve low values for the first four criteria and a high value for the remaining criterion.

Case 2 pertains to nine metal turning alternatives, designated A1 through A9. Four criteria were used to describe each alternative: cutting force component in the X-direction (C1), cutting force component in the Y-direction (C2), cutting force component in the Z-direction (C3), and material removal rate (C4). In this case, Type C criteria include C1, C2, and C3, whereas the Type B criterion is C4. The information on these nine alternatives is summarized in Table 2 [33]. The purpose of using MCDM methods in this context was to rank alternatives A1 to A9 to identify high-ranking options—those that simultaneously achieve low values on the first three criteria and a high value on the last criterion.

Case 3 involves six extraction alternatives for components from the *Cardiospermum Halicacabum* L. (A kind of climbing plant distributed in Vietnam. It belongs to the Sapindaceae family and was used in traditional medicine). The six extraction alternatives were performed by varying solvent concentrations and are designated as A1 through A6. Each alternative was evaluated using three criteria: total polyphenol content (C1), total saponin content (C2), and antioxidant activity (C3). All three criteria are Type B criteria (Table 3 [5]). The task for the MCDM methods was to rank alternatives A1 through A6 to identify the highest-ranking options, those simultaneously exhibiting high values for all three criteria.

Table 1. Metal grinding alternatives using slotted grinding wheels [12]

Alt.	C1	C2	C3	C4	C5
	μm	μm	μm	μm	mm^3/s
A1	0.281	0.3683	0.5687	0.3419	9.1667
A2	0.609	0.2632	0.3177	0.2216	13.750
A3	0.613	0.6379	0.7686	0.5712	18.3333
A4	0.558	0.2491	0.2740	0.2791	27.5000
A5	0.713	0.4502	0.5652	0.4541	36.6667
A6	0.683	0.545	0.6599	0.6358	18.3333
A7	0.592	0.4249	0.4157	0.4068	55.000
A8	0.624	0.3573	0.3684	0.3392	27.500
A9	0.720	0.3641	0.4018	0.4123	41.250

Table 2. Metal turning alternatives [33]

Alt.	*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

Table 3. Extraction alternatives [5]

Alt.	C1	C2	C3
A1	7.688	106.2	0.014
A2	9.418	111.2	0.029
A3	11.035	140.2	0.054
A4	13.957	187.2	0.022
A5	12.142	164.2	0.054
A6	19.716	96.2	0.039

3.2. The DEPART Method

To rank the alternatives using the DEPART method, the following procedure should be performed step-by-step [19].

Step 1. Define the set of criteria and the set of alternatives for the decision-making problem. Assume that there are *m* alternatives to be ranked, each alternative characterized by *n* criteria. Let x_{ij} denote the value of criterion *j* for alternative *i*, where *j=1,…,n* and *i=1,…,m*.

Step 2. Normalize the data using Eq. (1):

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}\left(x_{ij}\right)^2}} \tag{1}$$

Step 3. Calculate the positive and negative deviations using Eqs. (2) and (3), respectively:

$$dv_{ij}^{+} = \left|n_{ij} - t_j^{+}\right| \tag{2}$$

$$dv_{ij}^{-} = \left|n_{ij} - t_j^{-}\right| \tag{3}$$

where:

$$t_j^{+} = \begin{cases} max_i x'_{ij} & if \quad j \in B \\ min_i x'_{ij} & if \quad j \in C \end{cases} \tag{4}$$

$$t_j^{-} = \begin{cases} min_i x'_{ij} & if \quad j \in B \\ max_i x'_{ij} & if \quad j \in C \end{cases} \tag{5}$$

In Eqs. (4) and (5), the letters B and C respectively represent benefit type criteria and cost type criteria.

