An adaptive RANCOM-ST method for bias reduction using Statistical Thresholds

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Abstract. Determining the relative importance of criteria is a critical aspect of Multi-Criteria Decision Analysis (MCDA), directly influencing decision outcomes. Weighting methods in MCDA are generally divided into subjective approaches, based on expert opinions, and objective approaches, which derive weights from statistical data properties. Among subjective weighting methods, the RANking COMparison (RANCOM) approach has gained recognition for its simplicity and effectiveness in determining criteria importance. However, its standard formulation does not provide mechanisms for expert-driven adjustments after the initial weight computation, limiting its adaptability.

To address this limitation, this study proposes an adaptive RANCOM-ST method, which systematically refines expert weight adjustments through the use of Statistical Thresholds—calculated based on the mean and standard deviation of errors observed in simulation results. In the proposed approach, experts assess the correctness of the generated weights and indicate whether they should be increased or decreased using a three-level scale. This additional step enhances the robustness of the weighting process by incorporating statistical measures to reduce expert bias and improve consistency. Synthetic experiments demonstrate that RANCOM-ST leads to more stable and reliable results compared to the traditional RANCOM method. The findings highlight the potential of RANCOM-ST as an effective refinement for subjective weighting methods, making expert-based MCDA models more resilient to inconsistencies.

Keywords: RANCOM method· Subjective Weighting · MCDA.

1 Introduction

In Multi-Criteria Decision Analysis (MCDA), determining the importance of criteria is a fundamental step that significantly influences decision outcomes [3]. Weighting methods used in MCDA can be broadly categorized into two groups: subjective methods, which rely on expert opinions, and objective methods, which derive weights from statistical or mathematical properties of the data [13]. Objective weighting methods, such as entropy-based or standard deviation approaches,

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assign weights based on variability or distribution within the dataset, ensuring that criteria with greater differentiation receive higher importance [7]. In contrast, subjective methods depend on expert judgments, incorporating human knowledge and preferences to define the significance of each criterion. While both approaches offer advantages, subjective weighting is often favored in cases where quantitative data alone is insufficient to capture the complexity of decision problems [1].

Subjective weighting methods, however, are prone to inaccuracies, inconsistencies, and hesitation in expert evaluations, which can impact the reliability of decision support systems [2,13]. The development of robust and intuitive weighting techniques is essential to enhance their applicability, ensuring stable results even in complex decision-making scenarios. Among the recently proposed approaches, the RANking COMparison (RANCOM) method has gained attention for its ability to provide a straightforward yet effective way of determining criteria importance, reducing the impact of minor inconsistencies in expert assessments [16]. Despite its advantages, further improvements are necessary, particularly in applications involving crisp data, where precise and computationally efficient weighting methods are required.

This study introduces an adaptive RANCOM-ST method, which integrates Statistical Thresholds to mitigate bias in expert-based weighting. The core enhancement involves refining the traditional RANCOM approach by incorporating mean and standard deviation-based thresholds to evaluate the obtained weights. After executing the standard RANCOM procedure, experts are asked to assess the correctness of the generated weights and indicate whether specific weights should be increased or decreased, using a three-level scale. This additional verification step enhances the robustness of the weighting process by allowing expert feedback to be systematically adjusted based on statistical properties. Synthetic experiments demonstrate the potential for improved decision outcomes, validating the effectiveness of the proposed refinement in reducing expert bias and increasing the consistency of weight assignments.

The remainder of this paper is organized as follows: Section 2 presents the related works, discussing existing research on the RANCOM method and its applications. Section 3 describes the materials and methods, including the dataset and the details of the proposed RANCOM-ST approach. Section 4 reports the experimental setup and results, evaluating the improvements achieved by the proposed method. Finally, Section 5 provides the conclusions and outlines potential directions for future research.

