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Simulation-Aided Analysis of a Deviation-Based Pairwise Assessment Ratio Technique (DEPART) for MCDM

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Abstract

Multi-criteria decision-making (MCDM) methods provide structured approaches for evaluating alternatives based on multiple conflicting criteria. However, many existing MCDM techniques assess alternatives independently, either by aggregating weighted performance scores or by measuring deviations from reference points without a comparative basis. These approaches often fail to account for the relative nature of evaluations within the decision matrix, potentially leading to less reliable rankings. This research introduces a novel Deviation-Based Pairwise Assessment Ratio Technique (DEPART) for MCDM. Unlike conventional methods, DEPART evaluates alternatives through pairwise deviation ratios, ensuring a relative and holistic assessment. By incorporating all available decision data, this approach enhances the reliability and interpretability of rankings. To validate its effectiveness, a simulation-aided analysis is conducted. The evaluation process includes a benchmark example, a simulation analysis with varying criteria weights, and tests on randomly generated datasets with different problem sizes and performance ranges. Correlation coefficients are computed to measure consistency, while robustness is assessed using Analysis of Means (ANOM) and confidence intervals. The results demonstrate that DEPART provides stable and reliable rankings, making it a promising approach for solving MCDM problems.

Keywords: multi-criteria decision-making (MCDM), DEPART, simulation-aided, ANOM.

1 Introduction

Multi-criteria decision-making (MCDM) methods play a crucial role in solving complex decision problems where multiple conflicting criteria must be considered. These methods provide a structured framework to evaluate and prioritize alternatives based on various attributes, allowing decision-makers to make informed choices. Over the years, numerous MCDM techniques have been developed, each with its own methodological foundations, strengths, and limitations [1, 6, 7]. Decision-makers often have diverse preferences and value systems, influencing how they prioritize different solutions. The availability of multiple MCDM approaches enables decision-makers to select a method that aligns more closely with their preferences and decision-making style [3, 8, 23]. However, beyond individual preferences, the nature of the decision problem itself can impose constraints that limit the feasibility of certain solutions. In many cases, some solutions may not be practically viable due to contextual complexities, requiring decision-makers to seek solutions that are both logically and practically justifiable [10, 20, 35].

MCDM problems typically lack a single absolute optimal solution because they involve multiple conflicting criteria and objectives [22, 32]. It is often impossible to simultaneously maximize the utility and desirability according to all criteria, as improving one aspect may lead to compromises in others. This inherent trade-off highlights the necessity of employing diverse MCDM approaches to generate and compare multiple viable solutions rather than searching for a singular best outcome [9, 14]. A key consideration in MCDM is how decision matrices are constructed and interpreted. Decision matrices contain performance evaluations of alternatives across different criteria, but these values are often obtained relatively rather than independently. That is, the performance of an alternative on a specific criterion may be determined in comparison to other alternatives rather than assessed in isolation [2, 33]. This suggests that decision data should be analyzed holistically, avoiding an approach that examines alternatives independently without considering the relative nature of evaluations within the matrix. Ignoring the relational structure of the decision matrix can lead to incomplete assessments and suboptimal decision outcomes [13, 35].

Methods such as Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and Best-Worst Method (BWM) incorporate pairwise comparisons to evaluate alternatives and criteria in a relative manner [21, 26, 29]. These approaches emphasize a comparative and holistic perspective, ensuring that the relationships among alternatives are factored into the decision process. However, such methods heavily rely on subjective judgments, and as the number of alternatives and criteria increases, their practicality diminishes. Human cognitive limitations make it difficult to handle an extensive number of pairwise comparisons, leading to potential inconsistencies and reduced efficiency in decision-making. Methods like Simple Additive Weighting (SAW), Weighted Aggregated Sum Product Assessment (WASPAS), and Complex Proportional Assessment (COPRAS) evaluate alternatives based on their weighted performance scores [11, 18, 25]. These methods rely on a normalized decision matrix and account for the type of criteria (benefit or non-benefit) to determine the final rankings. Similarly, other techniques like Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), and Evaluation Based on Distance from Average Solution (EDAS) assess alternatives based on their deviations from reference points [27, 28, 34]. In these approaches, normalization is one of the few relative steps in the process, making only a partial adjustment to the raw performance values in the decision matrix. However, they still do not fully incorporate all available decision data in a holistic and relative manner [17, 24]. Methods based on weighted performance scores calculate the overall performance of each alternative independently, while methods that use deviations from reference points determine the total deviation or distance for each alternative separately, making the assessment non-relative. The present study does not aim to provide a detailed review of these methods. Instead, readers are referred to recent survey papers in the field that comprehensively discuss the advantages and drawbacks of different MCDM approaches [5, 16].

In this research, a novel Deviation-Based Pairwise Assessment Ratio Technique (DEPART) is introduced to address MCDM problems from a new perspective. The proposed method is based on the relative deviations of alternatives from reference points. Specifically, pairwise deviation ratios are computed for the alternatives, forming the basis for their evaluation. Unlike conventional methods that assess each alternative independently, DEPART evaluates alternatives in comparison to others. This holistic approach ensures that the complete structure of deviations within the decision matrix is accounted for, leading to a more reliable ranking of alternatives. By incorporating the entire set of available information, DEPART enhances the robustness and interpretability of decision outcomes.

To assess the effectiveness of the proposed method, a comparative simulation-aided analysis is conducted. Five well-established MCDM methods—WASPAS, COPRAS, TOPSIS, VIKOR, and EDAS—are selected for comparison. These methods are chosen due to their demonstrated efficiency and wide applicability in decision-making problems across various domains. Readers interested in the theoretical and practical aspects of these methods may refer to existing literature for further details [4, 12, 19, 30, 31]. The evaluation process follows a multi-stage approach. First, a benchmark comparative example is used to examine how DEPART's results align with those of the selected methods. Then, the same example is utilized in a simulation-aided analysis where criterion weights are varied randomly to observe the stability of rankings. Additionally, synthetic datasets representing MCDM problems with varying sizes (different numbers of alternatives and criteria) and different performance ranges are generated randomly. These datasets are analyzed using both DEPART and the selected methods, and correlation coefficients between the results are computed to assess consistency. To further validate the robustness of DEPART, Analysis of Means (ANOM) is applied. Moreover, confidence intervals (CIs) are computed to measure the degree of agreement between DEPART's outcomes and those of the selected MCDM methods under different conditions. The results of the conducted analyses highlight the reliability and stability of the proposed method.

The remainder of this paper is organized as follows. Section 2 presents the steps of the proposed method. In Section 3, a simple numerical example is provided to clarify the procedure for applying the proposed method. Section 4 introduces a benchmark example to compare the results of the proposed approach with some other MCDM methods. Section 5 evaluates the performance of DEPART in handling MCDM problems through a simulation-aided analysis. Finally, Section 6 presents the conclusions and future research directions.

2 Proposed method

The proposed method, DEPART (Deviation-Based Pairwise Assessment Ratio Technique), introduces a novel approach to multi-criteria decision-making by emphasizing relative deviations of the decision matrix. Unlike traditional methods such as TOPSIS and VIKOR, which evaluate each alternative individually based on its absolute deviations or distances from the ideal and anti-ideal solutions, DEPART focuses on pairwise ratios of deviations. By calculating the ratio of deviations for each pair of alternatives, this method leverages the entire deviation matrix for evaluation, rather than treating each alternative in isolation. This comprehensive utilization of deviations enhances the robustness of decision-making, ensuring more reliable and consistent results. The steps involved in implementing the DEPART method are as follows.

Step 1. Define the set of criteria and alternatives for the decision-making problem. Assume there are n alternatives (A_1, A_2, $\ldots$, A_n) and m criteria (C_1, C_2, $\ldots$, C_m). Assign a weight (w_j,$j \in \{1, 2, \ldots, m\}$) to each criterion, representing its importance in the evaluation process.

