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A New Method for Multi-Criteria Decision-Making: Adaptive Ranking with Ideal Evaluation (ARIE)

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Abstract. Decision makers frequently confront complex criteria, some requiring maximization, others minimization, and still others precise target attainment, yet classical Multi-Criteria Decision-Making (MCDM) methods (e.g., TOPSIS, VIKOR and SAW) offer limited flexibility to handle such mixed preference directions, often producing inconsistent or opaque rankings. To address these challenges, this study proposed the **Adaptive Ranking with Ideal Evaluation (ARIE)**, a fully flexible similarity-based framework that unifies benefit, cost, and target-type normalization under one roof. ARIE leverages a novel dual-parameter score function with a sensitivity exponent γ to control the nonlinearity of deviations and a balancing coefficient κ to tailor the trade-off between aspiration toward the ideal and avoidance of the anti-ideal to convert weighted normalized ratios into a single, interpretable closeness measure. We demonstrate ARIE in a case study of halal supplier selection, perform a sensitivity analysis between γ and κ values, and carry out comparative and simulation-based analyzes using MATLAB-generated weight scenarios against seven benchmark methods (CRADIS, MABAC, ARAS, MOORA, VIKOR, TOPSIS and SAW). The results show that ARIE's new scoring technique consistently yields more stable, transparent, and decision-maker-aligned rankings in diverse decision contexts.

2020 Mathematics Subject Classifications: 90B50, 68T37, 62C05

Key Words and Phrases: Multi-criteria decision-making (MCDM), arie method, adaptive ranking, ideal evaluation, performance analysis, decision modeling

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1. Introduction

Decision-making has become an increasingly complex and critical process across diverse domains such as business [1, 2], engineering [3, 4], healthcare [5, 6], and public policy [7], [8]. In the context of globalization, technological advancement, and increasingly interconnected challenges, both organizations and individuals face the need to evaluate alternatives under multiple, often conflicting, criteria [9, 10]. Multi-Criteria Decision-Making (MCDM) methods provide structured, logical, and repeatable tools to navigate such complexity [11]. These methods support the comparison of alternatives, weighting of criteria, and synthesis of preferences into consistent and interpretable rankings [12, 13].

MCDM has found widespread application in areas such as supplier selection [14], project prioritization [15], and sustainability evaluations [16] where decision-makers often need to manage trade-offs between cost, quality, risk, and environmental impact. Despite these advancements, current methods still face several limitations. Many traditional models assume criteria are either to be maximized or minimized. However, in real-world decision problems, some criteria are best evaluated by how closely they match a specific target value — a scenario poorly addressed in methods such as TOPSIS, VIKOR, and SAW. Furthermore, classical methods typically use static preference models and lack adjustable parameters for sensitivity control, making them less robust in dynamic environments where decision-maker attitudes or input data may vary [17, 18].

To address these gaps, this paper introduces a novel method: **Adaptive Ranking with Ideal Evaluation (ARIE)**. ARIE extends classical MCDM by integrating three key innovations:

- A *unified normalization framework* that incorporates benefit, cost, and a newly introduced **target-type** criterion — where the optimal value lies within, rather than at the edge of, the acceptable range.
- A *dual-parameter scoring function* governed by the sensitivity parameter γ and balancing coefficient κ, which together modulate the influence of deviations and the trade-off between closeness to the ideal and distance from the anti-ideal.
- A *comprehensive evaluation structure* validated through sensitivity analysis, comparative benchmarking against seven classical MCDM methods, and simulation-based robustness checks using real-world inspired data.

ARIE is designed to offer greater flexibility, stability, and adaptability compared to existing methods. It responds effectively to criteria directionality (max, min, or target), allows decision-makers to tune parameters based on risk preferences or aspiration levels, and maintains consistency across diverse decision environments.

The remainder of this paper is organized as follows. Section 2 presents a critical review of MCDM literature, with emphasis on current methodological gaps and the motivation for ARIE. Section 3 explains the ARIE methodology in detail, including its mathematical formulation and computational steps. Section 4 demonstrates the method's performance through a halal supplier selection case study, sensitivity analysis, comparative study, and simulation-based evaluation. Finally, Section 5 concludes the study and suggests future recommendations.