2 Related works

The RANCOM method was initially proposed to improve the reliability of subjective weighting under conditions where expert judgments could be prone to inaccuracies and hesitation. As introduced by Więckowski et al. in [16], RANCOM focuses on simplifying expert-based weighting by relying on comparative ranking judgments of criteria rather than requiring extensive pairwise comparisons.

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This fundamental idea has spurred multiple investigations aimed at adapting or extending the method to various decision-making contexts.

An early comparative exploration between RANCOM and Analytic Hierarchy Process (AHP), conducted by Więckowski et al. [17], highlighted RANCOM's capacity to yield robust outcomes in scenarios where a slight probability of error in expert opinion may arise, especially when dealing with five or more criteria. This work underscored the need for methods like RANCOM that can absorb inaccuracies and still produce consistent weights, and it laid a foundation for subsequent research targeting diversified application domains.

Further developments integrated RANCOM with other MCDA approaches to address evolving decision-making needs. For instance, Więckowski et al. [18] introduced a hybrid system combining RANCOM with ESP-SPOTIS to personalize criteria weighting in an electric vehicle selection problem, illustrating how RANCOM's flexibility can enhance user-centric decision support tools. More recently, software-oriented advancements by Shekhovtsov et al. [12] have extended the functionality of the "pymcdm" library, showcasing how RANCOM's straightforward ranking mechanism can be programmatically integrated alongside other well-known methods (e.g., AHP) to streamline data validation and facilitate scientific reporting.

A substantial body of research has also adapted RANCOM to uncertainty-driven or fuzzy environments. Więckowski et al. [15] proposed a fuzzy extension, Fuzzy RANCOM, using triangular fuzzy numbers to better handle ambiguous expert assessments, preserving the simplicity of the original approach. In a similar vein, Rani et al. [10] introduced an interval-valued intuitionistic fuzzy version of RANCOM to address location selection for offshore wind power stations under imprecise data, while Rani et al. [9] applied single-valued neutrosophic concepts in combination with RANCOM for Sustainable Human Resource Management evaluation. Both works illustrate RANCOM's adaptability for diverse fuzzy representations, confirming its relevance for complex real-world problems with high levels of uncertainty.

Other studies have continued pushing the boundaries of RANCOM's fuzzification to new forms of fuzzy sets. Korucuk and Aytekin [4] employed a polytopic fuzzy adaptation of RANCOM to identify and weight barriers to implementing Logistics 4.0 in corporate logistics companies, demonstrating how the method can capture expert opinions in highly dynamic or technologically complex settings. Mishra et al. [6] and Rani et al. [8] extended RANCOM to q-rung orthopair fuzzy rough sets and picture fuzzy sets, respectively, thereby broadening the spectrum of how "partial truth" or "hesitant" information can be represented in weighting schemes. Similarly, Mishra et al. [5] used an intuitionistic fuzzy environment to develop a hybrid IF-RCC-RANCOM-MACONT framework for assessing regions in logistics-centric circular economy solutions. Across these various fuzzy extensions, RANCOM remains at the core, demonstrating that its comparative ranking concept is well-suited for combination with different fuzzy theories.

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Beyond methodological expansions, the literature also showcases how RANCOM can serve as a foundation for comparative analyses. Shekhovtsov [11] introduced a novel weights similarity coefficient, using it to measure how close RANCOM-derived weights are to those obtained from other subjective weighting methods (e.g., AHP). Similarly, Więckowski et al. [14] employed RANCOM to generate the criteria weights in a sustainability-focused energy development case study, comparing the performance of different MCDA methods (COPRAS, PROMETHEE II, and EDAS) under the same weighting scheme.

Collectively, these studies confirm that RANCOM has become a significant focal point in multi-criteria decision-making research, demonstrating notable advantages when experts' inputs are prone to error, uncertainty, or hesitation. Its integrations—ranging from fuzzy adaptations to hybrid decision-support frameworks—reveal a method that is both theoretically robust and highly adaptable to emerging needs in modern decision-making. Building on this momentum, the present work endeavors to refine RANCOM's capabilities specifically for crisp data scenarios, addressing the frequent need for improved efficiency and simplicity in domains where exact input data is readily available yet still subject to minor inaccuracies in expert judgment.

