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A Novel Simplified Yielded Aggregation Index (SYAI) Method for Enhancing Multi-Criteria Decision-Making

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Abstract. This research introduces a new MCDM approach known as the Simplified Yielded Aggregation Index (SYAI) to overcome the main problems with traditional frameworks. The first step proposes a new way to normalize goal-type criteria, so decision-makers can assess alternatives according to their ideal targets, not just the extremes they reach. The second aim suggests using a unified transformation for all criteria, turning every criterion into a single type of value, making the decision more transparent and fairer. The third goal involves making a flexible ranking of possibilities by introducing a new weighted closeness score based on parameters around the ideal and anti-ideal references. A variety of scenarios and analyses involving sensitivity were conducted to compare SYAI with recognised MCDM methods, such as TOPSIS, VIKOR, WASPAS, and SAW. The results displayed that SYAI remained consistent with previous methods, as proved by the high Spearman correlation found in rankings. Having a unified approach and a tunable β parameter allowed the algorithm to respond flexibly to decisions without slowing down, and this is useful in situations like supply chain management and healthcare. The new developments make SYAI well-suited for various real-world uses, as it is both powerful, flexible, and scalable.

2020 Mathematics Subject Classifications: AMS classification codes

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1. Introduction

In traditional MCDM methods, the main division between criteria is benefit (making choices that maximize) and cost (choosing options that minimize). Because this classification is binary, it fails to address many decision problems that set clear goals and require meeting particular targets, rather than just reaching either maximum or minimum values. Challenges like these prevent the evaluation of important options that help a company achieve strict targets for things such as temperature, shipping, and choosing resources [1]. Although MCDM methods are widely used, there are considerable knowledge gaps within the field. One weakness is the narrow use of credible but basic decision frameworks that can strike a balance between theoretical integrity and computational efficiency. Most traditional MCDM techniques are based on rigid rules of aggregation and normalization which are not easily able to adjust to the complexity of the real world [2]. As seen in Pelissari et al. [3], decision-makers often struggle to grasp how trade-offs are packaged in different criteria – this is particularly difficult to grasp when mixing categories such as benefits, costs and goal-based metrics. This rigidity impedes successful communication, reducing transparency in decision-making and making traditional techniques less applicable in a dynamic or rapidly changing situation where the metrics of performance or preferences of stakeholders may change [4, 5]. Indeed, Rodzi et al. [6, 7] demonstrated how epistemic uncertainty can guide decision-making in the real world, through the examples of determining obstacles in digital agriculture and waste recycling in Seremban through the application of DEMATEL, reinforcing the necessity of more versatile, uncertainty-considering models [8].

By adding goal-type criteria, MCDM models improve the usefulness and effectiveness of the decision-making process. García et al. [9] discovered that vaguely stating performance criteria may cause people to make less effective decisions, especially when it comes to loan approvals. According to their studies, using target-specific evaluations is crucial for applying MCDM [9]. Hybrid models, which bring together popular MCDM approaches are necessary, according to [10], when choosing wisely under challenging situations where benefit and cost alone cannot guide the decision, including recent application-oriented frameworks such as the Adaptive Utility Ranking Algorithm (AURA) for blockchain enabled microfinance[11].

Advancements in the field of MCDM have aimed to address these challenges by integrating modern techniques that enhance traditional frameworks. Modern enhancements revolve around the creation of the MCDM methodologies based on unified normalization framework, flexible distance measures and modernizations in aggregation operators [12]. Innovations of this sort are necessary for the creation of models that support transparency and flexibility in the MCDM process [13, 14]. For instance, studies have revealed that the use of these comprehensively normalized algorithms increases the reliability of decision outcomes – as observed in energy and environmental modeling studies [2, 15]. In addition, the use of flexible distance measures is beneficial since it implies more responsive structure of decision-making that can correspond to the change of availability of data and contextual dynamics [16, 17]. These observations appear further justified by the contributions of Rodzi to bipolar neutrosophic hypersoft surroundings, pointing to the benefits of sound extension and scoring setups in responding to a deep ingenuity [18]. The possibility of infusing decision-making equipment with both theoretical strength and realism application continues to be a major avenue for future research as seen from the work of Rehman and Ali [19] on healthcare supply chains and research on renewable energy sustainability [20].

Asadabadi [21] highlights the possible synergy of MCDM methods and fuzzy set applications with an aim of addressing the uncertainties presented in prescribing decision context. This integration enables a more advanced perspective on the management of qualitative and quantitative criteria in parallel. In addition, advanced strategies have proven to be promising in giving decision makers a better sense of the trade-offs involved, for example, use of better measures of symmetry and sine entropy model [22, 23]. Jana et. al [24] has shown that when a hybrid MCDM framework includes bipolar fuzzy logic, it helps better address contradictory preferences and allow more accurate decisions when analyzing economic conditions. A recent study by Ashraf et al. [25] establishes that combination of spherical fuzzy Z-numbers with a Sugeno—Weber model results in considerably enhanced reliability of climate change evaluation due to enriched expert judgment semantics in deep uncertainty settings. The importance of similarity-based methods to improve decision accuracy in an uncertain environment has also been the focus of recent research; e.g., Hammad, Al-Sharqi, and Rodzi [26] introduced similarity measures on bipolar interval-valued fuzzy soft sets, which can be used to make more accurate comparisons of alternatives in MCDM applications. The use of these new practices guarantees that decision makers can compare alternatives with due regard even where criteria weights are unknown resulting in more knowledgeable decisions.

Furthermore, scientists have been calling for hybrid models made possible through blending different MCDM approaches and external parameters [27, 28]. For example, the use of fuzzy logic alongside the AHP helps create a more flexible structure for decision-making process that will embrace the qualitative analysis and hence deal with the complexity that would proceed normally in real-life situation [17, 29]. This hybridization makes it easier to understand the preferences of stakeholders and increases transparency of the decision-making process as a whole [30]. According to the recent research by Jana and Hezam [31], the merging of multi-polar fuzzy sets with the EDAS approach is effective in evaluating inconsistent expert opinions and enhancing the reliability of decisions in the industrial site selection problem. A recent work combining both MARCOS and CoCoSo techniques showed that integrating MCDM techniques could greatly enhance the robustness and accuracy of decisions made, especially in digital bank performance measurement [32]. Also, debates have been conducted on ways such as the Enhanced ELECTRE method and the use of interval-valued fuzzy sets to enhance the reliability of the previous approaches [33, 34].