Step 2. In this step, the decision matrix is normalized using the vector normalization method. This approach transforms the data into a nondimensional format, allowing for meaningful comparisons across criteria. One of the key advantages of this normalization method is that it preserves the nature of the criteria (whether they are benefit or non-benefit criteria) and ensures that negative values or zeros in the original data do not adversely affect the process. If x_{ij} represents the performance of alternative i on criterion j, the normalization is carried out using the following formula:

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

Step 3. In this step, the elements of positive deviations matrix (DV^+) and negative deviation matrix (DV^-) are calculated. The absolute deviation of each element from the best and worst possible values in each column is determined. The following formulas are used for the calculations in this step:

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

$$dv_{ij}^- = \left| x'_{ij} - t_j^- \right| \tag{3}$$

where:

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

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

Here, B represents the set of benefit criteria, while N represents the set of non-benefit criteria.

Step 4. In this step, two pairwise matrices of the alternatives are constructed based on the deviations obtained in the previous step: pairwise positive deviation ratio matrix (E^+) and pairwise negative deviation ratio matrix (E^-). To derive the elements of these two matrices, the weighted sum of the ratios of the deviations is calculated as follows. To ensure that ratios involving zero deviations can also be computed while preventing excessive reductions in the impact of deviations, the maximum positive and negative deviations are considered as reference deviations.

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

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

where:

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

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

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

Step 5. In this step, the pairwise positive and negative deviation ratio matrices calculated in the previous step are aggregated based on a parameter determined by the decision-maker (η). The aggregated pairwise deviation ratio matrix, represented as E, is obtained through this aggregation process. The elements of this matrix are calculated using the following relationship:

$$e_{kl} = \eta e_{kl}^+ + (1 - \eta)\, e_{kl}^-, \qquad k, l \in \{1, 2, \ldots, n\} \tag{10}$$

By adjusting η, decision-makers can emphasize either the positive or negative deviation ratios in the final ranking process.

Step 6. In this step, the sums of the columns of the aggregated pairwise deviation ratio matrix obtained in the previous step are calculated. These values represent the total deviation ratio of each alternative when compared to all other alternatives. These sums are used for determining the final score for each alternative.

$$e_l^s = \sum_{k=1}^{n} e_{kl}, \qquad l \in \{1, 2, \ldots, n\} \tag{11}$$

Step 7. Based on the aggregated pairwise deviation ratio matrix calculated in Step 5 and the column sums obtained in Step 6, the final score for each alternative is computed using the following equation:

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

The alternatives are then ranked based on their final scores, where a higher score indicates a more favorable alternative.

3 Illustrative example

To clarify using the DEPART method, a small numerical example involving three alternatives (A_1, A_2, A_3) and three criteria (C_1, C_2, C_3) is presented. The decision matrix, as shown in Table 1, incorporates performance values, including negative and zero entries, to demonstrate the method's robustness in addressing such data. The type and weight of each criterion are also provided in Table 1.

Table 1: Data for the illustrative example

	$C_1 \in B$	$C_2 \in N$	$C_3 \in B$
	$w_1 = 0.4$	$w_2 = 0.3$	$w_3 = 0.3$
A_1	20	0	-12
A_2	35	-2	-5
A_3	15	2	-17

Steps 1 and 2. Based on the decision matrix provided in Table 1, the normalized values can be calculated as follows.

$$\left[x'_{ij}\right]_{3\times 3} = \begin{bmatrix} 0.465 & 0 & -0.561 \\ 0.814 & -0.707 & -0.234 \\ 0.349 & 0.707 & -0794 \end{bmatrix}$$

For example:

$$x'_{11} = \frac{20}{\sqrt{20^2 + 35^2 + 15^2}} = 0.465$$

$$x'_{23} = \frac{-5}{\sqrt{(-12)^2 + (-5)^2 + (-17)^2}} = -0.234$$

Step 3. In this step, the positive (DV^+) and negative (DV^-) deviations matrices are calculated using the normalized decision matrix obtained in the previous step. The process begins by determining the best (t_j^+) and worst (t_j^-) possible values for each criterion.

$$\left[t_j^+\right]_{1\times 3} = \begin{bmatrix} 0.814 & -0.707 & -0.234 \end{bmatrix}$$

$$\left[t_j^-\right]_{1\times 3} = \begin{bmatrix} 0.349 & 0.707 & -0794 \end{bmatrix}$$

Then the absolute deviations of each normalized value from these values are computed as follows:

$$DV^+ = \left[dv_{ij}^+\right]_{3\times 3} = \begin{bmatrix} 0.349 & 0.707 & 0.327 \\ 0 & 0 & 0 \\ 0.465 & 1.414 & 0.561 \end{bmatrix}$$

$$DV^- = \left[dv_{ij}^-\right]_{3\times 3} = \begin{bmatrix} 0.116 & 0.707 & 0.233 \\ 0.465 & 1.414 & 0.561 \\ 0 & 0 & 0 \end{bmatrix}$$

For example:

$$dv_{11}^+ = |0.465 - 0.814| = 0.349$$

$$dv_{13}^{+} = |-0.561 - (-0.234)| = 0.327$$
$$dv_{11}^{-} = |0.465 - 0.349| = 0.116$$
$$dv_{13}^{-} = |-0.561 - (-0.794)| = 0.233$$

Step 4. In this step, pairwise positive (E^+) and negative (E^-) deviation ratio matrices are constructed using the deviations calculated in Step 3. The elements of these matrices are derived by computing the weighted sum of deviation ratios for each pair of alternatives, ensuring robust comparison even with zero deviations. Based on the values of the deviations, the obtained values of md^+ and md^- are both 1.414. It should be noted that while the two values are equal in this case, md^+ and md^- can generally differ.

$$E^+ = \left[e_{kl}^+\right]_{3\times3} = \begin{bmatrix} 1 & 0.765 & 1.166 \\ 1.318 & 1 & 1.551 \\ 0.865 & 0.666 & 1 \end{bmatrix}$$

$$E^- = \left[e_{kl}^-\right]_{3\times3} = \begin{bmatrix} 1 & 0.801 & 1.232 \\ 1.251 & 1 & 1.551 \\ 0.827 & 0.666 & 1 \end{bmatrix}$$

For example:

$$e_{12}^+ = 0.4\left(\frac{0+1.414}{0.349+1.414}\right) + 0.3\left(\frac{0+1.414}{0.707+1.414}\right) + 0.3\left(\frac{0+1.414}{0.327+1.414}\right) = 0.765$$
$$e_{23}^+ = 0.4\left(\frac{0.465+1.414}{0+1.414}\right) + 0.3\left(\frac{1.414+1.414}{0+1.414}\right) + 0.3\left(\frac{0.561+1.414}{0+1.414}\right) = 1.551$$
$$e_{21}^- = 0.4\left(\frac{0.465+1.414}{0.116+1.414}\right) + 0.3\left(\frac{1.414+1.414}{0.707+1.414}\right) + 0.3\left(\frac{0.561+1.414}{0.233+1.414}\right) = 1.251$$
$$e_{31}^- = 0.4\left(\frac{0+1.414}{0.116+1.414}\right) + 0.3\left(\frac{0+1.414}{0.707+1.414}\right) + 0.3\left(\frac{0+1.414}{0.233+1.414}\right) = 0.827$$

The matrices E^+ and E^- are of size 3x3, where the dimensions correspond to the number of alternatives.