3 The proposed approach

3.1 Overview of the RANCOM method

This section presents a recall of the RANCOM method, as described in [16]. The RANCOM method is an innovative approach for subjective weighting of criteria in decision-making problems. This procedure is based on establishing a ranking of criteria by experts, where lower values are assigned to more significant parameters. A crucial aspect of this method is the ability to define a ranking that allows ties, enabling the derivation of a properly structured weight vector that satisfies the condition of summing to 1.

Experts utilizing the RANCOM method can define the ranking of criteria using different techniques, including direct ranking, scoring, sorting algorithms, and the tournament method. Each of these techniques provides a structured approach to defining the ranking, which is particularly important when dealing with a large number of factors in the decision problem. As the number of criteria increases, the task of establishing an ordering relationship becomes more complex and prone to inconsistencies in evaluation. Therefore, the proposed techniques aim to simplify the ranking process for experts, and can be presented as:

Step 1. Define the criteria ranking
The expert determines the position of each criterion relative to the others. Lower values indicate higher importance. It is possible to assign the same rank to different criteria, allowing ties in the ranking. The ranking can consist of consecutive value or more dispersed values. However, the numerical values themselves do not affect the final outcome unless they indicate a different hierarchy of criteria.

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Step 2. Construct the matrix of ranking comparison
The MAtrix of ranking Comparison (MAC) is created based on pairwise comparisons of the ranking positions assigned by the expert. The elements of the MAC matrix are defined as follows:

$$MAC = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} \alpha_{11} & \alpha_{12} & \dots & \alpha_{1n} \\ \alpha_{21} & \alpha_{22} & \dots & \alpha_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{n1} & \alpha_{n2} & \dots & \alpha_{nn} \end{bmatrix} \end{array} \tag{1}$$

where n is the number of criteria, and the value of α_{ij} is determined as follows:

$$\alpha_{ij} = \begin{cases} IF\ f(C_i) < f(C_j)\ THEN & 1 \\ IF\ f(C_i) = f(C_j)\ THEN & 0.5 \\ IF\ f(C_i) > f(C_j)\ THEN & 0 \end{cases} \tag{2}$$

where $f(C)$ is the significance function of criterion C.

Step 3. Calculate the Summed Criteria Weights
Based on the MAC matrix, the horizontal vector of the Summed Criteria Weights (SCW) is computed as follows:

$$SCW_i = \sum_{j=1}^{n} \alpha_{ij} \tag{3}$$

Step 4. Compute the final criteria weights
Finally, preference values are approximated for each criterion. As a result, the weight vector W is obtained, where the i-th row contains the estimated preference value for C_i. The final weights for the criteria are determined as follows:

$$w_i = \frac{SCW_i}{\sum_{i=1}^{n} SCWi} \tag{4}$$

3.2 Proposed RANCOM-ST Method

The RANking COMparision - Statistical Thresholds (RANCOM-ST) procedure constitutes an extension of the original RANCOM approach, incorporating a post-processing mechanism that allows experts to holistically evaluate and, if necessary, adjust the preliminary weight vector. First, the standard RANCOM procedure is used to generate an initial set of weights, each reflecting the importance of a specific criterion. Once this preliminary vector has been established, an expert examines each weight in light of broader context, knowledge of the problem domain, and the relationships among criteria. If the expert considers a weight to be inappropriate, the first step is to determine the necessary direction

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of change: an increase is indicated if the current weight is deemed too low, and a decrease if the current weight is deemed too high. The subsequent challenge lies in deciding the magnitude of this adjustment.