When working with mixed categories (benefit, cost, and aim) or ambiguous data, decision-makers often struggle to grasp how trade-offs are managed across varied criteria. This rigidity can make interpretation difficult. Furthermore, traditional techniques' inability to adapt makes them less effective in dynamic or quickly changing situations where performance measures, data availability, or stakeholder preferences may change over time.

To close these gaps, new techniques that take use of unified normalization frameworks, flexible distance measures, and current developments in aggregation operators must be developed. By providing decision-makers with tools that are not only theoretically sound but also useful, interpretable, and sensitive to changing decision contexts, such advancements hold the potential to increase the transparency and adaptability of MCDM models.

To address these shortcomings, the Simplified Yielded Aggregation Index (SYAI) comes up as a new approach aimed at facilitating the process of aggregation without sacrificing the capability of incorporating the nowadays advancements in normalizations and dynamic weighting mechanisms. To address the problems seen in traditional approaches, a brand new goal-oriented technique for normalization has been developed. This approach allows leaders to choose the values they want for different requirements, which aids in evaluating alternatives broadly. This process first sets what is considered ideal for goal-type criteria, and then measures how far the real numbers are from these targets. By normalizing the data, it is now possible to compare different alternatives systematically on each separate dimension [35]. With this method, it becomes easier to consider practical needs when making decisions, helping to set and reach important operational goals. Many practical cases where target values should be preserved demonstrate the usefulness of the goal-oriented normalization framework. In temperature control systems, it allows evaluating performance by matching the set temperature more closely, instead of simply finding extreme values. Likewise, firms can measure their logistical performance in delivery by comparing the actual timing of deliveries to those they planned in advance [36]. When allocating resources, organizations can establish particular goals to shape decisions rather than use standard optimization approaches [37]. It helps ensure that the decision-making process produces accurate results by focusing on real-world needs.

The introduction of SYAI as a unified normalization process is a significant development in MCDM as it is applicable to cost, benefit, and goal-type criteria at once. Each traditional MCDM framework usually features normalization methods that are specific to the different criteria types. Despite being theoretically solid, this way of thinking can sometimes result in private biases and inconsistencies when evaluating various criteria. Typically, benefits are improved to the fullest, while costs are reduced at the same time, which leads to difficulties when judging these various aspects [1]. Avoiding these inconsistent outcomes, SYAI ensures that the results of the decision-making process are more understandable and reliable. The SYAI normalization approach uses the same transformation function to place all the normalized values into a valid interval, regardless of what traits the criteria are meant to assess. With this feature, the preprocessing stage becomes simpler, as only one process can be used to standardize all criteria, leading to a strong reduction in the complexity found in traditional MCDM methods. This allows those in charge to pay closer attention to the quality of their choices, rather than focusing too much on managing complicated normalization routines. This benefit is most useful when evaluating many options and criteria in a decision matrix.

The SYAI way boosts fairness and improves efficiency in decision-making by assigning equal value to all criteria on the same scale [10]. With this treatment, scores can be compared accurately across various approaches. Furthermore, its simplified structure allows computers to process large decision matrices at top speed without sacrificing reliability, which is important for swift and fast-changing settings [35]. One of the main goals in Multi-Criteria Decision-Making (MCDM) is to rank different alternatives by their performance. Although TOPSIS is widely acknowledged as an effective method in its area, it has limitations when it comes to adjusting the relative strengths of proximity to the ideal and distance from the anti-ideal scenario. This matters when priorities change, and it becomes essential to rank items with care to achieve more transparent and flexible ranks [38, 39]. Therefore, introducing the weighted closeness score with β helps overcome these challenges.

This new way of rating relationships provides users with built-in flexibility. β parameter determines how important being close to the best solution is compared to being far from the worst solution. As a result, the rankings can be adjusted to suit particular decision-making purposes, which also makes them more straightforward to interpret. This way, all the final scores fall within a fixed region, with better alternatives represented by higher scores which is necessary for easy comparison. Puška et al. [40] and Jakovljević et al. [41] pointed out that having consistent and transparent scoring matters a lot, as how scores are calculated can strongly impact the final MCDM results. The flexibility of the weighted closeness score method makes it practical for both big decision matrices and decision support systems. Offering rapid data processing, this type of system is excellent for supply chain management and healthcare, where time matters, and there is a need for prompt and informed choices. The β parameter, which the method includes, allows decision-makers to select the best ratio between ideal and anti-ideal distances, meaning operations can be tailored to readily handle shifting needs.

Facing recent global difficulties has made it clear that MCDM calls for advanced approaches. The COVID-19 pandemic caused significant challenges for healthcare systems in sharing resources and choosing who would supply essential medical supplies and equipment. This situation made it important to have a process adaptable to the dynamic weighting between balancing cost actions and importance in decisions [42]. The weighted closeness score can help decision-makers resolve problems involving numerous conflicting objectives [39]. Overall, a weighted closeness score with a parameter β significantly improves the method of ranking in MCDM by making it more flexible, efficient, and easy to understand. By allowing decision-makers to correctly adjust their preferences, this process improves the usefulness of TOPSIS and similar approaches, helping them come up with a more accurate answer for various types of problems. Being flexible is crucial for managing intricate decisions in fields that are rapidly evolving with more uncertainty.

To close the gaps left by classical methods, SYAI emerges as a user-friendly yet theoretically sound decision-making framework. It provides enhanced overview and evidence-based basis in the decision outcomes. This integration of classical approaches with growing innovations can greatly enhance operational effectiveness and interaction with stakeholders, filling notable gaps in current MCDM applications.

2. The Proposed Method

The Simplified Yielded Aggregation Index (SYAI) is a present-day, unified way to compare and sort different alternatives in MCDM situations. SYAI is designed to improve on TOPSIS, fixing its flaws by using an efficient method to integrate all criteria with a universal normalization function that can handle both positively valued benefit or cost and negatively valued goal criteria.

Unlike traditional approaches where several transformation rules are used, SYAI ensures that every criterion type always follows the same consistent and simple normalization model. This helps the model become faster, clearer and simpler to operate while still having strong theoretical bases.

SYAI stands out for relying on just a single parameter that can be tuned. β which controls the balance between being close to the best solution and being far from the worst solution. When β is greater than 0.5, it puts more weight on reaching the ideal solution. Conversely, β less than 0.5 is concerned more with sidestepping the anti-ideal. The weighting mechanism allows SYAI to respond to different needs and problems in decision making.

The SYAI method is presented in Figure 1, showing how the ranking is achieved from first creating the matrix to its final result.