Step 5. In this example, η is assumed to be 0.5, meaning that equal importance is given to both positive and negative deviations ratios. The aggregated pairwise deviation ratio matrix E is calculated as follows:

$$E = [e_{kl}]_{3\times3} = \begin{bmatrix} 1 & 0.783 & 1.199 \\ 1.284 & 1 & 1.551 \\ 0.846 & 0.666 & 1 \end{bmatrix}$$

For example:

$$e_{13} = (0.5 \times 1.166) + (0.5 \times 1.232) = 1.199$$
$$e_{31} = (0.5 \times 0.865) + (0.5 \times 0.827) = 0.846$$

Step 6. The column sums of the aggregated pairwise deviation ratio matrix are calculated as follows:

$$E^s = [e_l^s]_{1\times3} = \begin{bmatrix} 3.13 & 2.449 & 3.75 \end{bmatrix}$$

For example:

$$e_1^s = 1 + 1.284 + 0.846 = 3.13$$

Step 7. According to the values obtained in Steps 5 and 6, the final score for each alternative is computed as follows:

$$S_1 = \frac{1}{3}\left(\frac{1}{3.13} + \frac{0.783}{2.449} + \frac{1.199}{3.75}\right) = 0.32$$
$$S_2 = \frac{1}{3}\left(\frac{1.284}{3.13} + \frac{1}{2.449} + \frac{1.551}{3.75}\right) = 0.41$$

$$S_3 = \frac{1}{3}\left(\frac{0.846}{3.13} + \frac{0.666}{2.449} + \frac{1}{3.75}\right) = 0.27$$

Based on the computed final scores, S_2 has the highest value, followed by S_1. Therefore, A_2 is ranked first $A_2 \succ A_1 \succ A_3$. In this example, we intentionally selected a case where the final ranking could also be inferred from the decision matrix. This choice was made to clearly illustrate the step-by-step process of DEPART.

4 Comparative example

In the field of MCDM, evaluating the performance of a newly proposed method by comparing it with widely accepted approaches is essential for assessing its validity and effectiveness. A comparative analysis is conducted to examine the performance of DEPART against five well-established MCDM methods: WASPAS, COPRAS, TOPSIS, VIKOR, and EDAS. These methods have been extensively utilized in decision-making research due to their robustness, reliability, and adaptability in handling various types of decision problems. Each of these techniques possesses distinct methodological advantages, and a systematic comparison allows for assessing the alignment of DEPART's outcomes with those obtained from the selected methods.

To provide a comprehensive assessment, we employ a benchmark example adapted from the study by Keshavarz Ghorabaee, et al. [17]. This example consists of 10 alternatives evaluated across 7 criteria. In this study, it is assumed that all criteria have equal importance, and therefore, a uniform weight distribution of $w_j = 1/7$ is considered. The details of this example are presented in Table 2. The results of DEPART, along with those of the five selected MCDM methods, are summarized in Table 3. To assess the consistency of the rankings, the correlation coefficients between the results of DEPART and those of the other methods are calculated and shown in Table 3 as well.

Table 2: Data for the comparative example

	$C_1 \in B$	$C_2 \in B$	$C_3 \in B$	$C_4 \in N$	$C_5 \in N$	$C_6 \in N$	$C_7 \in N$
A_1	23	264	2.37	0.05	167	8900	8.71
A_2	20	220	2.2	0.04	171	9100	8.23
A_3	17	231	1.98	0.15	192	10800	9.91
A_4	12	210	1.73	0.2	195	12300	10.21
A_5	15	243	2	0.14	187	12600	9.34
A_6	14	222	1.89	0.13	180	13200	9.22
A_7	21	262	2.43	0.06	160	10300	8.93
A_8	20	256	2.6	0.07	163	11400	8.44
A_9	19	266	2.1	0.06	157	11200	9.04
A_{10}	8	218	1.94	0.11	190	13400	10.11

Table 3: Results of DEPART compared to other MCDM methods

	DEPART	WASPAS	COPRAS	TOPSIS	VIKOR	EDAS
A_1	1	1	1	1	1	1
A_2	3	2	2	3	5	3
A_3	6	6	6	8	7	6
A_4	10	10	10	10	10	10
A_5	7	7	7	9	6	7
A_6	8	8	8	6	8	8
A_7	2	3	3	2	2	2
A_8	4	4	4	4	3	4
A_9	5	5	5	5	4	5
A_{10}	9	9	9	7	9	9
r	—	0.987	0.987	0.903	0.951	1

All correlation values exceed 0.8, indicating a strong agreement between DEPART and the established methods, thereby confirming its validity. Notably, the results indicate a perfect alignment between the rankings obtained from DEPART and EDAS. Although the comparison results demonstrate a strong alignment between DEPART and the selected MCDM methods, it is essential to conduct additional analyses to assess whether these results are consistently replicable across different contexts and decision-making scenarios. Such further evaluations are necessary to determine the robustness and generalizability of DEPART's performance in varying conditions, ensuring its reliability and validity beyond the scope of the current example.

5 Simulation-aided analysis

To evaluate how well DEPART performs across a range of diverse scenarios and decision-making contexts, its robustness and generalizability are thoroughly analyzed through a simulation-aided analysis under varying conditions. This analysis is essential to ensure that the method's effectiveness remains consistent across different scenarios and decision-making contexts. The primary objective is to evaluate how well DEPART performs when exposed to various configurations of decision problems, which can include differences in the number of alternatives, criteria, and the characteristics of the decision matrix itself. This enables a more thorough understanding of DEPART's adaptability and reliability in real-world applications. First, a simulation analysis is conducted to examine the effect of changing criterion weights. For this purpose, the same comparative example from the previous section is considered. A total of 1000 sets of criteria weights are generated to observe how the scores and rankings of alternatives vary when using DEPART. Accordingly, the example is simulated 1000 times with different weight sets and solved using DEPART. The generated weights and detailed results are provided as supplementary material in Reference [15]. Figure 1 illustrates the variations in the scores of alternatives, showing that their scores remain fairly stable throughout the simulation process. Similarly, Figure 2 presents the changes in alternative rankings. While some fluctuations in rankings are observed, these variations fall within the natural range of decision-making processes.

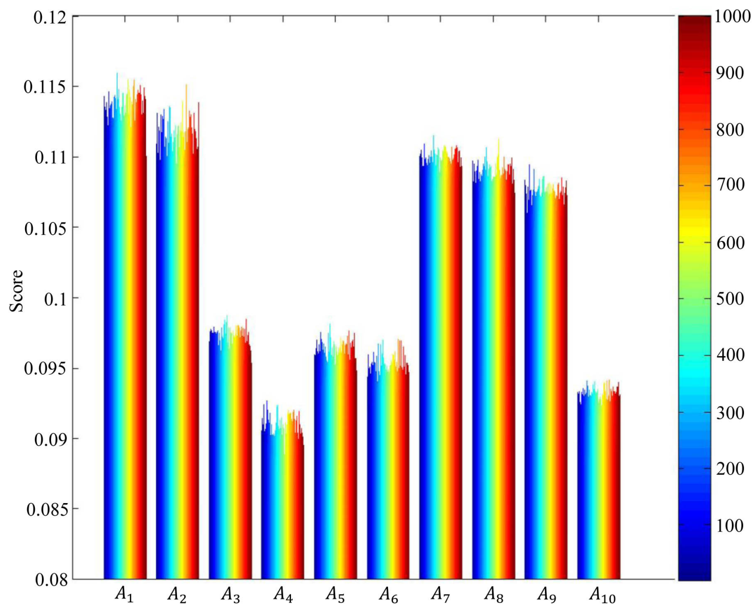

Figure 1: Variations in the scores of alternatives

To further confirm the stability of the results, the mean rank of alternatives (MRA) and mean score of alternatives (MSA) over all simulation runs are presented in Table 4. Additionally, the ranking obtained using equal weights from the previous section is presented as initial ranking of alternatives. As observed in Table 4, the ranks derived from MRA and MSA are entirely consistent with the initial ranks, confirming the stability of DEPART's results under varying criterion weight distributions.