In this study, the appropriate magnitude of adjustment is determined by generating a collection of random weight vectors, enabling the estimation of typical deviations across various vector dimensions. These deviations, quantified through both the mean and standard deviation, serve as the basis for a structured three-level adjustment scale: low, medium, and high. If an expert identifies only a slight discrepancy in a given weight, a minor (low) modification is applied, whereas more substantial deviations necessitate medium or high adjustments. Once all modifications are introduced, the adjusted weight vector undergoes renormalization to ensure that the sum of all weights remains equal to one, thereby preserving its probabilistic properties. By integrating this expert-driven refinement process with a systematic statistical foundation, RANCOM-ST enhances the original RANCOM method, ensuring both consistency and adaptability in the derived weight assignments.

3.3 Data generation for Statistical Thresholds

The experiment involves generating weight vectors for different numbers of criteria and analyzing their deviations from rankings obtained using the RANCOM method, which is a pairwise comparison-based approach. The core of the study consists of generating a reference weight vector that represents the significance of criteria, computing an alternative weight vector using the RANCOM method without any modifications, and measuring the differences between them. These differences are analyzed through histograms to examine the distribution of deviations across multiple scenarios with varying numbers of criteria.

For each number of criteria n in the range of 2 to 10, an independent experiment is conducted using 100,000 Monte Carlo simulations. In each iteration, a reference weight vector $\mathbf{w}$ is generated by randomly drawing values from a uniform distribution, followed by normalization to ensure that the sum equals one. This vector represents the true underlying significance of the criteria. Subsequently, the RANCOM method, which is based on pairwise comparisons, is applied to the same set of criteria without modifications. This method constructs a comparative dominance matrix, where each criterion is evaluated relative to others based on strict pairwise dominance conditions, ultimately producing a ranking-based weight vector $\mathbf{r}$. The difference vector $\mathbf{d} = \mathbf{r} - \mathbf{w}$ is then computed and stored for statistical analysis.

The absolute values of these differences are aggregated into histograms for each value of n, allowing for a visual examination of error distribution patterns. Additionally, the mean (μ) and standard deviation (σ) of the absolute differences are calculated to summarize the variability in the ranking-based estimations. The experimental data, including both individual differences and summary statistics, is stored in a structured format for further analysis.

Algorithm 1 outlines the complete process of conducting a Monte Carlo experiment for generating weight vector analysis and recording statistical data.

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Algorithm 1 Monte Carlo Experiment for Weight Vector Analysis

Input: Maximum number of criteria $N_{\max}$, Number of experiments M
Output: Raw data and statistical summaries
Initialize an empty dictionary *rawdata*
Initialize a matrix *statData* of size $(N_{\max} - 1, 2)$
for $n \leftarrow 2$ **to** $N_{\max}$ **do**
    Initialize an empty list *tmp*
    for $i \leftarrow 1$ **to** M **do**
        Generate a random normalized weight vector $\mathbf{w}$ of size n
        Compute the ranking-based weight vector $\mathbf{r}$ using pairwise dominance
        Compute the difference vector $\mathbf{d} = \mathbf{r} - \mathbf{w}$
        Append absolute values of $\mathbf{d}$ to *tmp*
    end for
    Store *tmp* in $rawdata[n]$
    Compute mean μ and standard deviation σ of $|tmp|$
    Store μ, σ in $statData[n-2]$
    Plot histogram of $|tmp|$ for visualization
end for
Save *rawdata*, $N_{\max}$, M, and *statData* to an external file

Fig. 1 presents a series of histograms illustrating the distribution of absolute deviations between random normalized weight vectors and weight vectors obtained using the traditional RANCOM method through Monte Carlo simulations. Each subplot corresponds to a different vector length n, ranging from $n = 2$ to 10. The x-axis in each histogram represents the magnitude of absolute deviations $|\mathbf{d}|$ between the random and RANCOM-derived weight vectors, while the y-axis denotes the frequency of occurrences for each deviation value across multiple Monte Carlo experiments.