Step 4: Construct the pairwise positive deviation matrix (E^+) and the pairwise negative ratio matrix (E^-) using Eqs. (6) and (7), respectively. In which w_j represents the weight of criterion *j*.

$$e_{kl}^{+} = \sum_{j=1}^{n} w_j \left(\frac{dv_{lj}^{+} + md^{+}}{dv_{kj}^{+} + md^{+}}\right) \quad k, l \in \{1,2,\dots,m\} \tag{6}$$

$$e_{kl}^{-} = \sum_{j=1}^{n} w_j \left(\frac{dv_{kj}^{-} + md^{-}}{dv_{lj}^{-} + md^{-}}\right) \quad k, l \in \{1,2,\dots,m\} \tag{7}$$

Where:

$$md^{+} = \max_{i,j}\left(dv_{ij}^{+}\right) \tag{8}$$

$$md^{-} = \max_{i,j}\left(dv_{ij}^{-}\right) \tag{9}$$

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

Step 5: Aggregate the E^+ matrix and the E^- matrix (determined in step 4) according to Eq. (10). In this context, η is a coefficient decided by the user, with a value ranging from 0 to 1. In the current study, the value of this coefficient was chosen to be 0.5 [19].

$$e_{kl} = \eta e_{kl}^{+} + (1-\eta) e_{kl}^{-}, \quad k, l \in \{1,2,\dots,m\} \tag{10}$$

Step 6: Calculate the total deviation ratio for each alternative using Eq. (11):

$$e_l^{s} = \sum_{k=1}^{m} e_{kl}, \quad l \in \{1,2,\dots,m\} \tag{11}$$

Step 7: Calculate the score for each alternative using Eq. (12). The alternatives are ranked in decreasing order of their score: the alternative with the highest score is assigned the first rank, whereas the one with the lowest score is assigned the m^{th} rank.

$$S_i = \frac{1}{n}\left(\sum_{l=1}^{n} \frac{e_{il}}{e_l^{s}}\right) \tag{12}$$

3.3. Other Methods Utilized

To validate the suitability of the DEPART method for ranking manufacturing alternatives, its ranking results were compared with those obtained from other MCDM methods. The SAW, TOPSIS, MOORA**,** COPRAS, RAM, and probability methods were employed in this study. SAW was selected for its simplicity among MCDM methods and its recognition as a foundational approach to developing other techniques [34]. TOPSIS, MOORA, and COPRAS were included for their widespread popularity and extensive use across diverse fields [35]. RAM was chosen as a relatively new method that can balance positive and negative criteria [36]. The probability method was also considered for its unique characteristic of not relying on "additive" calculations, thereby ensuring the precision of final decisions [37]. Furthermore, these six techniques are employed due to fundamental algorithmic distinctions inherent in each approach. The SAW method is grounded in the principle of linear addition. Following the normalization of criteria to a uniform scale, the performance index corresponding to one alternative is determined by the summation of the products between criteria values and their respective weights [38]. The TOPSIS method utilizes geometric distances. It identifies two hypothetical points representing the ideal best solution and the ideal worst solution. The optimal alternative is the one characterized by the shortest distance to the ideal best solution while simultaneously maintaining the largest separation measure from the ideal worst solution [39]. The MOORA method applies ratio analysis to evaluate alternatives. After normalization, the total value of the benefit-type criteria values is subtracted from the sum of cost-type criteria [40]. The COPRAS method assesses the relative and direct importance of alternatives based on the separate influences of benefit and cost criteria. A defining characteristic of COPRAS is its calculation of the utility degree expressed as a percentage [41]. The RAM method relies on a radical aggregation function in which the ranking index is computed as the root of the ratio of the sum of cost criteria to the sum of benefit criteria [36]. The probability method is based on the conceptual model of favorable probability, where each criterion is treated as an independent event. This approach transforms attribute values into probabilities via linear normalization and then computes the aggregate probability as the product of the individual probabilities [37].

To evaluate the similarity between the DEPART method and other MCDM techniques, several indices can be considered, such as the Weighted Spearman coefficient (WSPE), the Rank Similarity coefficient (RS), the Kendall's coefficient (KE), or the Spearman rank correlation coefficient [42]. Among these, coefficients like WSPE, RS, and KE typically assign higher priority weights to top-ranking alternatives and gradually reduce emphasis on lower-ranked alternatives [42]. In contrast, the Spearman coefficient performs an evaluation based on the entire ranking list with equal importance assigned to every position [43]. This approach helps reflect the effectiveness of the DEPART method compared to other MCDM methods more comprehensively and objectively, not only in identifying the optimal solution but also in the ability to categorize underperforming alternatives. For that reason, the Spearman coefficient was selected as the benchmarking tool in this research. This coefficient is calculated using Eq. (13), where *Di* symbolizes the ranking difference of the i alternative obtained from different methods [44,45].