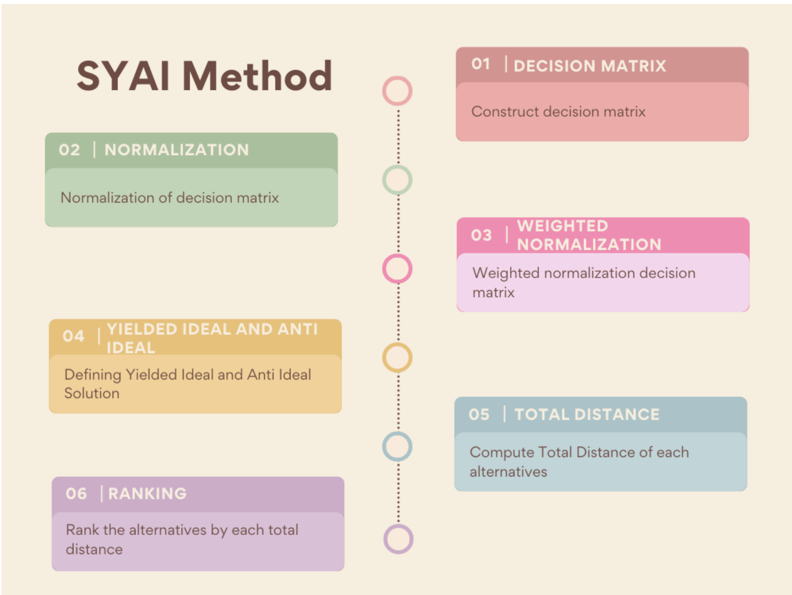

Figure 1: Step by step of SYAI Method

Below is a detailed explanation of the SYAI method steps:

Step 1: Construct the Decision Matrix

In the SYAI method, the evaluation process begins with constructing a decision matrix $X = [x_{ij}]$, where $i = 1, 2, \ldots, m$ denotes the alternatives and $j = 1, 2, \ldots, n$ represents the criteria. Each element x_{ij} captures the performance of alternative A_i on criterion C_j.

Formally, the matrix is defined as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

Step 2: Normalize the Decision Matrix

To ensure dimensionless comparability across mixed criteria, SYAI applies a unified normalization formula:

$$N_{ij} = C + (1 - C) \cdot \left(1 - \frac{|x_{ij} - x^*|}{R}\right) \tag{2}$$

where $C = 0.01$ is a fixed constant to prevent zero outputs, x^* is the ideal reference (maximum for benefit, minimum for cost, or target for goal criteria), and $R = \max(x_{ij}) - \min(x_{ij})$ is the range of criterion C_j.

Step 3: Calculate Weighted Normalized Matrix

The normalized scores are multiplied by the corresponding criterion weights w_j, with the constraint $\sum_{j=1}^{n} w_j = 1$, to reflect each criterion's relative importance:

$$v_{ij} = w_j \cdot N_{ij} \tag{3}$$

Step 4: Determine Yielded-Ideal and Anti-Ideal Solutions

Next, SYAI identifies the yielded ideal A_j^+ and anti-ideal A_j^- solutions:

$$A_j^+ = \max_i v_{ij}, \quad A_j^- = \min_i v_{ij} \tag{4}$$

Step 5: Compute Weighted Closeness Score

After determining the ideal A_j^+ and anti-ideal A_j^- solutions in Step 4, the next step is to measure how close each alternative is to these reference points. The distance of alternative i from the ideal and anti-ideal solutions is computed using the aggregated absolute differences across all criteria:

$$D_i^+ = \sum_{j=1}^{n} \left| v_{ij} - A_j^+ \right|, \quad D_i^- = \sum_{j=1}^{n} \left| v_{ij} - A_j^- \right| \tag{5}$$

Using these distances, the closeness score D_i for each alternative is calculated based on a weighted inverse-ratio formulation that allows tunable preference between ideal proximity and anti-ideal remoteness:

$$D_i = \frac{(1 - \beta) \cdot D_i^-}{\beta \cdot D_i^+ + (1 - \beta) \cdot D_i^-} \tag{6}$$

where:

- D_i^+ denotes the distance of alternative i from the ideal solution,

- D_i^- denotes the distance of alternative i from the anti-ideal solution,
- $\beta \in (0, 1)$ is a parameter that adjusts the relative importance between ideal proximity and anti-ideal remoteness.

This formulation ensures that the closeness score $D_i \in [0, 1]$, where a higher score indicates a better alternative. If $\beta > 0.5$, the method emphasizes closeness to the ideal solution; if $\beta < 0.5$, it gives more importance to avoiding the anti-ideal solution. This balance enables flexible decision-making aligned with the decision maker's preference structure.

Step 6: Rank the Alternatives

Finally, alternatives are ranked in descending order based on their computed closeness scores D_i. The alternative with the highest D_i is considered the best.

3. Computational Analyses

3.1. Numerical Example

In this section, a numerical example demonstrate the implementation of the Simplified Yielded Aggregation Index (SYAI) method for evaluating and ranking three alternatives ($A1, A2, A3$) based on four criteria: Cost, Quality, Delivery Time, and Temperature. The objective is to identify the most suitable alternative by applying the SYAI framework.

Problem Context and Criteria

The problem considers the evaluation of three alternatives under the following criteria:

- Cost ($C1$): Price of the alternative (Cost criterion).
- Quality ($C2$): Performance quality score (Benefit criterion).
- Delivery Time ($C3$): Number of days for delivery (Cost criterion).
- Temperature ($C4$): Temperature level, aiming for a target of 60°C (Goal criterion).

Criteria Weights and Types

Table 1 summarizes the criteria, types, and assigned weights.

Table 1: Criteria, Types, and Weights.

Criterion	Description	Type	Weight (w_j)
C1	Cost	Cost	0.25
C2	Quality	Benefit	0.25
C3	Delivery Time	Cost	0.25
C4	Temperature	Goal (60°C)	0.25

Initial Data and Decision Matrix

Table 2 shows the raw decision matrix.

Table 2: Decision Matrix.

Alternative	Cost	Quality	Delivery Time	Temperature
A1	200	8	4	30
A2	250	7	5	60
A3	300	9	6	85

3.1.1. Step-by-Step Procedure

Step 1: Compute Decision Matrix

The SYAI method relies on the decision matrix to store the basic performance values for each alternative against various criteria. In this step, the rows display the alternatives and the columns represent the different evaluation criteria. Ratings in the matrix are made by experts, from earlier data or by measuring the alternatives, showing how much each alternative matches the different criteria. This form of representation makes it easier to assess, standardize and compare data in the next phases of the SYAI process as shown in Table 3.