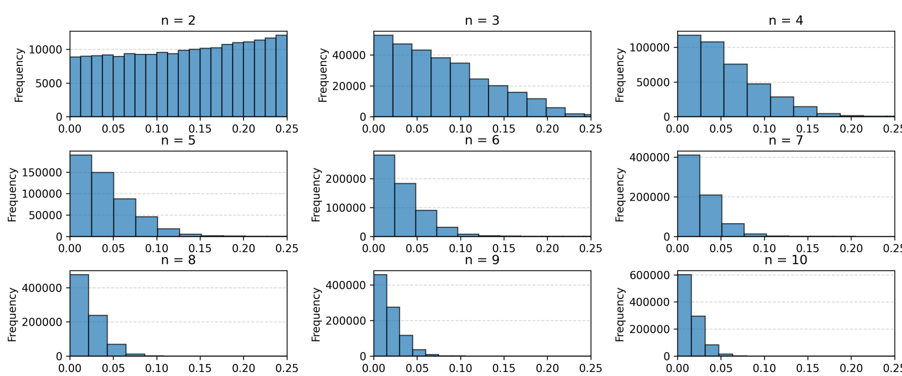

Fig. 1. Distribution of absolute deviations between random normalized weight vectors and ranking-based weight vectors from Monte Carlo simulations, depending on vector length

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Table 1. Mean absolute difference (μ) and standard deviation (σ) between the reference weight vector and the RANCOM-estimated weight vector for different numbers of criteria.

Criteria (n)	Mean (μ)	Standard Deviation (σ)
2	0.1323	0.0728
3	0.0813	0.0609
4	0.0563	0.0447
5	0.0415	0.0339
6	0.0322	0.0265
7	0.0259	0.0214
8	0.0213	0.0177
9	0.0180	0.0150
10	0.0155	0.0129

The results indicate that as n increases, the distribution of deviations becomes more concentrated near zero, suggesting that the differences between the two methods tend to decrease for longer weight vectors. Additionally, the shape of the distributions varies with n, where smaller vector lengths exhibit broader distributions, reflecting greater variability in deviations. These findings provide empirical insight into the behavior of weight deviations across different vector lengths and highlight the greater potential of the RANCOM-ST method, particularly for smaller values of n, where the traditional RANCOM approach has previously appeared less suitable.

Table 1 presents the mean absolute difference (μ) and standard deviation (σ) based on data presented on Fig. 1. The results indicate that both the mean absolute difference and the standard deviation decrease as the number of criteria increases. For $n = 2$, the mean absolute difference ($\mu = 0.1323$) and standard deviation ($\sigma = 0.0728$) are the highest, suggesting that the discrepancies between the RANCOM-estimated and reference weights are most pronounced when the number of criteria is small. As n increases, μ and σ progressively decline, reaching their lowest values for $n = 10$ ($\mu = 0.0155$, $\sigma = 0.0129$), indicating that the RANCOM method yields more accurate and stable results for larger decision-making problems. This trend suggests that RANCOM's effectiveness improves as the number of criteria increases, while for small n, the method exhibits higher deviations, making it less suitable in such cases. These findings provide empirical justification for the proposed RANCOM-ST method, which introduces an expert-driven adjustment step to address the greater discrepancies observed for small n and enhance the overall robustness of the weighting procedure.

Algorithm 2 presents the Adaptive RANCOM-ST Method for Bias Reduction, which extends RANCOM-ST by incorporating an adaptive adjustment mechanism. This approach improves the robustness of the weighting process, particularly for small n, where the standard RANCOM method tends to exhibit greater deviations. By dynamically refining weight adjustments based on statistical deviations and expert evaluation, the method ensures more accurate and reliable weight estimation.