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

For ranking alternatives using DEPART and most other MCDM methods, calculating criterion weights is essential [46]. Criteria weights can be determined through objective weighting methods, subjective weighting methods, and hybrid methods that integrate both subjective and objective factors [47,48]. While the application of subjective weighting methods yields criterion weights that depend heavily on the decision maker's subjective opinions, expertise, and potential bias toward a specific criterion, the use of objective weighting methods eliminates these factors [49,50]. Within the scope of this research, five objective weighting methods - the Equal, LOPCOW (LOgarithmic Percentage Change-driven Objective Weighting), Entropy, and SPC (Symmetry Point of Criterion) were employed to determine criterion weights**.** The Equations for calculating criterion weights using these five methods can be readily found in their respective literature [51-54]. All five weighting methods were applied simultaneously to each example to ensure the most generalizable assessment of the DEPART method's performance. Furthermore, this simultaneous application of five weighting methods for each example also served as a means to evaluate the stability of alternative rankings when obtained using various MCDM methods.

4. RESULTS AND DISCUSSION

4.1. Results and Discussion for Case 1

Tables 4-8, respectively, aggregate the rankings of metal grinding alternatives using a slotted grinding wheel when evaluated by different MCDM methods, corresponding to five cases in which criteria weights were determined by the equal, entropy, MEREC, LOPCOW, and SPC techniques. The final row of each Tables 4-8 presents the Spearman correlation coefficients between the DEPART approach and the six selected MCDM techniques.

Based on the results presented in Tables 4-8, a notable stability among the top-ranking alternatives is observed despite changes in the weighting methods. Alternative A4 frequently ranks in the first position when the criterion weights are calculated using the Equal weight and Entropy methods, whereas alternative A7 fills this position when the weights are calculated by the MEREC, LOPCOW, and SPC techniques. Notably, the DEPART approach constantly identifies A4 or A7 as the two best alternatives in most scenarios involving weight variations. These results demonstrate the strong adaptability and high reliability of the DEPART algorithm when subjected to fluctuation in input weighting data. Among the 9 alternatives, A4 ranks second in both C1 and C4, first in C2 and C3, and fourth in C5. Regarding alternative A7, compared to the 9 candidates, it ranks third in C1, sixth in C2, fifth in both C3 and C4, and first in C5. These findings indicate that both A4 and A7 present viable options for implementation in the slotted wheel grinding process because of their agreement in both technical criteria (represented by criteria C1 to C4) and economic criteria (represented by criterion C5).

Table 4. Rankings of alternatives in Case 1 using the Equal weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	6	7	7	7	7	6	7
A2	3	6	5	5	6	2	5
A3	9	9	9	9	9	9	9
A4	1	3	2	2	3	1	1
A5	7	4	6	6	4	7	6
A6	8	8	8	8	8	8	8
A7	2	1	1	1	1	3	2
A8	5	5	4	4	5	4	3
A9	4	2	3	3	2	5	4
r	-	0.7667	0.9167	0.9167	0.7667	0.9667	0.9167

Table 5. Rankings of alternatives in Case 1 using the Entropy weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	5	7	6	6	7	3	6
A2	2	5	3	3	6	2	3
A3	9	9	9	9	9	9	9
A4	1	2	1	1	2	1	1
A5	7	6	7	7	5	7	7
A6	8	8	8	8	8	8	8
A7	3	1	2	2	1	4	2
A8	4	4	4	5	4	5	4
A9	6	3	5	4	3	6	5
r	-	0.7667	0.9667	0.9333	0.6833	0.9500	0.9667

Table 6. Rankings of alternatives in Case 1 using the MEREC weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	7	9	7	7	9	7	7
A2	5	6	6	6	6	4	6
A3	9	8	9	9	8	9	9
A4	2	4	4	3	4	2	3
A5	6	3	3	5	3	6	5
A6	8	7	8	8	7	8	8
A7	1	1	1	1	1	1	1
A8	4	5	5	4	5	5	4
A9	3	2	2	2	2	3	2
r	-	0.8167	0.8667	0.9667	0.8167	0.9833	0.9667