Table 3: Decision Matrix.

Alternative	Cost	Quality	Delivery Time	Temperature
A1	200	8	4	30
A2	250	7	5	60
A3	300	9	6	85

Step 2: Normalize the Decision Matrix

Normalization converts all criteria to a dimensionless scale so no single factor dominates. Using $C = 0.01$, apply the unified formula using Equation (1). Using $C = 0.01$, max $\{300, 9, 6, 85\}$, min $\{200, 7, 4, 30\}$, and ideal $\{200, 9, 4, 60\}$, the normalized matrix is shown in Table 4:

Table 4: Normalized Decision Matrix.

Restaurant	C1	C2	C3	C4
A1	1	0.505	1	0.46
A2	0.505	0.01	0.505	1
A3	0.01	1	0.01	0.55

For illustration, below are example calculations:

$$\text{C1 (Cost, min-type)} \quad r_{11} = \frac{200}{200} = 1.000, \quad r_{21} = \frac{200}{250} = 0.505, \quad r_{31} = \frac{200}{300} = 0.010.$$

$$\text{C2 (Quality, max-type)} \quad r_{11} = \frac{8}{9} = 0.505, \quad r_{21} = \frac{7}{9} = 0.010, \quad r_{31} = \frac{9}{9} = 1.000.$$

$$\text{C3 (Delivery Time, min-type)} \quad r_{11} = \frac{4}{4} = 1.000, \quad r_{21} = \frac{4}{5} = 0.505, \quad r_{31} = \frac{4}{6} = 0.010.$$

$$\text{C4 (Temp, target-type, target = 60)} \quad r_{11} = 1 - \frac{|30-60|}{\max|85-60|, |30-60|} = 0.460,$$

$$r_{21} = 1 - \frac{|60-60|}{25} = 1.000, \quad r_{31} = 0.550.$$

Normalization ensures that each criterion, regardless of its original scale, contributes fairly to the final evaluation. This unified approach allows consistent comparison across cost, benefit, and target-type criteria, improving the robustness and interpretability of the decision-making process.

Step 3: Calculate Weighted Normalized Matrix

Weights $w_j = 0.25$ are applied uniformly by Equation (2) and the results is shown in Table 5.

Example Calculations for Weighted Normalized Matrix

Below are example calculations for Step 3 using the normalized values from Table 4 and equal weights $w_j = 0.25$:

$$\text{A1, C1 (Cost)} \quad v_{11} = r_{11} \times w_1 = 1.000 \times 0.25 = \boxed{0.25000}$$

and Table 5 illustrates weighted normalized decision matrix :

Table 5: Weighted Normalized Decision Matrix.

Alternative	Cost	Quality	Delivery Time	Temp
A1	0.25000	0.12625	0.25000	0.11500
A2	0.12625	0.00250	0.12625	0.25000
A3	0.00250	0.25000	0.00250	0.13750

Step 4: Identify Yielded Ideal and Anti-Ideal Solutions

The ideal and anti-ideal solutions are:

$$A_j^+ = [0.25, 0.25, 0.25, 0.25], \quad A_j^- = [0.0025, 0.0025, 0.0025, 0.115]$$

Step 5: Compute Weighted Closeness Score

Let's define the closeness score D_i based on distances from the ideal and anti-ideal points, blended using the parameter β, which is set to 0.5 in this study. The calculation is performed using Equation (5).

Example Calculation for A1 under C1 (Cost)

From the weighted normalized matrix:

$$v_{A1,C1} = 0.25000$$

From the ideal and anti-ideal values:

$$A^+_{C1} = 0.25000, \quad A^-_{C1} = 0.00250$$

Summing across all four criteria (not shown here in detail), we get:

$$D^+_1 = 0.25875, \quad D^-_1 = 0.61875$$

Using the closeness score formula with $\beta = 0.5$:

$$D_1 = \frac{\beta \cdot D^-_1}{\beta \cdot D^-_1 + (1-\beta) \cdot D^+_1} = \frac{0.5 \cdot 0.61875}{0.5 \cdot 0.61875 + 0.5 \cdot 0.25875} = \frac{0.309375}{0.43875} = \boxed{0.705128}$$

The corresponding distances and resulting closeness scores are illustrated in Tables 6 and 7.

Table 6: Distances to Ideal and Anti-Ideal Solutions.

Alternative	**Ideal Distance** (D^+_i)	**Anti-Ideal Distance** (D^-_i)
A1	0.25875	0.61875
A2	0.49500	0.38250
A3	0.60750	0.27000

Table 7: Closeness Scores of Alternatives.

Alternative	**Closeness Score** (D_i)
A1	0.705128
A2	0.435897
A3	0.307692

In Table 6, the absolute distances of each alternative from the ideal and anti-ideal solutions are provided. These values were then used to compute the closeness scores shown in Table 7 using the weighted formula in Equation (5). The closeness score reflects how close each alternative is to the ideal condition while factoring in its distance from the least desirable outcome. As shown, Alternative A1 has the highest closeness score, suggesting it is the most favorable option. A2 and A3 follow, with lower scores indicating comparatively reduced performance across the evaluated criteria.

Step 6: Rank the Alternatives

Finally, the alternatives are ranked in descending order based on their computed closeness scores D_i, as shown in Figure 2. The alternative with the highest score is considered the most favorable, as it indicates closer proximity to the ideal solution and greater distance from the anti-ideal.