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Algorithm 2 Adaptive RANCOM-ST Method for Bias Reduction

```
Require: Weight vector w = [w_1, w_2, ..., w_n]
        Statistical data table statData
Ensure: Adjusted ranking vector R
n ← length of weight vector
Initialize matrix M of size n × n with zeros
                              ▷ Extract mean and standard deviation from data table
μ ← statData[n − 2, 0]                                  ▷ Mean correction factor
σ ← statData[n − 2, 1]                                  ▷ Standard deviation
                                    ▷ Phase 1: Compute Pairwise Ranking Matrix
for i = 1 to n do
    for j = 1 to n do
        if w_i > w_j then
            M[i, j] ← 1
        else if w_i < w_j then
            M[i, j] ← 0
        else
            M[i, j] ← 0.5
        end if
    end for
end for
Compute row-wise sums: S[i] = Σ_{j=1}^{n} M[i, j]
Normalize these sums:
            S[i] ← S[i] / Σ_{k=1}^{n} S[k]
                                 ▷ Phase 2: Expert-Driven Statistical Correction
for i = 1 to n do    ▷ The expert assess whether S[i] is lower or higher than w[i].
    if S[i] < w_i then
        diff ← w_i − S[i]
        if diff is low then
            S[i] ← S[i] + (μ − σ)
        else if diff is medium then
            S[i] ← S[i] + μ
        else if diff is high then
            S[i] ← S[i] + (μ + σ)
        end if
    else if S[i] > w_i then
        diff ← S[i] − w_i
        if diff is low then
            S[i] ← S[i] − (μ − σ)
        else if diff is medium then
            S[i] ← S[i] − μ
        else if diff is high then
            S[i] ← S[i] − (μ + σ)
        end if
    end if
end for
Normalize final values:
            R[i] = S[i] / Σ_{k=1}^{n} S[k]
return R
```

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4 Experiment and discussion

In the presented experiment, a dataset containing statistical data obtained from Algorithm 1 is utilized. The primary objective is to evaluate the proposed approach outlined in Section 3.2. To achieve this, expert responses to additional queries associated with the RANCOM-ST procedure are simulated.

The experiment follows a structured process as detailed below. A series of simulations are performed, where the number of criteria varies from 2 to 10. For each scenario, a Monte Carlo simulation of size 100,000 is executed. The true weight vectors are randomly generated and subsequently processed using both the original RANCOM method and an improved version RANCOM-ST method with statistical data. The differences between the estimated weights and the true weights are then analyzed.

Formally, for each number of criteria, the process is executed as follows:

- Generate a true weight vector for the given number of criteria.
- Compute the estimated weight vector using the RANCOM approach.
- Apply the improved RANCOM-ST method incorporating statistical adjustments.
- Compute the deviations between the true weights and the estimated weights for both methods.
- Store and analyze the deviation results.

The RANCOM-ST method itself is simulated using the following procedure. Given a weight vector of length n, an $n \times n$ matrix is initialized with zeros. The matrix elements are filled based on pairwise comparisons of weight values. If one weight is greater than another, the corresponding matrix entry is set to 1; if smaller, it is set to 0; and in the case of equality, it is assigned a value of 0.5.

Subsequently, the row sums of the matrix are computed and normalized. Statistical parameters μ and σ, retrieved from the statistical dataset, are then used to adjust the weight estimates. These adjustments ensure that discrepancies between the computed and true weight distributions are minimized. The level of adjustment is determined as follows:

- If the difference is less than $\mu - 0.5\sigma$, it is considered low, and the adjustment is $\mu - \sigma$.
- If the difference is between $\mu - 0.5\sigma$ and $\mu + 0.5\sigma$, it is considered medium, and the adjustment is μ.
- If the difference is greater than $\mu + 0.5\sigma$, it is considered high, and the adjustment is $\mu + \sigma$.

These corrective measures bring the estimated weights closer to the true values. The final weight estimates are normalized to ensure they sum to one. This methodology allows for a comparative evaluation of the original and improved RANCOM-ST approaches, demonstrating the impact of statistical adjustments on the accuracy of the weight estimation process.