Table 7. Rankings of alternatives in Case 1 using the LOPCOW weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	7	9	7	7	9	7	7
A2	5	6	6	6	6	4	6
A3	9	8	9	9	8	9	9
A4	2	4	4	3	4	2	2
A5	6	3	3	5	3	6	5
A6	8	7	8	8	7	8	8
A7	1	1	1	1	1	1	1
A8	4	5	5	4	5	5	4
A9	3	2	2	2	2	3	3
r	-	0.8167	0.8667	0.9667	0.8167	0.9833	0.9833

Table 8. Rankings of alternatives in Case 1 using the SPC weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	7	9	7	7	9	7	7
A2	5	6	6	6	6	4	6
A3	9	8	9	9	8	9	9
A4	2	4	4	3	4	1	2
A5	6	3	3	5	3	6	5
A6	8	7	8	8	7	8	8
A7	1	1	1	1	1	2	1
A8	4	5	5	4	5	5	4
A9	3	2	2	2	2	3	3
r	-	0.8167	0.8667	0.9667	0.8167	0.9667	0.9833

Furthermore, the consistency of the DEPART approach is further confirmed by the classification of inefficient alternatives. In every scenario, DEPART, along with most other MCDM methods, reaches a consensus by ranking A3 in 9th place and A6 in 8th place. This information suggests that the use of the DEPART approach is effective in eliminating poor alternatives, similarly to other MCDM approaches.

The Spearman coefficients between the DEPART approach and methods MOORA and COPRAS are relatively low (ranging from 0.6833 to 0.8167), which can be explained by significant differences in their ranking approaches. Both MOORA and COPRAS focus on the absolute values of alternatives following normalization. The final scores represent the aggregated overall value of an alternative across all criteria. In contrast, the DEPART method emphasizes deviations through pairwise comparison. Rather than simply summing criterion values, DEPART examines the differences between alternatives for each specific criterion to determine their relative advantages or limitations. However, in most cases where criteria weights are derived using different weighting methods, the alternatives identified as optimal by DEPART are largely consistent with those selected by methods MOORA and COPRAS. Especially, the correlation coefficients between the DEPART approach and the remaining methods, including SAW, TOPSIS, RAM, and probability, are very high across all weighting scenarios. This finding indicates that, in terms of rank correlation, identification of the best alternatives, and pinpointing the worst ones, the DEPART approach is evaluated to be as effective as these established methods.

Based on all the analyses performed above, the DEPART approach is identified as appropriate for ranking the alternatives in this research.

4.2. Results and Discussion for Case 2

Tables 9-13 present the ranking outcomes of the metal turning alternatives (A1 to A9, respectively) when evaluated using various MCDM methods. These Tables 9-13 correspond to scenarios where criteria weights were defined using the five different methods: Equal, Entropy, MEREC, LOPCOW, and SPC. The Spearman's correlation coefficient between the DEPART approach and these six MCDM techniques is also summarized in the final row of each table.

Table 9. Rankings of alternatives in Case 2 using the Equal weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	8	9	8	8	9	7	9
A2	9	8	9	9	8	9	8
A3	2	2	2	2	2	2	2
A4	7	7	7	7	7	8	7
A5	6	3	3	3	3	6	3
A6	3	4	5	5	4	5	5
A7	4	6	6	6	6	3	6
A8	5	5	4	4	5	4	4
A9	1	1	1	1	1	1	1
r	-	0.8667	0.8500	0.8500	0.8667	0.9333	0.8333

Table 10. Rankings of alternatives in Case 2 using the Entropy weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	8	9	8	8	9	7	9
A2	9	8	9	9	8	9	8
A3	2	2	2	2	2	2	2
A4	7	7	7	7	7	8	7
A5	6	3	3	3	3	6	3
A6	3	4	5	5	4	5	5
A7	4	6	6	6	6	3	6
A8	5	5	4	4	5	4	4
A9	1	1	1	1	1	1	1
r	-	0.8667	0.8500	0.8500	0.8667	0.9333	0.8333