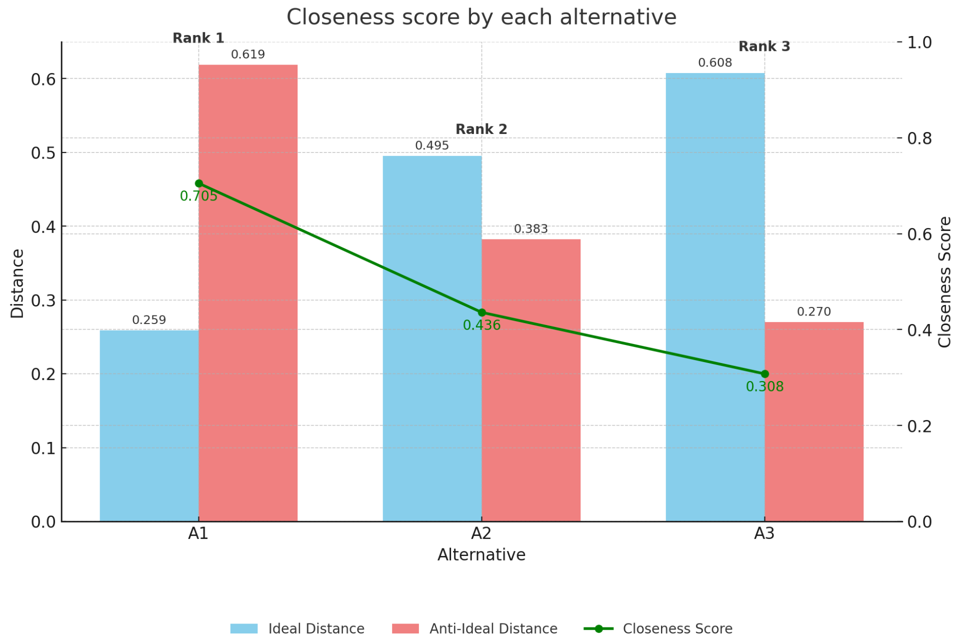

Figure 2: Closeness score by each alternatives

From the Figure 2, Alternative A1 scores 0.705 for closeness, while A2 receives 0.436 and A3 gets 0.308. It is consistent with the expected distance relationships: A1 scores closest to the ideal, whereas A3 shows the greatest distance from the ideal. These results confirm that A1 is the optimal choice under the SYAI framework, supported by both the calculated scores and the graphical illustration.

3.2. Sensitivity analysis

For multi-criteria decision-making, it is necessary to ensure that the final rankings remain solid when input conditions change. Sensitivity analysis is a useful way to check how changes in the decision variables affect the quality and stability of each option. For this study, both the weights given to the criteria and the β parameter are examined through sensitivity analysis in SYAI. This helps confirm that the closeness results are constant and the rankings of the alternatives are still secure if there are any changes in assumptions or preferences.

The analysis is performed in two stages. Weight sensitivity analysis means examining how the rankings alter when various weights are given to the different criteria. In β sensitivity analysis, we look into how the importance given to both proximity options is reflected in the scores and places the locations receive. Altogether, these analyses provide information on the model's sensitivity and steer decision-makers in choosing the appropriate parameters. Figure 3 shown the weight sensitivity for each alternatives.

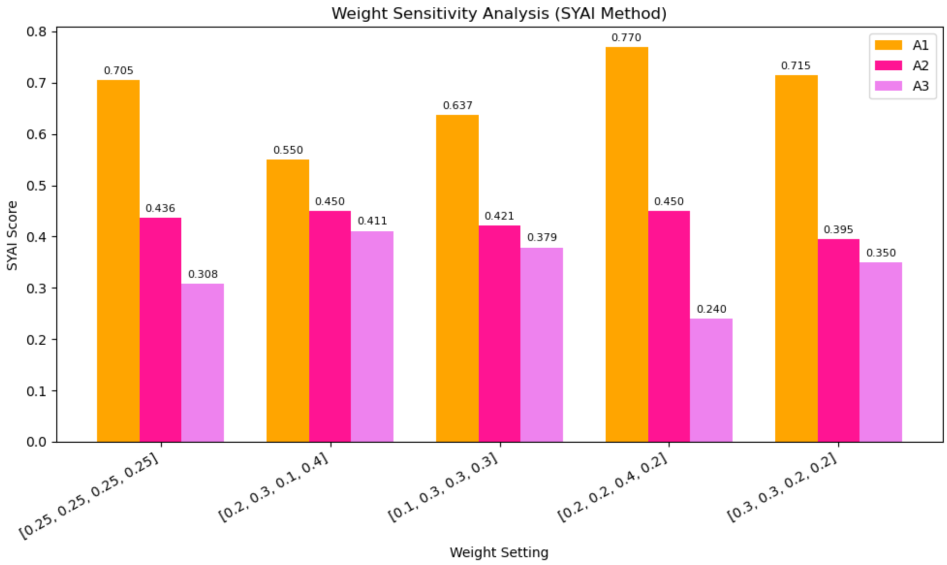

Figure 3: Weight Sensitivity Analysis (SYAI Method)

To test how sensitive the SYAI method is to weight adjustments, the evaluation considered how different weights were applied to the four decision criteria: Cost, Quality, Delivery Time, and Temperature as shown in Figure 3. In all cases, β was set to 0.5 so that both ideal and anti-ideal distances were given equal importance. All three alternatives (A1, A2, and A3) were compared across multiple settings, to reflect differences in the importance attached to each criterion.

Results show that the ranking of alternatives stays similar, regardless of the adjustments to the weights. Among all four scenarios, Alternative A1 always had the highest SYAI closeness, showing its high performance even with different weight priorities. Alternative A2 ranked second with scores between 0.395 and 0.45, and alternative A3 remained the least preferred with scores ranging from 0.24 to 0.4111. This repeated ranking clearly indicates that SYAI can handle different preferences among decision-makers.

In general, the SYAI with $\beta = 0.5$ shows that it can provide dependable conclusions, even when the strength of each factor changes. Because the average grades remain stable, the approach can work well in settings where opinions on importance may be different between people or situations.

After examining weight sensitivity, the main goal in the following phase is to observe the impact of β sensitivity on the closeness scores and ranking results within the SYAI system. Figure 4 presents a line chart of β sensitivity.

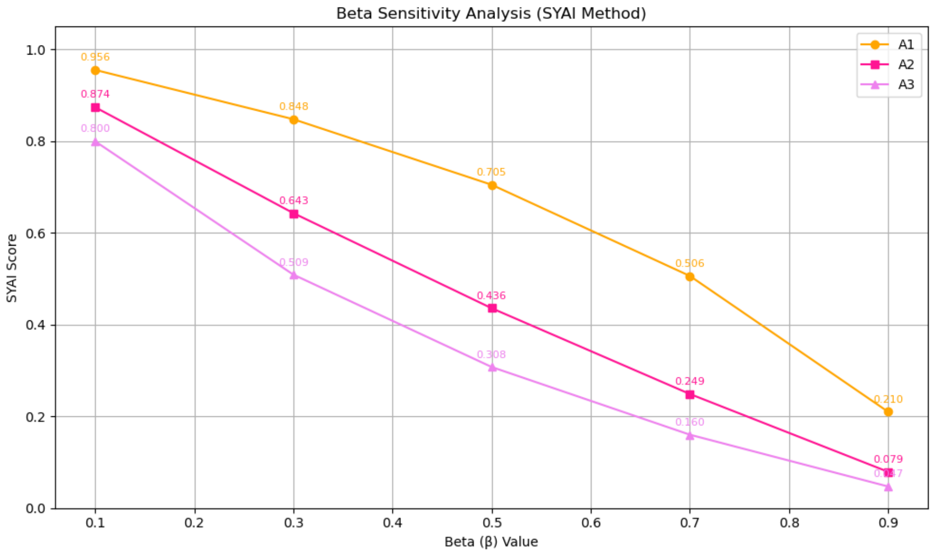

Figure 4: β Sensitivity Analysis (SYAI Method)

The line in the Figure 4 shows the impact of the β parameter on SYAI scores, but all criteria remain with the same weight of 0.25. The equal value given to each criterion makes the comparison fair and without bias. To control how close a solution is to the ideal and how far it is from the anti-ideal, four experts use the β parameter with five settings: 0.1, 0.3, 0.5, 0.7, and 0.9. Choosing a small β gives extra importance to avoiding the undesirable outcomes, whereas a large β focuses on selecting the very best (ideal) outcome.