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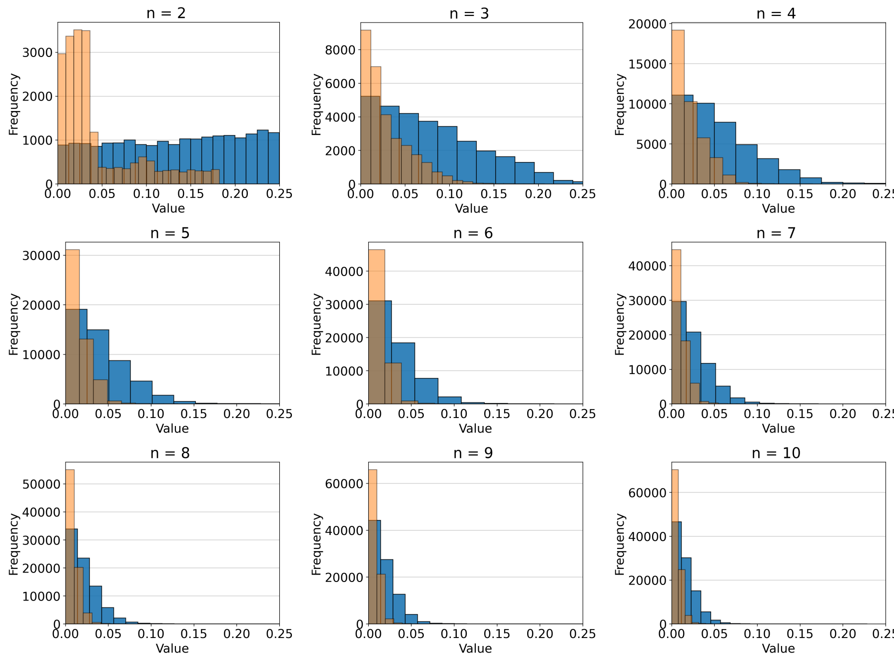

Fig. 2. Distribution of absolute deviations between true and estimated weights for RANCOM (blue) and RANCOM-ST (orange) methods. The histograms represent results from 10,000 Monte Carlo simulations conducted for varying numbers of criteria.

Fig. 2 illustrates the comparative analysis between the RANCOM method (blue bars) and the RANCOM-ST method (orange bars). Histograms present distributions of absolute deviations between true and estimated weight vectors for varying numbers of criteria ($n = 2$ to $n = 10$). Each histogram represents the aggregated results from 10,000 Monte Carlo simulations, offering comprehensive insights into each method's performance.

The analysis clearly demonstrates that RANCOM-ST consistently achieves smaller deviations compared to the original RANCOM approach. For smaller criteria sets ($n = 2, 3, 4$), RANCOM produces larger deviations characterized by broader, flatter distributions, indicating reduced accuracy. Conversely, RANCOM-ST yields distributions concentrated closer to zero, reflecting increased precision and reliability.

As the number of criteria increases ($n \geq 5$), deviations for both methods decrease, demonstrating improved estimation accuracy with more criteria. Nonetheless, the superiority of the RANCOM-ST method remains evident, consistently resulting in lower deviations than RANCOM. This indicates that the statistical adjustments incorporated into RANCOM-ST substantially improve accuracy, particularly for low-dimensional scenarios where the discrepancy between methods is most pronounced.

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In conclusion, the experiment confirms that the proposed RANCOM-ST method notably enhances estimation accuracy compared to the original RANCOM approach across all tested scenarios. The most significant benefits of RANCOM-ST are observed for cases involving fewer criteria, highlighting its potential for practical applications.