2. Literature Review

Nowadays, MCDM techniques are widely used to guide important decisions in engineering, environmental planning, education and finance. They are designed to weigh different conflicting factors and direct decision-makers to the best solutions. There are many MCDM methods that differ in their basic concepts, strengths and weaknesses. Here, the most prominent MCDM approaches are studied to compare their outcomes and underline the need to build more flexible strategies. One of the most prominent MCDM techniques is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), introduced by Hwang and Yoon [19]. TOPSIS ranks alternatives based on their proximity to the Positive Ideal Solution (PIS) and distance from the Negative Ideal Solution (NIS). Its has been applied in supplier selection [20, 21], project prioritization [22, 23], and environmental management [24, 25]. On the other hand, the use of fixed points and the same significance for distances rise difficulty to handle real life challenges [26, 27].

The Simple Additive Weighting (SAW) or Weighted Sum Model (WSM) [28] is another foundational method that aggregates weighted criteria scores. While SAW is easy to use and understand [29], it struggles to handle cases where different choices affect each other [30]. For the Additive Ratio Assessment (ARAS) method [31], alternatives are judged against an optimal solution to determine their performance. It is an efficient and effective process when considering both cost and benefit factors [32, 33]. The approach is still sensitive to changes in data and fails to offer reliable results [34, 35].

Moreover, the Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) [36] extends TOPSIS and ARAS by integrating multiple evaluation perspectives. CRADIS effectively incorporates the deviation of each alternative from ideal and anti-ideal points [37, 38]. Nevertheless, it still depends on static benchmarks and may face scalability issues with large datasets. The Multi-Attributive Border Approximation Area Comparison (MABAC) method [39] proposes a shift from static ideals to a border approximation area for comparison. The method is found effective in dealing with negative values and less responsive to outliers [40, 41] which is good for making decisions in unpredictable situations. Even so, MABAC can be complex to compute when there are numerous criteria and its interpretation may not be clear.

Next, the MOORA method (Multi-Objective Optimization by Ratio Analysis) uses normalizing through ratios to ensure simplicity and fast computing, as seen in Brauers (2010, 2006) and Chakraborty (2011) [42]. It may result in unfair rankings when criteria are not valued equally [43, 44]. VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) [45] aims to find a compromise by minimizing regret and maximizing the overall group utility [46, 47]. Sometimes, the decisions made from the model are unclear as they depend on the personal views and opinions of the participants [48, 49].

A range of comparative analysis study between MCDM methods has been conducted to discuss the benefits and weaknesses of every MCDM method. Li et al. [50] proposed and compared extended TOPSIS, MOORA, ARAS, SAW and other methods. The proposed extended MCDM methods are found robust and effective in solving decision-making problems. Abacıoğlu et al. [51] investigates the evolving landscape of green universities using CRADIS, MABAC and other methods. The study analyzes how the significance of the six sustainability criteria changes when different MCDM weighting methods are applied. Some weighting techniques affect the final rankings as they may emphasize certain criteria more than others. In order to improve sustainability through drilling machine efficiency, Ramdani et al. [52] compared TOPSIS with VIKOR. The TOPSIS approach is found to exhibit a strong association with reference ranking, particularly with regard to specific energy. On the other hand, the VIKOR coefficient shows a moderate degree of similarity. Anic [53] compared VIKOR, MABAC, and other methods in tower geodetic micro-network application. It was shown that change was reflected in a different ranking list compared to the corresponding ranking lists provided using the MABAC, and other methods.

In other applications, Susilo and Wahyuni [54] compared SAW and TOPSIS methods in decision support system in contraceptive methods application. The results show that SAW more accurately reflects expert opinions and more effective than TOPSIS. George et al. [55] compared TOPSIS, VIKOR, and MOORA methods for vendor selection in manufacturing industry. Muni et al. [56] compared MABAC, MOORA and other methods to select the best egg supplier. The results of the sensitivity test show that MABAC has the highest value of 4.4274 percent, then MOORA with a value of 2.3442 percent and the other method with a value of 0.4573 percent. Hendrawan [57] employed MOORA, ARAS, and other methods for location development priorities. The study's results are expected to reveal how different MCDM methods rank industrial area development locations. Mete [58] utilized VIKOR, ARAS, SAW, and other methods to analyze the Turkish insurance companies' financial performance traded. According to the result, there is a strong relationship between ARAS and SAW with Proximity Indexed Value (PIV), while the relationship with VIKOR is moderate. Kumar et al. [59] used MOORA, TOPSIS, ARAS, and other methods to solve milling process optimization problems. The study finds 255 rpm, 82 mm/min feed rate, and 0.75 mm depth of cut as the optimal machining parameters, with six MCDM methods agreeing on this result. In these studies, it is shown that there is no single MCDM method that works best in every case, so it remains important to choose methods that are suited to each unique problem.