Table 11. Rankings of alternatives in Case 2 using the MEREC weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	9	9	9	9	9	9	9
A2	8	7	7	7	7	8	7
A3	2	2	2	2	2	2	2
A4	7	8	8	8	8	7	8
A5	3	3	3	3	3	3	3
A6	4	4	4	4	4	6	4
A7	5	5	5	6	5	5	6
A8	6	6	6	5	6	4	5
A9	1	1	1	1	1	1	1
r	-	0.9833	0.9833	0.9667	0.9833	0.9333	0.9667

Table 12. Rankings of alternatives in Case 2 using the LOPCOW weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	8	9	8	8	9	8	9
A2	9	7	9	9	8	9	8
A3	2	2	2	2	2	2	2
A4	7	8	7	7	7	7	7
A5	5	3	3	3	3	6	3
A6	3	4	4	4	4	4	4
A7	4	6	5	6	5	3	6
A8	6	5	6	5	6	5	5
A9	1	1	1	1	1	1	1
r	-	0.8667	0.9500	0.9167	0.9333	0.9667	0.9000

Table 13. Rankings of alternatives in Case 2 using the SPC weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	9	9	9	9	9	9	9
A2	8	7	7	7	7	8	7
A3	2	2	2	2	2	2	2
A4	7	8	8	8	8	7	8
A5	3	3	3	3	3	3	3
A6	4	4	4	4	4	5	4
A7	5	5	5	5	5	4	6
A8	6	6	6	6	6	6	5
A9	1	1	1	1	1	1	1
r	-	0.9833	0.9833	0.9833	0.9833	0.9833	0.9667

According to the data presented in Tables 9-13, a high level of agreement is observed between the alternative rankings obtained from the DEPART approach and those generated by the six other MCDM techniques. The most prominent highlight is that, regardless of the method employed for criteria weighting or the specific MCDM approach used for ranking, alternative A9 consistently achieves rank 1, and A3 consistently achieves rank 2. A9 represents the alternative with the highest material removal rate (criterion C4) among the candidates. This result indicates that identifying A9 as the optimal solution satisfies the economic objective of the ranking process. Both criteria C2 (cutting force component in the Y-direction) and C3 (cutting force component in the Z-direction) for A9 exhibit moderate values relative to the other alternatives, being neither excessively high nor low. Criterion C1 (cutting force component in the X-direction) for A9 is nearly equivalent to that of A4 and only slightly higher than those of A7 and A8. These results suggested that selecting A9 as the best alternative adequately meets the technical requirements of the ranking mission. Also, the application of DEPART, along with other MCDM methods, successfully selects an alternative that simultaneously ensures economic and technical factors for the machining process. Furthermore, both the DEPART approach and other MCDM techniques consistently identify A1, A2, and A4 as the three least efficient alternatives across all five scenarios in which criteria weights are determined by different methods. This further suggests that the DEPART technique is not only as effective as other MCDM methods in determining the best alternative A9 but also consistent with them in pinpointing the most inefficient options.

Regarding stability across alternative ranks, the DEPART method achieves a high level of agreement compared to the six MCDM techniques, with the minimum Spearman coefficient being 0.85. Particularly in cases where the criterion weights are calculated using the MEREC method (Table 11) and the SPC method (Table 13), the Spearman coefficients between the DEPART approach and the six discussed MCDM techniques are exceptionally high, nearly reaching the maximum, ranging from 0.9333 to 0.9833. This confirms that DEPART not only accurately identifies the best and worst alternatives but also maintains ranking stability across all alternatives, comparable to MCDM methods widely recognized in the scientific community. In summary, the data analysis in this example further demonstrates the appropriateness of the DEPART approach for practical application.

4.3. Results and Discussion for Case 3

Tables 14-18, respectively, list the ranks of the *Cardiospermum Halicacabum* L. extraction options (A1 to A6) when evaluated using various MCDM methods. These Tables 14-18 correspond to scenarios where the criteria weights were computed by applying the five different methods: Equal, Entropy, MEREC, LOPCOW, and SPC. The Spearman's correlation coefficient between the DEPART approach and other MCDM methods is also shown in the final row of each table.