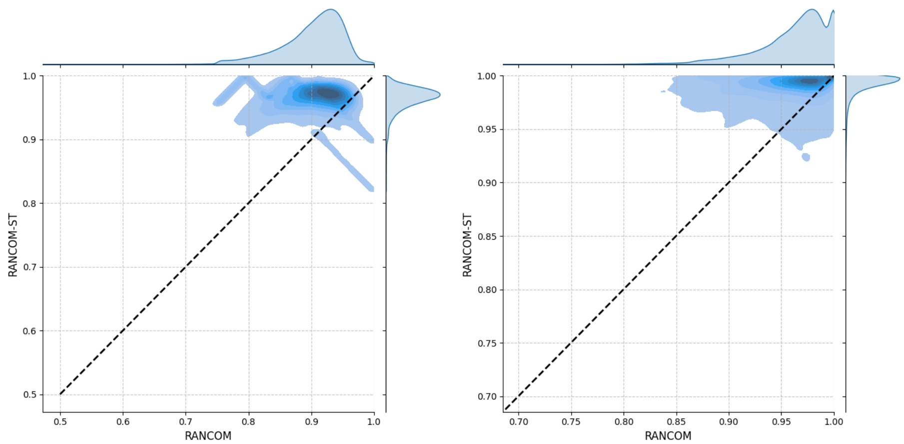

Fig. 3. Comparison of RANCOM and RANCOM-ST methods based on the Weight Similarity Coefficient (WSC2, left) and the Pearson correlation coefficient (right).

Fig. 3 presents a comparison of the RANCOM and RANCOM-ST methods based on two evaluation criteria: the Weight Similarity Coefficient (WSC2) on the left [11] and the Pearson correlation coefficient on the right. Each plot visualizes joint kernel density estimations, where darker regions indicate higher densities, reflecting the frequency of specific result combinations obtained from the experiments. The dashed diagonal lines, extending from (0.5, 0.5) to (1.0, 1.0), represent the ideal scenario of perfect agreement between the two methods. The majority of data points are concentrated near the upper-right corner (1.0, 1.0), indicating a generally high level of similarity and correlation between the methods. However, the left plot, which depicts WSC2 values, exhibits a wider dispersion along the vertical axis, suggesting variations in performance between the methods. In contrast, the right plot, representing Pearson correlation coefficients, shows a more concentrated distribution with minimal deviations from the diagonal, indicating that both methods produce highly consistent correlation values. Notably, the results demonstrate that the proposed RANCOM-ST approach achieves visibly better performance, as evidenced by the higher concentration of points closer to the ideal diagonal, particularly in the WSC2 evaluation, where the method consistently yields improved similarity measures.

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5 Conclusions

This study introduced the RANCOM-ST method, an adaptive extension of the RANCOM approach, designed to mitigate bias in subjective weighting methods within MCDA. By integrating statistical thresholds into the traditional ranking-based weighting process, the proposed method enhances expert-driven adjustments, ensuring more consistent and reliable weight assignments.

Through Monte Carlo simulations, the experimental results demonstrated that RANCOM-ST consistently outperforms the standard RANCOM method, particularly for smaller numbers of criteria, where weight estimation discrepancies are more pronounced. The statistical threshold mechanism effectively refines expert evaluations by leveraging mean and standard deviation-based adjustments, thereby reducing variability and improving alignment with true weight distributions. This structured correction process addresses the inherent limitations of purely subjective weighting techniques, offering a robust mechanism to enhance decision support systems.

Comparative analyses, including the WSC2 coefficient and Pearson correlation coefficient evaluations, further validated the superior performance of RANCOM-ST. The results illustrated that the proposed method consistently achieves higher weight similarity and correlation values, reinforcing its effectiveness in reducing inconsistencies and enhancing accuracy in expert-based MCDA models.

In conclusion, RANCOM-ST represents a significant refinement of subjective weighting methodologies, offering an improved balance between expert intuition and numerical rigor. Future research could explore its application in hybrid MCDA frameworks, extend its integration with fuzzy and interval-based uncertainty modeling, and investigate its adaptability to large-scale decision-making scenarios. Additionally, further empirical validations across diverse application domains would provide deeper insights into the method's practical impact and scalability. Moreover, ongoing optimization and refinement of the algorithm could further enhance its accuracy and robustness, potentially leading to even greater improvements in performance.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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