The second simulation-aided analysis conducted in this research focuses on the degree of consistency

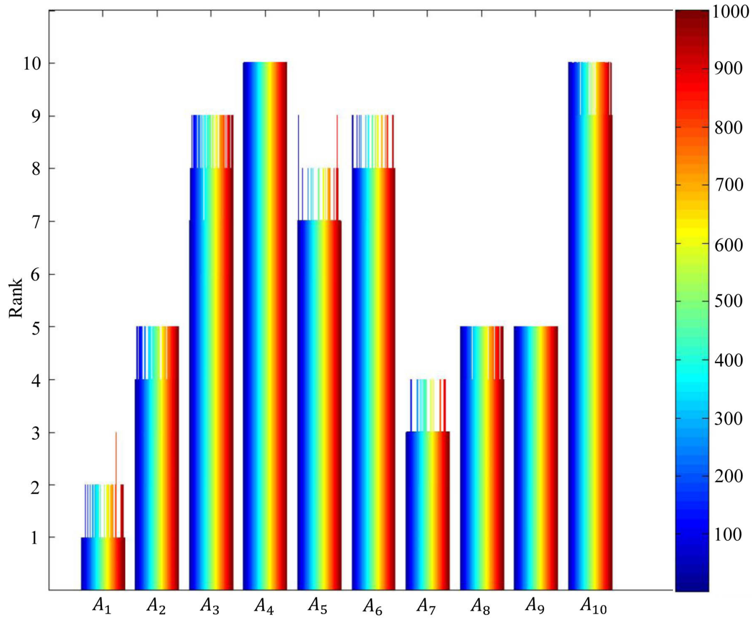

Figure 2: Variations in the rank of alternatives

Table 4: Initial ranks vs. MRA and MSA for stability analysis

	Initial Rank	MRA	MRA Rank	MSA	MSA Rank
A_1	1	1.03	1	0.110963	1
A_2	3	2.982	3	0.107922	3
A_3	6	6.613	6	0.0948	6
A_4	10	9.892	10	0.087159	10
A_5	7	6.713	7	0.094418	7
A_6	8	7.776	8	0.093367	8
A_7	2	2.514	2	0.10825	2
A_8	4	3.707	4	0.107031	4
A_9	5	4.767	5	0.105354	5
A_{10}	9	9.006	9	0.090737	9

Table 5: Description of different datasets

Dataset No.	Problem size		Number of runs	Number of problems per run	Range of values for decision matrix
	Number of alternatives	Number of criteria			
1	10	10	10	500	[1, 10]
2	25	25	10	500	[1, 10]
3	50	50	10	500	[1, 10]
4	10	10	10	500	[10, 100]
5	25	25	10	500	[10, 100]
6	50	50	10	500	[10, 100]
7	10	10	10	500	[100, 1000]
8	25	25	10	500	[100, 1000]
9	50	50	10	500	[100, 1000]

between the results obtained by DEPART and those produced by other methods. For this analysis, nine distinct datasets are considered. These datasets are generated with randomly assigned values for the weights of criteria, the types of criteria (benefit or non-benefit), and the performance values of the alternatives, i.e., the decision matrix. To account for different sizes and complexities of decision problems, three distinct problem sizes are defined, corresponding to small, medium, and large-scale decision-making problems. Each dataset consists of 500 decision problems, and the simulation process is repeated 10 times (10 runs) for each dataset. This results in a total of 5000 decision-making problems per dataset and 45,000 decision problems across all nine datasets. The description related to different datasets are presented in Table 5. The simulation data is provided as supplementary material in Reference [15]. The simulation process, including data generation and problem-solving, was carried out using MATLAB.

The results obtained from DEPART for each decision problem are compared with those of the five selected MCDM methods (WASPAS, COPRAS, TOPSIS, VIKOR, and EDAS). The correlation between the rankings produced by DEPART and those of the other methods is calculated to evaluate the consistency and alignment of DEPART's outcomes. The simulation results are analyzed based on the correlation coefficient, which serves as a key metric for assessing the agreement between DEPART and the established methods.

To further analyze the robustness of DEPART, the alignment of its results with those of the other methods will be tested using the ANOM technique. ANOM is a statistical technique used to compare the means of multiple groups or factors to identify significant differences between them. It evaluates the group means in comparison to their overall mean at a 95% confidence level. This procedure is particularly useful in quality control settings due to its resemblance to control charts. Points that fall outside the upper and lower critical lines indicate significant differences from the overall mean, highlighting groups with statistically distinct means. In the context of this study, ANOM is used to assess the robustness of the results obtained from DEPART compared to other MCDM methods. Each run of the simulation is treated as a separate group for the analysis. The correlation between the results of DEPART and the other methods for each dataset is analyzed using ANOM. If the means of the correlation coefficients in each run fall within the upper and lower critical limits, it indicates that the results are stable and robust across different runs. This robustness check helps ensure that DEPART's performance is reliable and that the differences observed between methods are statistically significant. In essence, ANOM serves as a powerful tool to validate the stability of DEPART's performance across varying conditions, providing further evidence of its effectiveness in decision-making tasks. The statistical analyses related to ANOM were conducted using JMP SAS software, and the associated analysis files are provided as supplementary material in Reference [15].

The first method analyzed for its correlation with DEPART across different datasets is WASPAS. As depicted in Figure 3, the mean correlation values obtained from each run consistently remain within the upper and lower decision limits of the ANOM analysis across all datasets. This indicates that the agreement between DEPART and WASPAS is not only statistically significant but also stable under varying decision-making conditions.

A similar trend is observed for the other four MCDM methods—COPRAS, TOPSIS, VIKOR, and EDAS—as illustrated in Figures 4 to 7. In each case, the mean correlation values across different runs and datasets remain well within the acceptable range, with no significant deviations beyond the control limits. This result confirms that the consistency of DEPART's rankings is not restricted to a specific dataset or problem structure but rather holds across a broad spectrum of decision-making scenarios, encompassing different numbers of alternatives, criteria, and value ranges.

The stability of correlation values across all datasets suggests that the agreement between DEPART and the selected methods is not merely incidental. Instead, it reflects a systematic and repeatable pattern, reinforcing the robustness of DEPART in comparison to established MCDM techniques. The ability of DEPART to maintain a high degree of consistency across multiple simulations demonstrates that its decision-making performance remains reliable even when subjected to significant variations in problem size and data characteristics. This robustness is a key factor in validating DEPART as a practical and dependable tool for real-world decision-making problems, ensuring that its rankings are both reproducible and resilient to changes in the decision environment.

To further assess the strength of the correlation coefficients between DEPART and the selected MCDM methods, confidence intervals were calculated at a 95% confidence level. These intervals