According to the Figure 4, the order of alternatives does not change with different β values: A1 gets the highest SYAI score, A2 takes second place, and A3 comes third. For instance, A1 changes from a score of 0.9556 at $\beta = 0.1$ to 0.2099 at $\beta = 0.9$, while A2 goes from 0.8743 to 0.0791, and A3 falls from 0.8000 to 0.0471. Since β is paying less attention to anti-ideal closeness and more to ideal closeness, the drop is reasonable. The fact that the SYAI rankings remain the same for all β values means the method is trustworthy for decision-making in any situation.

3.3. Comparative analysis

In this comparative analysis, the Simplified Yielded Aggregation Index (SYAI) method is evaluated alongside other prominent Multi-Criteria Decision-Making (MCDM) methods such as TOPSIS, SAW, ARAS, WASPAS, VIKOR and MOORA. This evaluation utilizes the flotation machine selection problem as a study case by Stanujkić et. al [43] where five alternatives are analyzed according to ten criteria. There are three categories in which the criteria fall: constructional parameters economical parameters and technical parameters. These criteria are provided with specific weights depending on their relevance in making the decision and each one of the criteria has optimization directions issued to it (whether to maximize or minimize the value). The weights and optimization directions of the criteria are summarized in Table 8.

Table 8: The Evolutional Criteria and Criteria Weights.

Criteria	Criteria Names	Opt.	Criteria Weights
C1	The size and the shape of the machine	max	0.070
C2	The volume or the capacity of the machine	min	0.070
C3	The construction of agitation and aeration system	max	0.070
C4	The number of the machines	max	0.140
C5	Investments	min	0.200
C6	Terms of payment and maintenance	max	0.080
C7	Operating costs	min	0.120
C8	Warranty period	max	0.125
C9	Delivery time	min	0.050
C10	Maintenance conditions	max	0.075

Table 8 summarizes the criteria names, their optimization directions, and the corresponding weights used in the SYAI method, along with the other MCDM methods for comparison. The decision making has five alternative that are analysed as follows: C1 to C4 are the constructional parameters with better being a higher value for C1 and C3, respectively and vice versa for C2 and C4. C5, up to C7, are economical parameters, and the task is to minimize investments and operating costs and maximize terms of payment and maintenance. C8 to C10 are technical parameters and include both objectives of maximization and minimization. The outcome of this analysis indicates that the SYAI method has similar rankings to other methods especially in situations where the decision-makers have to be able to balance values and make wise decisions based on sturdy and interpretable rankings.

In this comparative study, the rating of alternatives according to the given criteria was based on the application of the SYAI method. The results of SYAI were compared with the rankings received from other MCDM methods. In this calculation, β is equal to 0.05 and C is 0.01. Python programming has been utilized to compute the analysis. Table 9 shown the comparison score values of the MCDM Method.

Table 9: Comparison of MCDM Method Scores and Ranks.

Alternative	TOPSIS	VIKOR	SAW	SYAI	COBRA	WASPAS	MOORA
A1	0.2160 (4)	0.883 (4)	0.6761 (4)	0.1975 (4)	0.0204 (4)	0.6679 (4)	-0.0024 (4)
A2	0.4546 (3)	0.413 (3)	0.7788 (3)	0.5375 (3)	0.0022 (3)	0.7739 (3)	0.0659 (3)
A3	0.7239 (2)	0.000 (1)	0.8867 (2)	0.7900 (1)	-0.0190 (1)	0.8831 (2)	0.1253 (1)
A4	0.7402 (1)	0.275 (2)	0.8951 (1)	0.7025 (2)	-0.0116 (2)	0.8903 (1)	0.1201 (2)
A5	0.0400 (5)	1.000 (5)	0.6063 (5)	0.0167 (5)	0.0340 (5)	0.5973 (5)	-0.0428 (5)

Table 9 compares five alternatives (A1 to A5) using several multi-criteria decision-making (MCDM) techniques, such as TOPSIS, VIKOR, SAW, SYAI, COBRA, WASPAS, and MOORA. Each column shows the score determined by a certain approach, while each row represents an alternative. The table shows how rankings change amongst methods showing how each method assesses choice factors in a different way. Figure 5 demonstrates the score comparison across each methods.