In this example, the efficiency of the DEPART approach compared to the other MCDM methods achieves an even higher degree of consensus than in the two previous examples. Across all scenarios in which criteria weights are calculated using five different methods, both the DEPART approach and the mentioned MCDM techniques consistently rank alternative A5 1st, A1 6th, and A2 5th. Even for the remaining alternatives, their positions, as defined by the DEPART technique, show only minor differences compared with the rankings obtained from the six MCDM techniques. Reviewing the data in Table 3, it is observed that alternative A5 has criteria C1 (total polyphenol content), C2 (total saponin content), and C3 (antioxidant activity) ranked 3rd, 2nd, and 1st, respectively, among the 6 alternatives, all of which are very high rankings. This result signifies that, in this example, the use of the DEPART approach successfully identified the optimal alternative for extracting useful active compounds from the six established candidates with the highest possible content. Conversely, pointing out A1 as the least efficient alternative helps practitioners exclude this option because most of its criteria rankings are poor. Specifically, according to the data in Table 3, criteria C1, C2, and C3 for this alternative are ranked 6th, 5th, and 6th, respectively. In summary, regarding the identification of both alternatives - the best and the worst, the DEPART approach in this example is verified to be as effective as other MCDM methods.

Table 14. Rankings of alternatives in Case 3 using the Equal weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	6	6	6	6	6	6	6
A2	5	5	5	5	5	5	5
A3	3	2	2	2	2	2	2
A4	4	4	4	4	4	4	4
A5	1	1	1	1	1	1	1
A6	2	3	3	3	3	3	3
r	-	0.9430	0.9430	0.9430	0.9430	0.9430	0.9430

Table 15. Rankings of alternatives in Case 3 using the Entropy weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	6	6	6	6	6	6	6
A2	5	5	5	5	5	5	5
A3	3	3	3	3	3	2	2
A4	4	4	4	4	4	4	4
A5	1	1	1	1	1	1	1
A6	2	2	2	2	2	3	3
r	-	1	1	1	1	0.943	0.943

Table 16. Rankings of alternatives in Case 3 using the MEREC weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	6	6	6	6	6	6	6
A2	5	5	5	5	5	5	5
A3	3	2	3	2	2	2	2
A4	4	4	4	4	4	4	4
A5	1	1	1	1	1	1	1
A6	2	3	2	3	3	3	3
r	-	0.9430	1	0.9430	0.9430	0.9430	0.9430

Table 17. Rankings of alternatives in Case 3 using the LOPCOW weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	6	6	6	6	6	6	6
A2	5	5	5	5	5	5	5
A3	2	2	2	2	2	2	2
A4	3	3	4	3	3	3	4
A5	1	1	1	1	1	1	1
A6	4	4	3	4	4	4	3
r	-	1	0.9430	1	1	1	0.9430

Table 18. Rankings of alternatives in Case 3 using the SPC weight method

Alt.	DEPART	COPRAS	TOPSIS	RAM	MOORA	SAW	Probability
A1	6	6	6	6	6	6	6
A2	5	5	5	5	5	5	5
A3	2	2	2	2	2	2	2
A4	4	4	4	4	4	4	4
A5	1	1	1	1	1	1	1
A6	3	3	3	3	3	3	3
r	-	1	1	1	1	1	1

When examining the Spearman coefficients between the DEPART approach and other approaches, it is noted that in this instance, the coefficients are very high, with the minimum value being 0.9430. Among these, many cases have Spearman's correlation coefficient between the DEPART approach and other MCDM methods equal to 1. These values confirm that the rankings of alternatives confirmed by the DEPART approach are highly coherent with those produced by other MCDM techniques. In conclusion, for this example, the DEPART approach is once again confirmed to be appropriate for ranking alternatives in the extraction process of *Cardiospermum Halicacabum* L. because it is identified to be as effective as other well-known and widely applied methods.

Thus, across the three implemented examples and each weighting method, both the best and worst alternatives found by the DEPART approach are equivalent to those found by other MCDM methods. The consistently high Spearman correlation coefficients between the DEPART approach and other MCDM techniques further demonstrate the suitability and reliability of the DEPART technique to rank alternatives in the considered cases. However, to provide a more comprehensive basis for evaluating the efficiency of the DEPART approach compared to others, a sensitivity analysis must be performed [52,53]. This is the content presented in the subsequent section of this article.