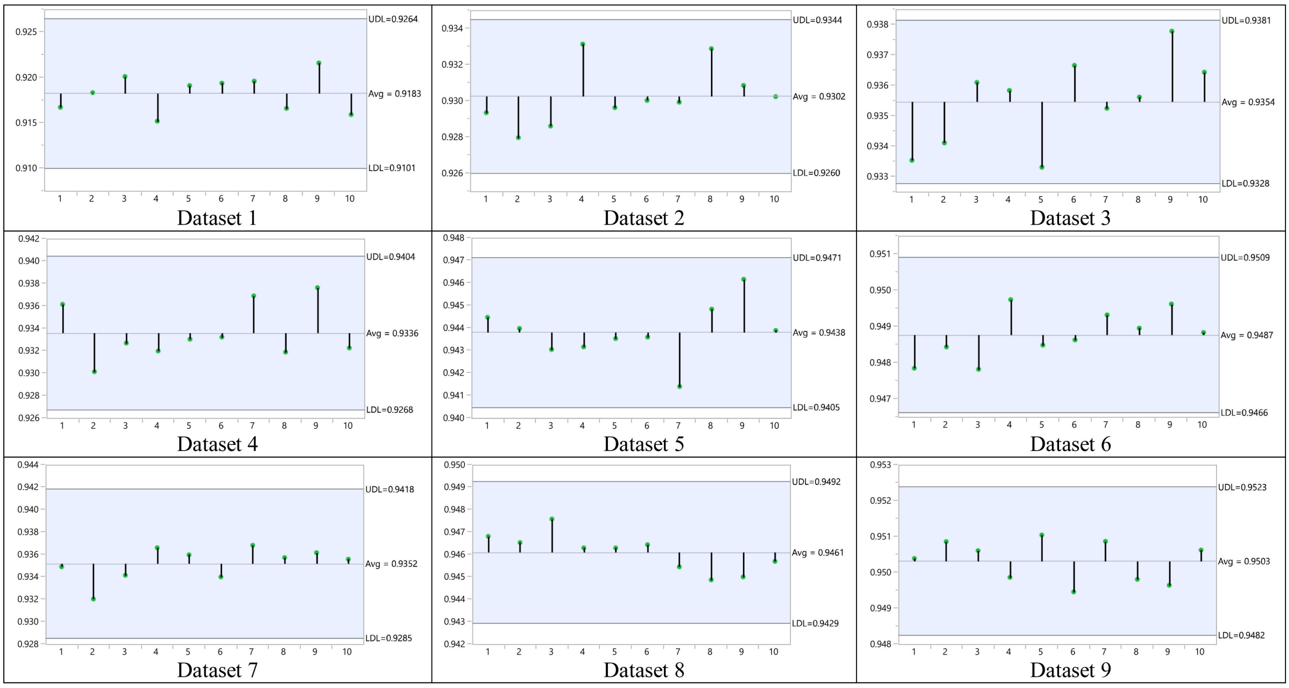

Figure 3: ANOM analysis of correlation between DEPART and WASPAS

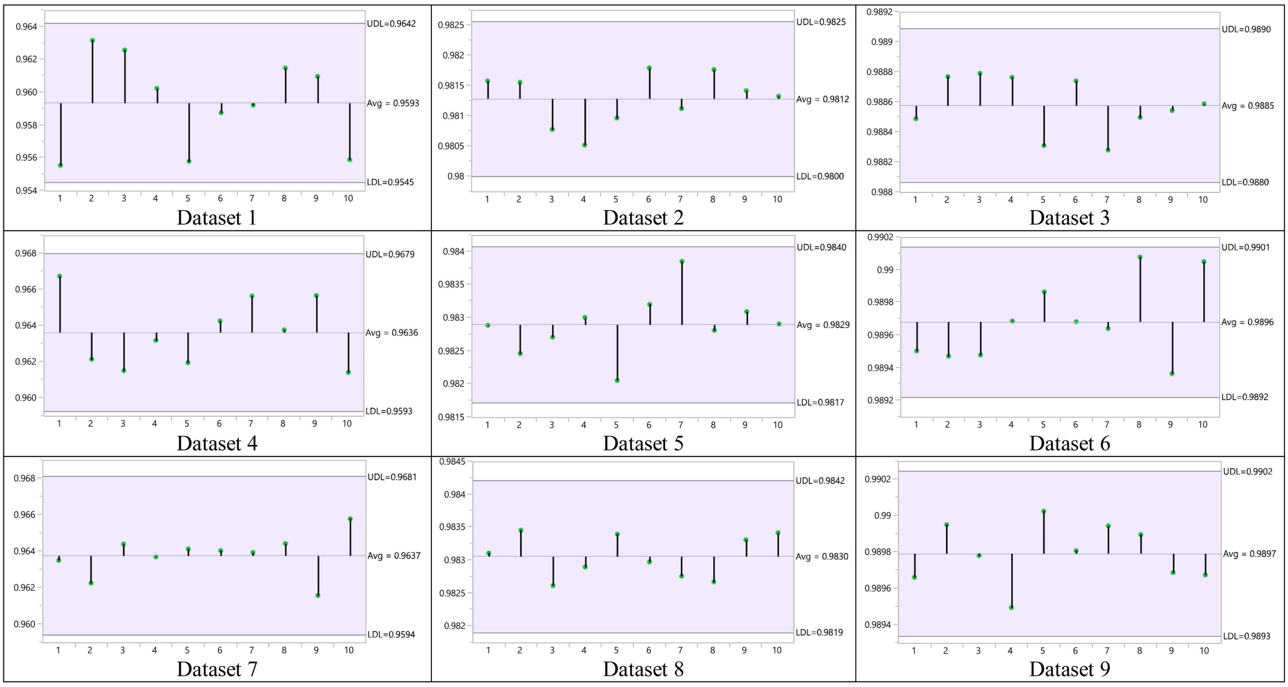

Figure 4: ANOM analysis of correlation between DEPART and COPRAS

provide an estimate of the range within which the mean of the correlation values is expected to fall, offering a measure of the statistical reliability of the observed results. A narrower CI indicates greater precision in the correlation estimate, while a wider CI suggests more variability across different runs.

The confidence intervals for the correlation coefficients were computed using Minitab software and are presented in Tables 6 to 8. Table 6 reports the CI values for datasets with decision matrix values in the range of [1,10] (Datasets 1 to 3). Table 7 provides the CI values for datasets with values in the range of [10,100] (Datasets 4 to 6), and Table 8 presents the CI results for datasets with values in the range of [100,1000] (Datasets 7 to 9). These confidence intervals offer further validation of DEPART's consistency by demonstrating that the correlation values remain statistically significant across varying problem scales and data distributions.