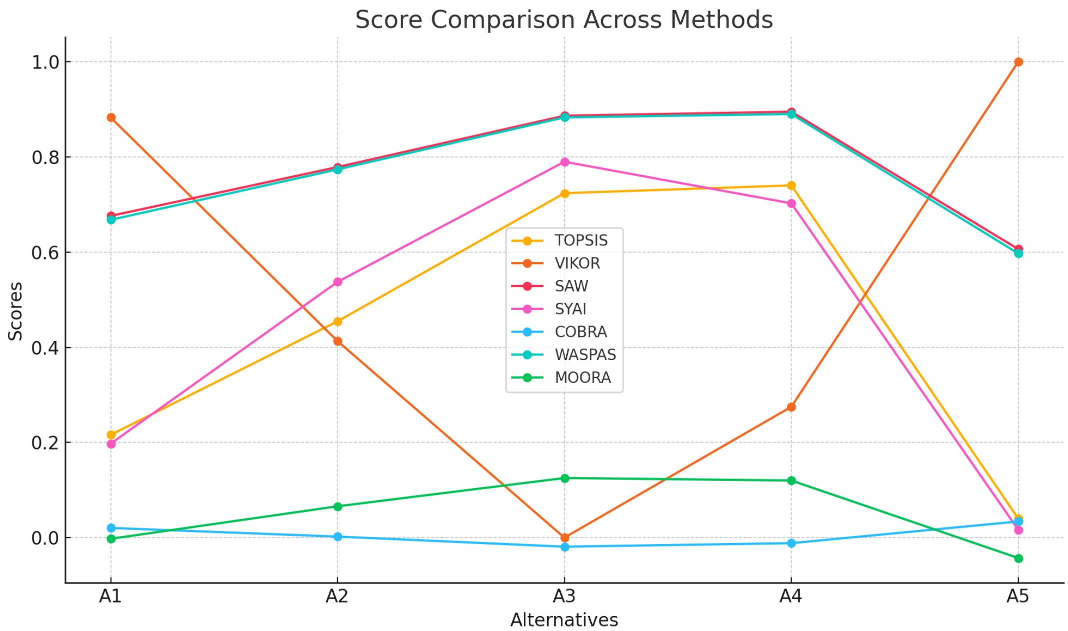

Figure 5: Scores of Five Alternatives Evaluated Using Seven MCDM Methods

The line chart in Figure 5 compares five possible alternatives (A1–A5) that were evaluated using TOPSIS, VIKOR, SAW, SYAI, COBRA, WASPAS, and MOORA methods from Multi-Criteria Decision-Making (MCDM). Most of these techniques value higher scores as better, but both VIKOR and COBRA reverse this, valuing lower scores for better results. For instance, by using VIKOR, A3 is at the top with 0.000 as its score, and A5 comes in last with 1.000. COBRA also ranks A3 highest at -0.0190 and A5 lowest at 0.0340, proving again that these two have opposite preferences.

While the scoring procedures may differ, the majority of methods tend to reach fairly similar rankings. In all four methods, SAW, SYAI, WASPAS, and MOORA, A3 is consistently the best and often the top-ranked option. Meanwhile, A5 stays at the bottom with extremely low scores, including 0.0167 in SYAI, 0.0340 in COBRA, and -0.0428 in MOORA. Combining all the results from the different methods improves the trust in the decision outcome and highlights A3 as the best-chosen alternative.

The powerful agreement among the different methods shows that the ranking is both solid and reliable, especially indicating that A3 is better than A5. Despite the fact that these methods can be different in rules and how complex they are, they all lead to the same general preference ranking. Being consistent allows people to believe in the final recommendations because the outcome does not vary a lot from one method to another.Numerous techniques such as TOPSIS and VIKOR are applied in MCDM to verify the dependability of the results. Looking at the correlation between their scores shows if the methods tend to be the same or vary because of their own approach. Figure 6 illustrates Spearman correlation coefficients matrix of each methods.

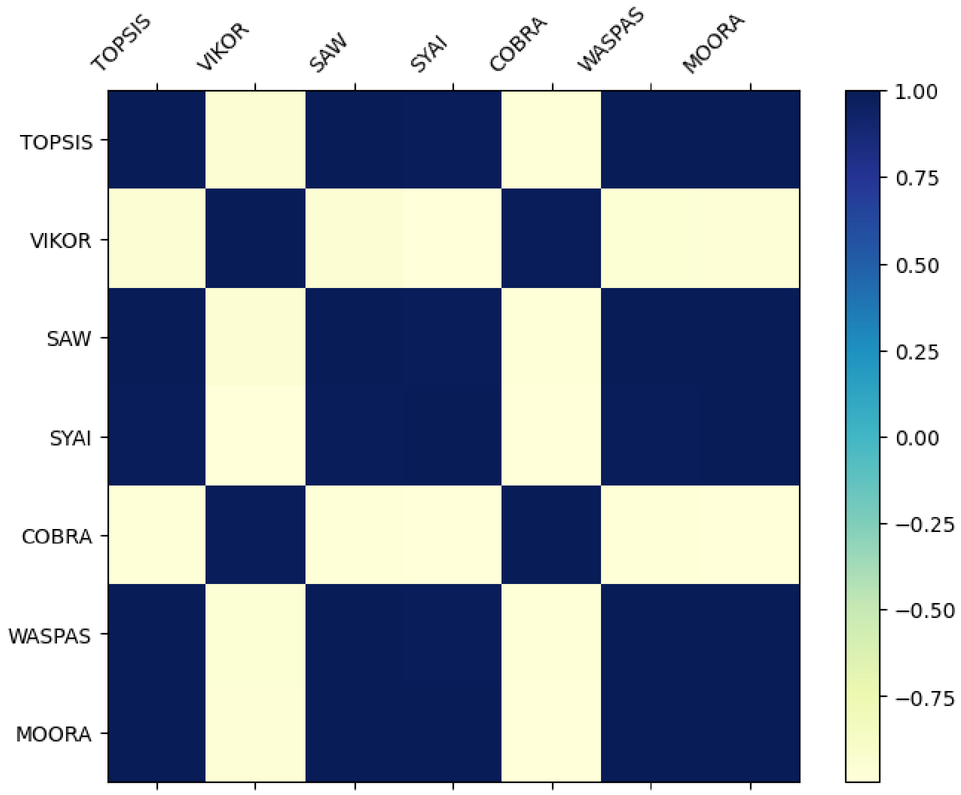

Figure 6: Correlation Matrix of MCDM Methods

The heatmap in Figure 6 represents the ways in which seven MCDM methods correlate with each other. It demonstrates that most methods are highly correlated in their results. For example, TOPSIS and SAW nearly perfectly match, with a Spearman correlation coefficients of 0.9999, suggesting they give almost the same results. In addition, MOORA is highly similar to WASPAS (0.9980), and SYAI matches well with MOORA (0.9961) and SAW (0.9876). The fact that MOORA and WASPAS match very closely (0.9980) indicates that they tend to provide reliable and similar results.

On the other side, COBRA has strong negative relationships with methods like TOPSIS (-0.9895), SAW (-0.9890), and WASPAS (-0.9896), proving once more that its scores are opposite to what is expected. VIKOR is also designed so that a lower value is preferred, which can be seen in its strong correlation with COBRA (0.9847), meaning both models select the same alternatives based on lower numbers instead of higher ones. As a result, MCDM methods generally produce the same trends, yet it is important to carefully interpret or merge COBRA and VIKOR, given their unique inverted logic. Scattter matrix of each methods is shown in Figure 7.