These findings further highlight the limitations of existing methods when applied across varying contexts and underscore the need for more adaptive and versatile approaches. CRADIS and MABAC approaches can fix many problems with traditional ways, yet they usually struggle with complexity, variation or do not adapt in real time. Although SAW, MOORA and ARAS are simple, they lack the robustness required for many applications. Even though VIKOR and TOPSIS find middle choices, they do this by sticking to fixed standards and assumptions. Alternatively, the proposed ARIE method addresses these issues by constantly changing the references and the way values are decided in real time. ARIE is not meant to take over from present models, but improves how reliable decisions can be by including flexibility, visibility and advanced computation. The next part outlines the ARIE methodology and compare it with current MCDM techniques.

3. Methodology

ARIE method delivers a comprehensive framework to evaluate and prioritize alternatives in MCDM issues. This method is proposed as an improvement to the classical TOPSIS, introducing a similarity-based approach with greater flexibility through risk-sensitive tuning and multi-type normalization. It is designed to handle criteria of different nature (benefit, cost, target) in MCDM problems, and each phase is designed to bolster the robustness, flexibility, and clarity of the resulting rankings. The step-by-step flowchart of the ARIE procedure is presented in Figure 1.

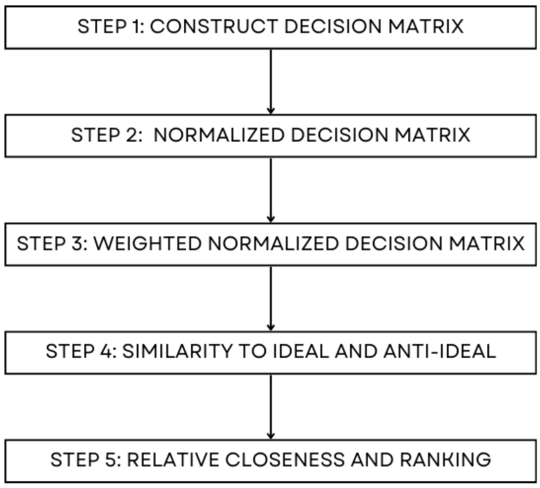

Figure 1: ARIE Method Flowchart.

The following is a detailed explanation of the ARIE method procedure.

Step 1: Construct the Decision Matrix

In the MCDM behavior, there must be the number of criteria, $j = 1, 2, \ldots, n$, and alternatives, $i = 1, 2, \ldots, m$ to create a decision matrix form as below:

$$X = [x_{ij}]_{m \times n} \tag{1}$$

The raw decision matrix $X = x_{ij}$ underpins the entire evaluation process where each element x_{ij} denotes the performance score of the ith alternative on the jth criterion. To ensure comparability across diverse criteria, practitioners typically agree on consistent scoring scales, conduct calibration workshops to align interpretation, and perform data-quality checks such as outlier detection and handling of missing values before proceeding to ARIE's multi-type normalization step. This rigorous grounding of x_{ij} values in validated since context-specific metrics is essential for generating credible similarity assessments and, ultimately, robust and interpretable rankings.

Step 2: Normalize the Decision Matrix

To ensure dimensionless and comparable criteria values, the decision matrix is normalized. This normalized process eliminates the unit measurement in the decision matrix including price, percentage, ratio, and points. In this method, three types of normalization are introduced:

- **Max-type (benefit) criterion** where higher values are recommended:

$$r_{ij} = \frac{x_{ij}}{x_j^{\max}} \tag{2}$$

- **Min-type (cost) criterion** where lower values are preferable:

$$r_{ij} = \frac{x_j^{\min}}{x_{ij}} \tag{3}$$

- **Target-type (goal)**: For criteria with a desired target value x_j^T:

$$r_{ij} = 1 - \frac{|x_{ij} - x_j^T|}{\max\left(|x_j^{\max} - x_j^T|, |x_j^{\min} - x_j^T|\right)} \tag{4}$$

x_{ij} is the original value of the ith alternative with respect to the jth criterion, while $x_j^{\max}$ is the maxmimum value of the jth criterion across al alternatives in step 1. ARIE method uses x_j^T as the benchmark for each criterion whether set by expert consensus, regulatory standards, historical averages, or strategic goals and normalizes each alternative's score x_{ij} by its distance from this target so that those closest to the benchmark score highest. By applying benefit, cost, and target-based normalization, the method avoids distortions from inappropriate scaling, accurately reflects each criterion's true preference direction, and with its innovative inclusion of target-based transformation outperforms classical models in ensuring consistent, fair, and balanced comparisons across mixed criteria.