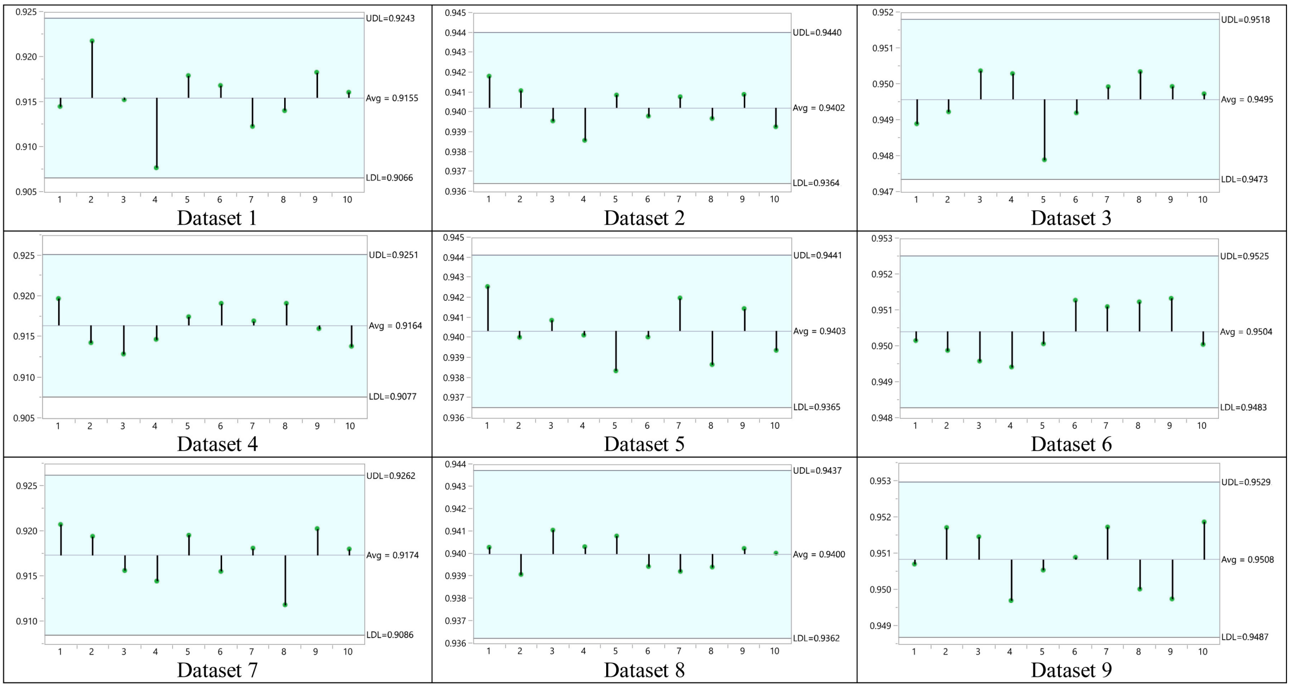

Figure 5: ANOM analysis of correlation between DEPART and TOPSIS

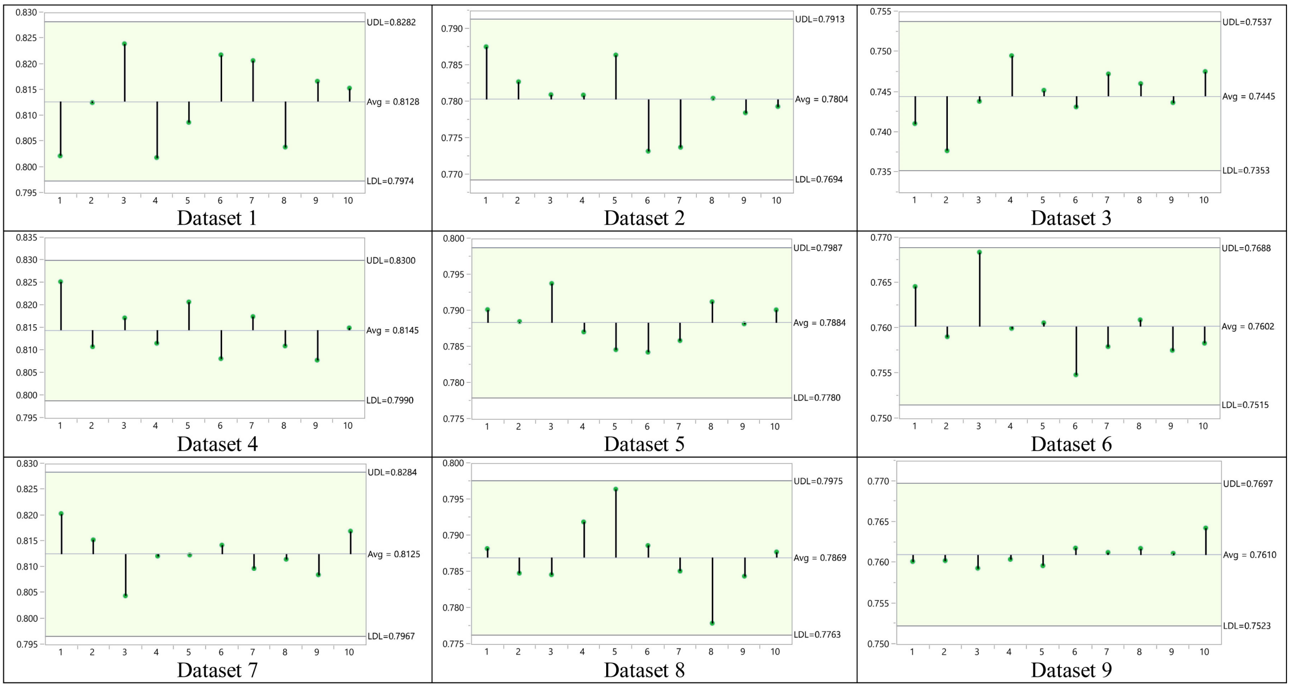

Figure 6: ANOM analysis of correlation between DEPART and VIKOR

As shown in the tables, the CI values for the correlation between DEPART and WASPAS consistently indicate that the mean correlation coefficient is above 0.9. A similar trend is observed for TOPSIS, where the mean correlation remains consistently above 0.9 across all datasets. For COPRAS, the mean correlation with DEPART exceeds 0.95 in all cases, further confirming the strong alignment between these two methods. Although the correlation with VIKOR is somewhat lower compared to other methods, the mean value still remains above 0.7, indicating a strong relationship. Additionally, the mean correlation between DEPART and EDAS consistently exceeds 0.96, with many cases showing values above 0.99. This finding reinforces the exceptionally high similarity between DEPART and EDAS, which was also observed in the comparative example discussed earlier.

It is important to note that the CI values are reported up to three decimal places in the tables,

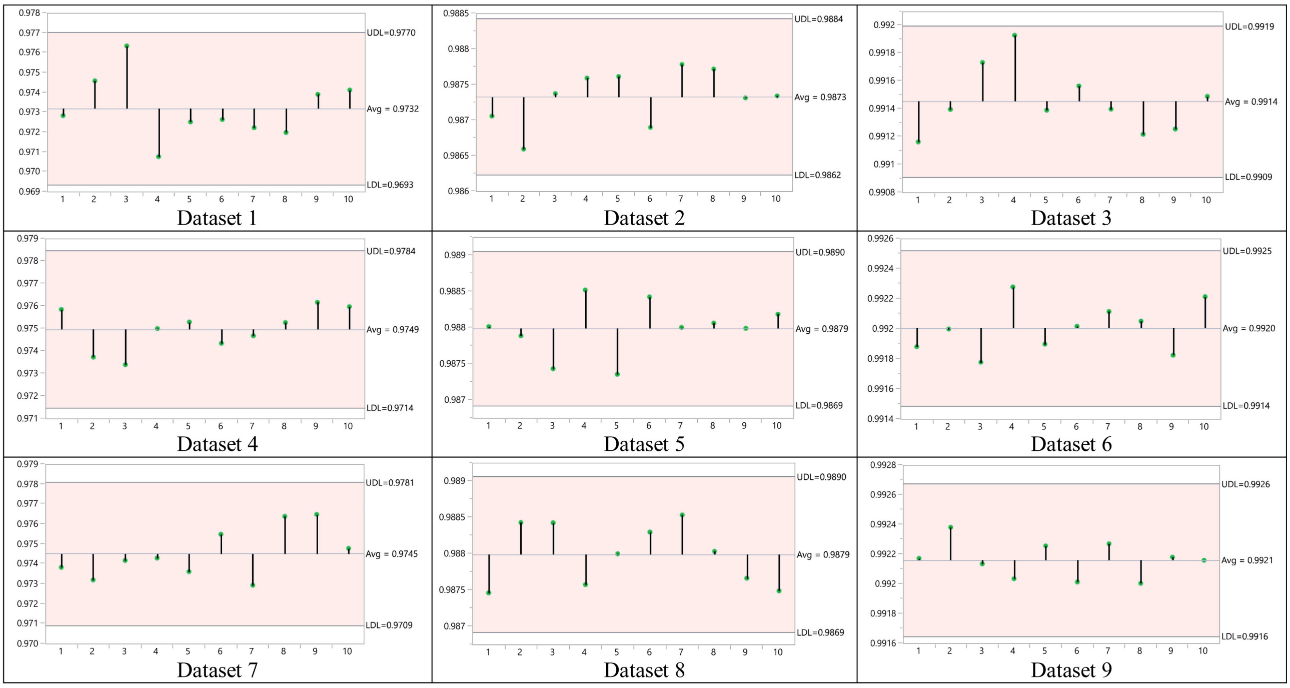

Figure 7: ANOM analysis of correlation between DEPART and EDAS

Table 6: CI for correlation coefficients in datasets with values within [1, 10]