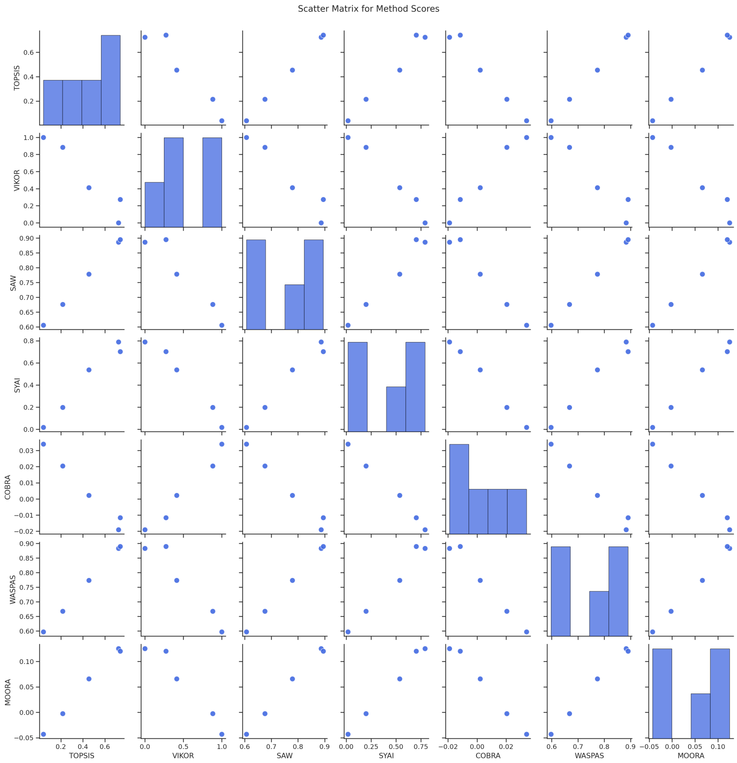

Figure 7: Scatter Matrix of MCDM Methods

Figure 2 presents a scatter plot that highlights the connections between the seven MCDM methods (TOPSIS, VIKOR, SAW, SYAI, COBRA, WASPAS, and MOORA and five alternatives. Several methods in the scatter plots show a strong linear pattern, indicating a close relationship between them. It is evident from the plots and their high correlation values of 0.9999, 0.9999, and 0.9980 that TOPSIS and SAW, SAW and WASPAS, and MOORA and WASPAS display strong similarities. This means that the order in which each alternative is ranked is quite similar across different methods.

Furthermore, a strong inverse relationship is found between COBRA and SAW, TOPSIS, and WASPAS in the scatter plot. This is reflected in the correlation table, where COBRA has strong negative correlations with these methods, for instance, -0.9890 with SAW, -0.9895 with TOPSIS, and -0.9896 with WASPAS. The shape of the scatter plots makes it clear that COBRA ranks results in a way where lower scores are considered higher. Overall, the scatter matrix proves helpful for correlation analysis by highlighting how alike or different the outcomes are from one method to another.

3.4. Simulation-based Analysis

This section reports the findings of simulation based evaluation to determine the simplicity and stability of the SYAI method depending on the size of different decision matrices.This analysis attempt to assess the consistency, variability, and responsiveness of the method to input fluctuation, respectively, in repeated randomized simulations from matrices of various sizes. Specifically the average standard deviation and variance of the rankings obtained from matrices of different sizes, which explains how well the method can adapt to more complex and more numerous challenges. The results of the analysis based on the simulation are displayed in Table 10.

Table 10: Simulation-Based Analysis Results for SYAI Method

Matrix Size	**5×5**	**9×8**	**12×10**	**13×15**
Mean Standard Deviation	0.2608	0.1229	0.1280	0.0956
Variance	0.0680	0.0151	0.0164	0.0091

According to the simulation analysis shown in Table 10, the average standard deviation and variance of SYAI scores are displayed for every size of decision matrix tested. Expressing the stability and sensitivity of SYAI depends on having these metrics. If the mean standard deviation is lower, the scores are less spread out, which indicates the rankings of alternatives are somewhat more consistent. On the other hand, having a high standard deviation means the scores from the method are more spread out, which may indicate a lack of stability. For the smallest matrix (5x5), the standard deviation was highest, meaning the ranking results varied more. On the other hand, both 12x10 and 13x15 standard deviations were lower, which means the rankings there were more consistent.

The values of the variances indicate the spread of SYAI results. The 5x5 matrix is the highest in variance (0.0680), indicating that there is greater change in scores with different inputs. The variance reduces with the increase in size of the matrix by 0.0091 in the 13x15 matrix, meaning that SYAI is more stable in larger problems. Comparing the standard deviation and variance between two matrix sizes can also aid in making sure the method is stable as MCDM problems increase. Figure 8 presents the boxplot on the ranking stability with relation to the sizes of the matrices.

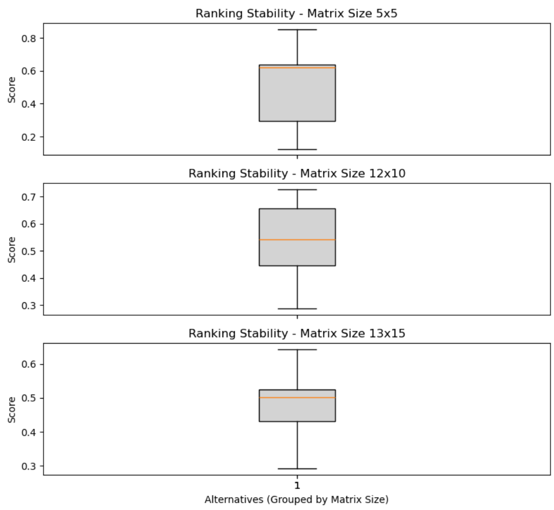

Figure 8: Ranking Score Distributions for Different Decision Matrix Sizes.

The boxplots in Figure 8 for the SYAI method show that the results are stable and there are no outliers for the three matrix sizes tried. Greater differences in closeness scores among alternatives can be observed in the spread of scores for the 5x5 matrix. By comparison, the interquartile ranges of the 12x10 and 13x15 matrices demonstrate that the scores are more closely clustered around the median. This means the SYAI method gives more consistent and less jagged outputs as the problem's size increases, proving it can handle bigger decisions smoothly.

4. Conclusion

All in all, the SYAI method offers a notable improvement in MCDM by uniting normalization processes for different types of criteria in a single model. By including a flexible closeness score using β , the method makes it possible for decision-makers to adjust how sensitive preferences are between the best and worst options. The method of goal-oriented normalization is useful in areas such as logistics, temperature control, and healthcare, where it is important to reach specific aims. Analysis and results from simulations prove that SYAI follows traditional MCDM methods, confirming it to be robust and reliable. SYAI bridges the gaps in traditional MCDM methods, making it user-friendly and rooted in theory, and it improves the transparency, flexibility, and decision-making in complicated situations.

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