Step 3: Weighted Normalized Decision Matrix

The normalized values are multiplied by the corresponding criteria weights, w_j, where $\sum_{j=1}^{n} w_j = 1$ given by:

$$v_{ij} = w_j \cdot r_{ij} \tag{5}$$

The weights w_j capture each criterion's relative importance and may be established through subjective techniques, like AHP and BWM methods, objective methods, such as, Entropy and MEREC methods, or decision-makers judgment [60, 61]. Once applied to the normalized scores, they produce the matrix $V = [v_{ij}]$, in which higher-priority criteria exert a proportionally greater influence and variables with wider numerical ranges are balanced. Incorporating weights at this stage both embeds stakeholder preferences (or data-driven priorities) and sets the foundation for meaningful similarity calculations. Keeping $\sum_j w_j = 1$ further guarantees that comparisons across alternatives remain transparent and interpretable.

Step 4: Compute Similarity to Ideal and Anti-Ideal Solutions

To evaluate how close each alternative is to the best (ideal) and worst (anti-ideal) alternatives by using a similarity-based approach. Let:

$$v_j^{\max} = \max_i v_{ij}, \quad v_j^{\min} = \min_i v_{ij}$$

A linear similarity model is used by setting the sensitivity parameter $\gamma = 1$. Then:

$$\mathrm{Sim}_i^{\mathrm{best}} = \sum_{j=1}^{n} \left(\frac{v_{ij}}{v_j^{\max}} \right)^{\gamma} \tag{6}$$

$$\mathrm{Sim}_i^{\mathrm{worst}} = \sum_{j=1}^{n} \left(\frac{v_j^{\min}}{v_{ij}} \right)^{\gamma} \tag{7}$$

Here, $v_j^{\max}$ and $v_j^{\min}$ denote the highest and lowest weighted normalized scores for criterion j. The sensitivity parameter γ controls how sharp deviations from these benchmarks are penalized. Larger values γ intensify penalties, while smaller ones temper them, thus capturing both the proximity of an alternative to the ideal and its distance from the nadir. By framing this assessment as a similarity measure rather than a raw distance, interpretability is enhanced and the approach seamlessly supports both benefit and cost criteria. The exponentiation governed by γ also accommodates non-linear preference patterns to model risk-averse behavior when $\gamma > 1$ or risk-seeking tendencies when $\gamma < 1$.

Step 5: Compute Relative Closeness and Ranking

A balancing parameter $\kappa \in [0, 1]$ allows decision makers to control the emphasis between being close to the ideal and far from the worst. The formula is defined as:

$$RC_i = \frac{\kappa \cdot \mathrm{Sim}_i^{\mathrm{best}}}{\kappa \cdot \mathrm{Sim}_i^{\mathrm{best}} + (1 - \kappa) \cdot \mathrm{Sim}_i^{\mathrm{worst}}} \tag{8}$$

This improvement address the classical RC formula used in TOPSIS. When $\kappa = 0.5$, the method behaves like a neutral model where equal importance is given to similarity to the best and separation from the worst. A value of $\kappa > 0.5$ places more emphasis on closeness to the ideal, which is suitable for optimistic or goal-driven decision strategies. On the other hand, $\kappa < 0.5$ focuses more on avoiding poor alternatives which may align with conservative or risk-averse thinking. The RC score remains within the range $[0, 1]$ where each alternative is ranked in descending order of RC_i. The top-ranked alternatives is considered the most suitable under the given preferences.

4. Computational Analyses

This section presents four sub-sections: a numerical example demonstrating the application of the ARIE framework in halal supplier selection, a sensitivity analyses, as well as comparative analysis comparing the performance of ARIE and other MCDM methods and a simulation-based analysis. The numerical example was computed in Microsoft Excel, while all subsequent analyses were performed in MATLAB software. The numerical data presented in this section was created by the authors for illustrative purposes in this study. The goal of this section is to evaluate the validity and stability of the ARIE method through these computational analyses.

4.1. Numerical Example

In the halal food production industry, the selection of an appropriate supplier is a critical decision that significantly affects the company's operations, compliance with halal standards, and overall company's reputation. The decision-making process must carefully balance multiple criteria, such as halal certification compliance, cost efficiency, delivery performance, product quality, and supplier reputation. This example demonstrates the implementation of the **Adaptive Ranking with Ideal Evaluation (ARIE)** method to evaluate and rank five suppliers $(S_1, S_2, S_3, S_4, S_5)$ based on their performance across these criteria. The objective is to determine the most suitable supplier by applying the ARIE method.