Problem size	Runs	WASPAS	COPRAS	TOPSIS	VIKOR	EDAS
10	1	(0.910, 0.922)	(0.952, 0.959)	(0.908, 0.921)	(0.790, 0.813)	(0.970, 0.975)
	2	(0.912, 0.924)	(0.959, 0.966)	(0.915, 0.928)	(0.801, 0.823)	(0.971, 0.977)
	3	(0.914, 0.926)	(0.959, 0.966)	(0.908, 0.921)	(0.812, 0.835)	(0.973, 0.979)
	4	(0.909, 0.921)	(0.956, 0.963)	(0.901, 0.914)	(0.790, 0.813)	(0.967, 0.973)
	5	(0.913, 0.925)	(0.952, 0.959)	(0.911, 0.924)	(0.797, 0.820)	(0.969, 0.975)
	6	(0.913, 0.925)	(0.955, 0.962)	(0.910, 0.923)	(0.810, 0.833)	(0.969, 0.975)
	7	(0.913, 0.925)	(0.955, 0.962)	(0.905, 0.918)	(0.809, 0.832)	(0.969, 0.975)
	8	(0.910, 0.922)	(0.957, 0.965)	(0.907, 0.920)	(0.792, 0.815)	(0.969, 0.974)
	9	(0.915, 0.927)	(0.957, 0.964)	(0.911, 0.924)	(0.805, 0.828)	(0.971, 0.976)
	10	(0.909, 0.922)	(0.952, 0.959)	(0.909, 0.922)	(0.804, 0.826)	(0.971, 0.976)
25	1	(0.926, 0.932)	(0.980, 0.982)	(0.939, 0.944)	(0.779, 0.795)	(0.986, 0.987)
	2	(0.924, 0.931)	(0.980, 0.982)	(0.938, 0.943)	(0.774, 0.790)	(0.985, 0.987)
	3	(0.925, 0.931)	(0.979, 0.981)	(0.936, 0.942)	(0.772, 0.789)	(0.986, 0.988)
	4	(0.930, 0.936)	(0.979, 0.981)	(0.935, 0.941)	(0.772, 0.789)	(0.986, 0.988)
	5	(0.926, 0.932)	(0.980, 0.981)	(0.938, 0.943)	(0.778, 0.794)	(0.986, 0.988)
	6	(0.926, 0.933)	(0.980, 0.982)	(0.937, 0.942)	(0.765, 0.781)	(0.986, 0.987)
	7	(0.926, 0.933)	(0.980, 0.982)	(0.938, 0.943)	(0.765, 0.781)	(0.986, 0.988)
	8	(0.929, 0.936)	(0.980, 0.982)	(0.936, 0.942)	(0.772, 0.788)	(0.986, 0.988)
	9	(0.927, 0.933)	(0.980, 0.982)	(0.938, 0.943)	(0.770, 0.786)	(0.986, 0.988)
	10	(0.927, 0.933)	(0.980, 0.982)	(0.936, 0.942)	(0.771, 0.787)	(0.986, 0.988)
50	1	(0.931, 0.935)	(0.988, 0.989)	(0.947, 0.950)	(0.734, 0.747)	(0.990, 0.991)
	2	(0.932, 0.936)	(0.988, 0.989)	(0.947, 0.950)	(0.730, 0.744)	(0.990, 0.991)
	3	(0.934, 0.938)	(0.988, 0.989)	(0.948, 0.952)	(0.737, 0.750)	(0.991, 0.992)
	4	(0.933, 0.937)	(0.988, 0.989)	(0.948, 0.951)	(0.742, 0.756)	(0.991, 0.992)
	5	(0.931, 0.935)	(0.987, 0.988)	(0.946, 0.949)	(0.738, 0.752)	(0.990, 0.991)
	6	(0.934, 0.938)	(0.988, 0.989)	(0.947, 0.950)	(0.736, 0.749)	(0.991, 0.992)
	7	(0.933, 0.937)	(0.987, 0.988)	(0.948, 0.951)	(0.740, 0.754)	(0.991, 0.992)
	8	(0.933, 0.937)	(0.988, 0.989)	(0.948, 0.951)	(0.739, 0.752)	(0.990, 0.991)
	9	(0.935, 0.939)	(0.988, 0.989)	(0.948, 0.951)	(0.736, 0.750)	(0.990, 0.991)
	10	(0.934, 0.938)	(0.988, 0.989)	(0.948, 0.951)	(0.740, 0.754)	(0.991, 0.992)

which results in some values appearing identical. Detailed results of the analyses are available as supplementary material in Reference [15].

To examine variations in correlation values, the pooled standard deviation was computed for each

Table 7: CI for correlation coefficients in datasets with values within [10, 100]

Problem size	Runs	WASPAS	COPRAS	TOPSIS	VIKOR	EDAS
10	1	(0.931, 0.941)	(0.963, 0.969)	(0.913, 0.926)	(0.813, 0.836)	(0.973, 0.978)
	2	(0.925, 0.935)	(0.958, 0.965)	(0.907, 0.920)	(0.799, 0.822)	(0.971, 0.976)
	3	(0.927, 0.937)	(0.958, 0.964)	(0.906, 0.919)	(0.805, 0.828)	(0.970, 0.975)
	4	(0.926, 0.937)	(0.959, 0.966)	(0.908, 0.921)	(0.800, 0.823)	(0.972, 0.977)
	5	(0.928, 0.938)	(0.958, 0.965)	(0.911, 0.923)	(0.809, 0.832)	(0.972, 0.977)
	6	(0.928, 0.938)	(0.961, 0.967)	(0.912, 0.925)	(0.796, 0.819)	(0.971, 0.976)
	7	(0.931, 0.941)	(0.962, 0.968)	(0.910, 0.923)	(0.806, 0.828)	(0.972, 0.977)
	8	(0.926, 0.936)	(0.960, 0.966)	(0.912, 0.925)	(0.799, 0.822)	(0.972, 0.977)
	9	(0.932, 0.942)	(0.962, 0.968)	(0.909, 0.922)	(0.796, 0.819)	(0.973, 0.978)
	10	(0.927, 0.937)	(0.958, 0.964)	(0.907, 0.920)	(0.803, 0.826)	(0.973, 0.978)
25	1	(0.942, 0.946)	(0.982, 0.983)	(0.939, 0.945)	(0.782, 0.797)	(0.987, 0.988)
	2	(0.941, 0.946)	(0.981, 0.983)	(0.937, 0.942)	(0.780, 0.796)	(0.987, 0.988)
	3	(0.940, 0.945)	(0.981, 0.983)	(0.938, 0.943)	(0.786, 0.801)	(0.986, 0.988)
	4	(0.940, 0.945)	(0.982, 0.983)	(0.937, 0.942)	(0.779, 0.794)	(0.987, 0.989)
	5	(0.941, 0.946)	(0.981, 0.982)	(0.935, 0.941)	(0.776, 0.792)	(0.986, 0.988)
	6	(0.941, 0.946)	(0.982, 0.984)	(0.937, 0.942)	(0.776, 0.791)	(0.987, 0.989)
	7	(0.938, 0.943)	(0.982, 0.984)	(0.939, 0.944)	(0.778, 0.793)	(0.987, 0.988)
	8	(0.942, 0.947)	(0.981, 0.983)	(0.935, 0.941)	(0.783, 0.798)	(0.987, 0.988)
	9	(0.943, 0.948)	(0.982, 0.983)	(0.938, 0.944)	(0.780, 0.795)	(0.987, 0.988)
	10	(0.941, 0.946)	(0.982, 0.983)	(0.936, 0.942)	(0.782, 0.797)	(0.987, 0.988)
50	1	(0.946, 0.949)	(0.989, 0.990)	(0.948, 0.951)	(0.758, 0.771)	(0.991, 0.992)
	2	(0.946, 0.950)	(0.989, 0.990)	(0.948, 0.951)	(0.752, 0.765)	(0.991, 0.992)
	3	(0.946, 0.949)	(0.989, 0.990)	(0.948, 0.951)	(0.761, 0.774)	(0.991, 0.992)
	4	(0.948, 0.951)	(0.989, 0.990)	(0.947, 0.950)	(0.753, 0.766)	(0.991, 0.992)
	5	(0.946, 0.950)	(0.989, 0.990)	(0.948, 0.951)	(0.754, 0.767)	(0.991, 0.992)
	6	(0.947, 0.950)	(0.989, 0.990)	(0.949, 0.952)	(0.748, 0.761)	(0.991, 0.992)
	7	(0.947, 0.950)	(0.989, 0.990)	(0.949, 0.952)	(0.751, 0.764)	(0.991, 0.992)
	8	(0.947, 0.950)	(0.989, 0.990)	(0.949, 0.952)	(0.754, 0.767)	(0.991, 0.992)
	9	(0.948, 0.951)	(0.989, 0.990)	(0.949, 0.952)	(0.751, 0.763)	(0.991, 0.992)
	10	(0.947, 0.950)	(0.989, 0.990)	(0.948, 0.951)	(0.751, 0.764)	(0.991, 0.992)

dataset and method, as shown in Table 9. This measure provides a single estimate of standard deviation across multiple independent runs, offering a comprehensive view of variability. As observed, the standard deviation decreases with an increasing number of alternatives and criteria, indicating greater stability in larger decision problems. This reduction is also somewhat noticeable with wider value ranges. Additionally, the pooled standard deviation for EDAS is notably lower than that of other methods, whereas VIKOR exhibits the highest standard deviation, reflecting greater variation in its correlation values.