4.4. Sensitivity Analysis

Based on the data presented in Tables 4-8, the average Spearman coefficient values for each MCDM method and each of the five weighting techniques in Example 1 were calculated. From the data in Tables 9-13, the average Spearman values for each MCDM method under the five weighting techniques in Example 2 were determined. Similarly, from the data in Tables 14-18, the average Spearman coefficient values for each MCDM method across the five weighting techniques in Example 3 were computed. All these calculated values have been consolidated in Table 19. The last two rows of this Table 19, respectively, provide the mean Spearman coefficient for each method across the three implemented cases and list the methods' positions based on these mean Spearman values.

Table 19. Average Spearman coefficient values of MCDM methods when utilizing various weighting methods

Case	MCDM method						
	DEPART	SAW	TOPSIS	RAM	MOORA	COPRAS	Probability
1	0.8983	0.8550	0.8350	0.9217	0.9367	0.9183	1
2	0.9367	0.8933	0.9400	0.9500	0.9800	0.9800	0.9800
3	0.9257	0.9771	0.9657	0.9486	0.9486	0.9486	1
Average	0.9202	0.9085	0.9136	0.9401	0.9551	0.9490	0.9933
Rank	5	7	6	4	2	3	1

According to the data in Table 19, it is observed that in all three implemented examples, the mean Spearman coefficient values for each MCDM method across five different criteria weighting techniques are very high. The lowest mean Spearman value in this Table 19 is 0.8350, belonging to the TOPSIS method in Example 1. All data in this table reflect that the seven methods employed are appropriate for ranking alternatives in all three cases studied. The relatively low mean Spearman coefficient for the TOPSIS method in Example 1 can be explained by the high sensitivity of this method to changes in criteria weights. This implies that the occurrence of the rank reversal phenomenon in the TOPSIS method is a limitation that has been reported in several studies [55,56].

The fact that the probability method consistently yields the highest mean Spearman coefficient compared to other MCDM methods in all three cases can be explained by its avoidance of additive calculations, instead performing aggregate probability calculations via the product of individual probabilities, which makes the rankings less susceptible to fluctuations in criteria weights [37].

Through the three cases performed above in three different fields, slotted wheel grinding, metal turning, and chemical extraction, with numerous differences such as the number of options to be ranked and the number of benefit-type and cost-type criteria in each case, alongside the use of five different methods to calculate criteria weights, it has been consistently observed that the best option and worst option identified by the DEPART technique are similar to those found using other MCDM methods. Furthermore, the Spearman coefficients between the DEPART technique and other MCDM techniques are very large. Additionally, the sensitivity analysis results in Table 19 continue to show that each method has a high capability to maintain alternative rankings when the criteria weights are computed using different techniques. The summarized information is sufficient to conclude that the DEPART technique is identified as appropriate for use in the implemented examples. Nevertheless, a review of all MCDM methods used shows that the probability method is the most dominant across all scenarios performed. This finding implies a recommendation that while both the DEPART technique and the six other MCDM techniques used in this study are evaluated as applicable for ranking alternatives in production activities, probability should be prioritized as the primary choice.

5. CONCLUSION

The ranking of production alternatives in every field is critically important as it significantly influences all technical and economic factors. This study evaluated the application of a recent MCDM technique, the DEPART technique, in ranking production alternatives across three distinct domains including metal grinding with slotted grinding wheels, metal turning, and chemical extraction of *Cardiospermum Halicacabum* L. Through a comparison of ranking results between the DEPART technique and other MCDM approaches, it was confirmed that the DEPART approach is appropriate for ranking production alternatives. However, among all the MCDM methods utilized in this research, a recommendation for production line managers or technological engineers is that the use of the probability method should be prioritized as the primary choice for ranking production alternatives.

This research has only assessed the appropriateness of the DEPART technique in ranking production alternatives when criteria weights are calculated using objective weighting methods. The absence of user input in evaluating the relative importance of criteria is considered a limitation in assessing production alternatives. In the future, when assessing production alternatives, the feasibility of the DEPART technique should be evaluated using subjective weighting approaches or hybrid weighting methods. This issue becomes even more critical when the criteria for evaluating production alternatives involve uncertain data, rapidly changing data during the production process, or ambiguous data.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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