Problem Context and Criteria

The company has shortlisted five suppliers for an evaluation based on the following criteria:

- Halal Compliance, C_1: The ability of the supplier to meet stringent halal certification standards (Benefit criterion).
- Cost, C_2: The price per unit of raw materials supplied (Cost criterion).
- Delivery Time, C_3: The time taken to deliver the goods, measured in days (Target-type criterion).
- Product Quality, C_4: Consistency and adherence to quality standards required by the manufacturer (Benefit criterion).
- Supplier Reputation, C_5: The supplier's standing in the market based on past performance and reliability (Benefit criterion).

The weights assigned to the criteria were determined through consultations with stakeholders, prioritizing halal compliance and product quality, while considering cost and delivery time. Table 1 summarizes the criteria and their corresponding weights.

Initial Data and Decision Matrix

Table 1: Criteria and Weights for Halal Supplier Selection.

Criterion	Description	Type	Weight (w_j)
C_1	Ability to meet halal certification standards	Benefit	0.3
C_2	Price per unit of raw materials (MYR)	Cost	0.2
C_3	Time taken for delivery (in days)	Goal	0.15
C_4	Consistency and adherence to quality standards	Benefit	0.25
C_5	Market perception and reliability	Benefit	0.10

The decision matrix includes raw data provided by the suppliers during the selection process.

Step 1: Decision Matrix Construction

Each entry x_{ij} denotes the performance score of supplier i on criterion j, each row represents one of the five suppliers, and each column corresponds to one of the five evaluation criteria.

$$X = [\, x_{ij} \,] \quad (i = 1, \ldots, 5;\ j = 1, \ldots, 5),$$

Table 2 presents the 5×5 decision matrix.

Table 2: Decision Matrix for Halal Supplier Selection.

Supplier	C_1	C_2	C_3	C_4	C_5
S_1	8	25,000	15	9	8
S_2	9	28,000	20	7	9
S_3	6	22,000	25	8	7
S_4	7	30,000	10	10	9
S_5	10	24,000	12	9	10

Step 2: Normalization Decision Matrix

The decision matrix is normalized using equations (2), (3), and (4) shown in Table 3.

Table 3: Normalized Decision Matrix.

Supplier	C_1	C_2	C_3	C_4	C_5
S_1	0.8000	0.8800	1.0000	0.9000	0.8000
S_2	0.9000	0.7857	0.5000	0.7000	0.9000
S_3	0.6000	1.0000	0.0000	0.8000	0.7000
S_4	0.7000	0.7333	0.5000	1.0000	0.9000
S_5	1.0000	0.9167	0.7000	0.9000	1.0000

Normalization ensures that all raw scores each originally in different units and ranges are converted into a common, dimensionless scale so no single criterion can dominate the results.

$$x_1^{\max} = 10, x_2^{\min} = 22,000, x_3^{\max} = 25, x_3^{\min} = 10, x_3^T = 15, x_4^{\max} = 10, x_5^{\max} = 10$$

The target type value, x_j^T, can be adjust by decision makers' preferences like 8, 14 or even 21. Each raw score x_{ij} is transformed using the normalization formula that matches its criterion's orientation wether benefit, cost, or target so that each values reflects whether higher, lower, or benchmark-proximity values are preferable.

$$\begin{aligned}
&\text{C1 (Max-type):} \\
&\qquad r_{11} = \frac{8}{10} = 0.8000, \quad r_{21} = \frac{9}{10} = 0.9000, \\
&\text{C2 (Min-type):} \\
&\qquad r_{12} = \frac{22\,000}{25\,000} = 0.8800, \quad r_{22} = \frac{22\,000}{28\,000} = 0.7857, \\
&\text{C3 (Target-type):} \\
&\qquad r_{13} = 1 - \frac{|15-15|}{\max\{25-15,\ |10-15|\}} = 1.0000, \\
&\qquad r_{23} = 1 - \frac{|20-15|}{\max\{25-15,\ |10-15|\}} = 0.5000.
\end{aligned}$$

Step 3: Weighted Normalization

The weighted-normalized matrix is given by:

$$V = \begin{bmatrix} 0.2400 & 0.1760 & 0.1500 & 0.2250 & 0.0800 \\ 0.2700 & 0.1571 & 0.0750 & 0.1750 & 0.0900 \\ 0.1800 & 0.2000 & 0.0000 & 0.2000 & 0.0700 \\ 0.2100 & 0.1467 & 0.0750 & 0.2500 & 0.0900 \\ 0.3000 & 0.1833 & 0.1050 & 0.2250 & 0.1000 \end{bmatrix}$$

Each alternative is calculated as follows:

$$\text{For } v_{11} = 0.30 \cdot 0.8000 = 0.2400,$$

$$\text{For } v_{23} = 0.15 \cdot 0.5000 = 0.0750$$

Step 4: Similarity to Ideal and Anti-Ideal Solutions

In this step, we quantify each alternative's proximity to both the ideal (best) and anti-ideal (worst) solutions using a similarity-based approach:

Table 4: Similarity Computation.