6 Conclusions

This research introduced the Deviation-Based Pairwise Assessment Ratio Technique (DEPART) as a novel approach to multi-criteria decision-making (MCDM). By considering deviation ratios in a pairwise manner, DEPART offers an evaluation framework that captures the relative nature of assessments within the decision matrix. This approach allows for a more comprehensive analysis by incorporating all available decision data, leading to improved ranking reliability. To validate the effectiveness of DEPART, a comprehensive series of simulation-aided analyses were performed. The first validation step involved a comparative example, which revealed that DEPART's results closely align with those of well-established MCDM techniques, particularly EDAS. This suggests that DEPART can be used interchangeably with traditional methods while offering distinct advantages in terms of relative and holistic assessments. The second validation involved a simulation study where criteria weights were varied, and it was found that DEPART's rankings remained stable across different weighting scenarios, highlighting its adaptability and robustness under different decision contexts. Furthermore, a large-scale experiment involving 45,000 randomly generated decision problems confirmed DEPART's consistency in providing reliable rankings across diverse problem structures and

Table 8: CI for correlation coefficients in datasets with values within [100, 1000]

Problem size	Runs	WASPAS	COPRAS	TOPSIS	VIKOR	EDAS
10	1	(0.930, 0.939)	(0.960, 0.966)	(0.914, 0.927)	(0.808, 0.832)	(0.971, 0.976)
	2	(0.927, 0.936)	(0.959, 0.965)	(0.912, 0.925)	(0.803, 0.827)	(0.970, 0.975)
	3	(0.929, 0.939)	(0.961, 0.967)	(0.909, 0.922)	(0.792, 0.816)	(0.971, 0.976)
	4	(0.931, 0.941)	(0.960, 0.966)	(0.908, 0.921)	(0.800, 0.823)	(0.971, 0.976)
	5	(0.931, 0.940)	(0.960, 0.967)	(0.913, 0.926)	(0.800, 0.824)	(0.970, 0.976)
	6	(0.929, 0.938)	(0.960, 0.967)	(0.909, 0.922)	(0.802, 0.825)	(0.972, 0.978)
	7	(0.931, 0.941)	(0.960, 0.967)	(0.911, 0.924)	(0.798, 0.821)	(0.970, 0.975)
	8	(0.930, 0.940)	(0.961, 0.967)	(0.905, 0.918)	(0.799, 0.823)	(0.973, 0.979)
	9	(0.931, 0.941)	(0.958, 0.964)	(0.913, 0.926)	(0.796, 0.820)	(0.973, 0.979)
	10	(0.930, 0.940)	(0.962, 0.968)	(0.911, 0.924)	(0.805, 0.828)	(0.972, 0.977)
25	1	(0.944, 0.949)	(0.982, 0.983)	(0.937, 0.943)	(0.780, 0.796)	(0.986, 0.988)
	2	(0.944, 0.948)	(0.982, 0.984)	(0.936, 0.941)	(0.777, 0.792)	(0.987, 0.989)
	3	(0.945, 0.949)	(0.981, 0.983)	(0.938, 0.943)	(0.776, 0.792)	(0.987, 0.989)
	4	(0.943, 0.948)	(0.982, 0.983)	(0.937, 0.943)	(0.784, 0.799)	(0.986, 0.988)
	5	(0.943, 0.948)	(0.982, 0.984)	(0.938, 0.943)	(0.788, 0.804)	(0.987, 0.988)
	6	(0.944, 0.948)	(0.982, 0.983)	(0.936, 0.942)	(0.780, 0.796)	(0.987, 0.989)
	7	(0.943, 0.947)	(0.981, 0.983)	(0.936, 0.942)	(0.777, 0.792)	(0.987, 0.989)
	8	(0.942, 0.947)	(0.981, 0.983)	(0.936, 0.942)	(0.770, 0.785)	(0.987, 0.988)
	9	(0.942, 0.947)	(0.982, 0.984)	(0.937, 0.943)	(0.776, 0.792)	(0.986, 0.988)
	10	(0.943, 0.948)	(0.982, 0.984)	(0.937, 0.942)	(0.779, 0.795)	(0.986, 0.988)
50	1	(0.948, 0.951)	(0.989, 0.990)	(0.949, 0.952)	(0.753, 0.766)	(0.991, 0.992)
	2	(0.949, 0.952)	(0.989, 0.990)	(0.950, 0.953)	(0.753, 0.766)	(0.992, 0.993)
	3	(0.949, 0.952)	(0.989, 0.990)	(0.949, 0.953)	(0.752, 0.765)	(0.991, 0.992)
	4	(0.948, 0.951)	(0.989, 0.990)	(0.948, 0.951)	(0.754, 0.766)	(0.991, 0.992)
	5	(0.949, 0.952)	(0.989, 0.990)	(0.948, 0.952)	(0.753, 0.766)	(0.991, 0.992)
	6	(0.947, 0.950)	(0.989, 0.990)	(0.949, 0.952)	(0.755, 0.768)	(0.991, 0.992)
	7	(0.949, 0.952)	(0.989, 0.990)	(0.950, 0.953)	(0.754, 0.767)	(0.991, 0.992)
	8	(0.948, 0.951)	(0.989, 0.990)	(0.948, 0.951)	(0.755, 0.768)	(0.991, 0.992)
	9	(0.948, 0.951)	(0.989, 0.990)	(0.948, 0.951)	(0.754, 0.767)	(0.991, 0.992)
	10	(0.949, 0.952)	(0.989, 0.990)	(0.950, 0.953)	(0.757, 0.770)	(0.991, 0.992)

Table 9: Pooled standard deviations of correlation values

Dataset No.	WASPAS	COPRAS	TOPSIS	VIKOR	EDAS
1	0.06904	0.04070	0.07457	0.12966	0.03226
2	0.03554	0.01074	0.03190	0.09257	0.00923
3	0.02257	0.00429	0.01872	0.07769	0.00455
4	0.05749	0.03658	0.07332	0.13055	0.02935
5	0.02796	0.00986	0.03187	0.08743	0.00891
6	0.01804	0.00385	0.01773	0.07299	0.00433
7	0.05588	0.03638	0.07423	0.13356	0.03008
8	0.02662	0.00970	0.03153	0.08933	0.00901
9	0.01738	0.00381	0.01800	0.07344	0.00431

varying data distributions. In addition to these validation efforts, statistical stability was rigorously assessed using Analysis of Means (ANOM), which demonstrated that the correlations between DEPART and the selected MCDM methods stayed within acceptable decision limits across all datasets. Confidence interval analyses further reinforced the alignment between DEPART and other MCDM methods, showing a strong agreement in decision-making results. Notably, an examination of pooled standard deviations indicated that DEPART's rankings become more stable as the size and complexity of the decision problems increase. This suggests that DEPART is not only effective in small-scale problems but also excels in handling larger and more complex decision-making scenarios.

Several important directions for further research can be explored. One promising direction is the application of DEPART to real-world decision-making problems in diverse fields such as supplier evaluation, employee performance assessment, and energy resource management. These areas would benefit from DEPART's ability to account for relative performance of alternatives, making it a powerful tool for practical decision support. Additionally, extending DEPART to uncertain environments, such as fuzzy and probabilistic decision settings, would significantly enhance its applicability in scenarios where uncertainty and imprecision play a critical role in decision-making. Another potential area of development is the exploration of computational improvements to streamline DEPART's implementation in large-scale decision problems. This could involve optimizing the assessment process or developing hybrid models that combine DEPART with other advanced MCDM methods for improved efficiency and scalability. Furthermore, comparisons with other emerging MCDM techniques, especially those designed for big data environments, would be valuable in assessing DEPART's relative strengths and weaknesses in handling complex decision problems. Lastly, future research could focus on developing user-friendly tools and software to facilitate the adoption of DEPART in practical applications. By making the method more accessible to decision-makers across various industries, DEPART could become a standard tool for addressing multi-criteria decision-making challenges, helping to drive more informed and reliable decisions in both academic and real-world settings.

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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