Alternatives	S_{best}	S_{worst}
S_1	4.3800	3.2361
S_2	3.7857	3.3778
S_3	3.1000	3.6083
S_4	3.8333	3.3349
S_5	4.5167	2.8778

275 With

$$v_j(max) = [0.3000, 0.2000, 0.1500, 0.2500, 0.1000],$$
$$v_j(min) = [0.1800, 0.1467, 0.0000, 0.1750, 0.0700]$$

276 Similarity values computed by letting $\gamma = 1$,

$$\text{Sim}_1^{\text{best}} = \frac{0.2400}{0.3000} + \frac{0.1760}{0.2000} + \frac{0.1500}{0.1500} + \frac{0.2250}{0.2500} + \frac{0.0800}{0.1000} = 4.3800$$
$$\text{Sim}_1^{\text{worst}} = \frac{0.1800}{0.2400} + \frac{0.1467}{0.1760} + \frac{0.0000}{0.1500} + \frac{0.1750}{0.2250} + \frac{0.0700}{0.0800} = 3.2361$$

277 **Step 5: Relative Closeness and Ranking**

278 Let $\kappa = 0.5$,

$$RC_1 = \frac{0.5 \cdot 4.3800}{0.5 \cdot 4.3800 + (1 - 0.5) \cdot 3.2361} = 0.5751,$$
$$RC_2 = \frac{0.5 \cdot 3.7857}{0.5 \cdot 3.7857 + (1 - 0.5) \cdot 3.3778} = 0.5285$$

279 The final ranks and scores with $S_5 \prec S_1 \prec S_4 \prec S_2 \prec S_3$ are shown in Figure 2.

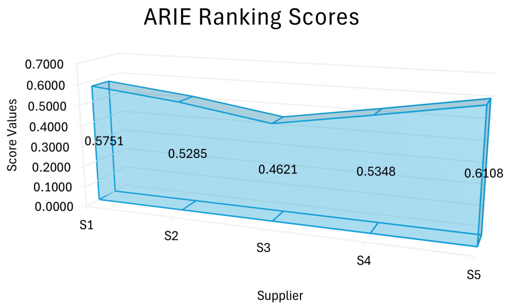

Figure 2: Final Score using ARIE Method.

280 Based on the figure, supplier S_5 is the best option as it excels in halal compliance,
281 product quality, and reputation while keeping costs and delivery schedules under control.

Supplier S_3, on the other hand, is placed last among the alternatives indicate that it does not satisfy any of the standard requirements of supplier selection. By combining dynamic normalization with ideal/anti-ideal similarity measures and adaptive scoring, ARIE captures subtle performance nuances and directly reflects stakeholder priorities. This thorough example demonstrates ARIE's resilience and suitability for choosing halal suppliers. ARIE offers a valuable tool for intricate decision-making situations requiring the evaluation and balancing of numerous parameters. In the following section, we explore how the two key ARIE parameters shape the ranking outcomes.

4.2. Sensitivity Analysis

This sub-section examines the sensitivity of two parameters in the ARIE method: the γ parameter and the κ parameter. The same data in numerical example has been used in this section by using MATLAB. Each sensitivity analysis focused on a different objective, for example, Figure 3 below focuses on the γ parameter, with the κ parameter fixed at 0.5, and vice versa for Figure 4.

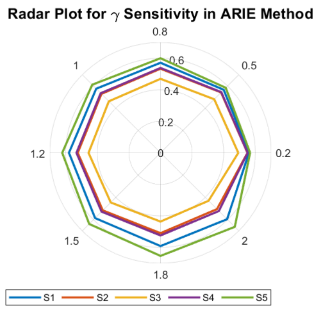

Figure 3: Radar Plot for Sensitivity Analysis of γ using ARIE Method.

Based on the figure, the radar chart consists of radial axes representing the γ parameter, which ranges from 0.2 to 2. The distance from the center represents the score RC_i of an alternative. Each line represents one alternative, which is supplier, where line that close to the outer edge represents higher scores which perform better than others. While line that close to the center edge represents lower scores which perform worse. S_5 ranks first across all the parameter values while S_3 being the last rank with different parameter values. S_3 maintains robust and consistently perform well since it remains close to the outer edge. All supplier sensitive under lower γ values as the line moves inward as the parameter γ decreases. In the radar plot, when $\gamma < 1$ all the supplier values bunch up into a nearly circular shape reflecting a risk-seeking stance that softens performance gaps and treats most alternatives as similarly acceptable. As γ grows above 1, the supplier plot becomes increasingly spiky and irregular, since exponentiation amplifies even small differences typical of risk-averse behavior that punishes deviation from the ideal. Figure 4 shows the impact of sensitivity parameter κ on the final score by implementing ARIE method.

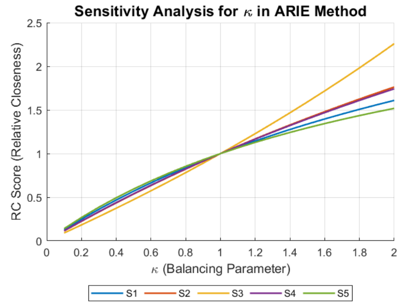

Figure 4: Line Chart for Sensitivity Analysis of κ using ARIE Method.

Based on the figure, the κ sensitivity plot shows that all alternatives start at $RC = 0$ when $\kappa = 0$ since only the anti-ideal term remains and converge at $RC = 1$ when $\kappa = 1$ because the formula reduces to pure similarity to the ideal. As κ grows from 0 to 1, each RC curve rises smoothly, with steeper slopes for suppliers whose best-vs-worst similarity gap is larger. Once κ exceeds 1, the denominator's anti-ideal component becomes negative, causing RC to jump above 1 and the curves to fan out: suppliers with the greatest performance contrast (e.g., S_3 soar highest, while those with smaller contrasts (e.g., S_5 climb more modestly. This behavior underscores why κ is typically bounded in [0,1] to maintain RC scores within [0,1] and retain a balanced trade-off between closeness to the ideal and distance from the worst. Next sub-section discusses the relationship of ARIE method between various MCDM methods.

4.3. Comparative Analysis

This section analyses the ranking order between ARIE, and CRADIS, MABAC, ARAS, MOORA, VIKOR, TOPSIS, SAW methods using MATLAB software. The data illustrated in this section are based on the data in numerical example. Figure 5 illustrates a comparative analysis between the ARIE and other existing MCDM methods.

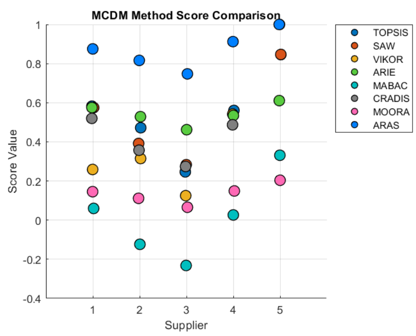

Figure 5: Ranking Score Comparison of MCDM Methods.

Based on Figure 5, the bubble chart represents x-axis as the supplier 1 until 5, and y-axis as the score values of MCDM methods. Five suppliers are ranked in the figure utilizing a variety of decision-making techniques. Each scatter shows how suppliers are assessed using various ranking methods. Since some points overlap because of identical ranking values, MATLAB's jitter function is utilized to make sure all scatter plots are viewable. Although VIKOR typically ranks alternatives in ascending order, it here follows the descending order used by the other methods to enhance figure readability and interpretation. As the top-performing supplier, supplier 5 continuously receives the highest scores across the majority of approaches, while supplier 3 is still at the bottom, having the lowest scores across all techniques. Other MCDM systems establish similar ranking patterns when compared to the evaluation produced by the ARIE method. Supplier 5 shows excellent performance since it reaches one of the highest positions in the ARIE rankings. Supplier 3 maintains a low ranking position as it consistently performs poorly in different assessments. The supplier ranking approach in ARIE establishes a more moderate grading structure than ARAS which gives steep scores to the top supplier candidate. ARIE maintains consistent scoring patterns which enables the method to separate superior performing suppliers from subpar ones without creating artificial advantages.

For SAW, TOPSIS, CRADIS, MOORA, and MABAC methods exhibit a similar pattern to ARIE. MABAC allows negative values because it calculates the deviation of alternatives from the border approximation area. Values below the reference point result in negative scores [62] indicates weaker performance. Out of all the approaches that have been analyzed, supplier 5 is constantly recognized as the best option. The overall scores from MOORA and MABAC are comparatively lower, indicating that these approaches may use more rigorous evaluation criteria, even though SAW and CRADIS give it better marks. Notably, supplier 3 continuously earns the lowest score despite the variations in ranking methods, indicating that its poor performance is unaffected by the particular methodology used. As a result, ARIE delivers a consistent and balanced ranking. These results demonstrate the durability and consistency of the ranking techniques and guarantee a trustworthy MCDM framework for supplier selection decision-making. Figure 6 provides the comparison of Spearman and Pearson correlation coefficient for ARIE across MCDM methods.

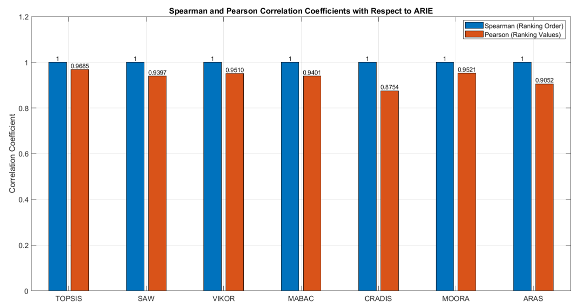

Figure 6: Spearman and Pearson Correlation Coefficients for ARIE Method.

This study used two different statistical analysis techniques, the Pearson and Spearman correlation coefficients, to determine the direction and strength of the association between two methods. The Pearson correlation method identifies linear associations between methods yet Spearman approaches method ordering without requiring assumptions of normal distribution [63]. The monotonic strength of correlation appears as continuous upward or downward changes according to the Spearman coefficient although Pearson produces a measure of both direction and strength [64]. The values of the correlation coefficient range from -1 to 1. Based on the above figure, the orange bars show Pearson (ranking values) correlations, the blue bars show Spearman (ranking order) correlations. The Spearman correlations have reached 1.0 for each method which exhibits closely matching strength to Pearson correlations that slightly lower at 0.9685, 0.9521 and 0.9510. The visual depicts correlation strength through value labels placed above each bar which simplifies comparison between measures. The results demonstrate that ARIE shows strong correspondence with most ranking techniques, but does not match the correlation level of VIKOR. The proposed ARIE method stands out through its comparative analysis with the renowned existing MCDM methodologies presented in Table 5.

Table 5: Comparison of ARIE Method with Existing MCDM Method.

Method	Adaptability	Outliers	Proximity Weighting	Complexity
ARIE	High	Balanced	Tunable	Moderate
CRADIS	Medium	Balanced	Implicit	Low
MABAC	Medium	Robust	Approximate	High
ARAS	Stable	Effective	Implicit	Low
MOORA	Stable	Stable	Implicit	Low
TOPSIS	Medium	Stable	Fixed	Low
VIKOR	Medium	Balanced	Fixed	Moderate
SAW	Medium	Vulnerable	NA	Low

Table 5 presents an extensive comparison of ARIE with other prominent MCDM techniques. Four main areas are the focus of the comparison: adaptability, outliers, proximity weighting, and complexity. The customizable parameters of ARIE make it unique among the methods that allow decision makers to modify the model for the best results in various situations. Because of its great degree of adaptability, ARIE is especially flexible for applications that need dynamic ranking modifications. By combining ideal and anti-ideal references with structured boundary approximation, MABAC and CRADIS also demonstrate strong adaptability and work well in multi-objective optimization scenarios. MABAC demonstrates exceptional resilience in managing extremes and computational complexity by providing stability against outliers and extreme values. MOORA and ARAS offer a stable complexity for issues requiring fast computations.

TOPSIS and CRADIS are able to maintain a compromise between ranking accuracy and computational efficiency by utilizing distance-based weighting approaches. The systems' methods to proximity weighting differ; ARIE is notable for its adaptability, whereas TOPSIS and VIKOR use fixed or structured weighting processes that improve stability. One important conclusion is that the changes in weight have a major influence on ranks in ARIE, CRADIS, MABAC, ARAS, and MOORA, where the sensitivity to criteria weights is most noticeable. These methods are dependable in decision-making scenarios where accurate weighting is required due to their high sensitivity and excellent highlighting of important factors. Overall, the table shows that although ARIE offers a flexible and well-balanced framework for decision-making, each MCDM approach has unique advantages that allow it to be applied to various situations depending on the requirements for adaptability, outliers, weighting, and complexity. Next sub-section focuses on different decision matrix size, and various iterations or situations in random MCDM problems between ARIE and other MCDM approaches.

4.4. Simulation-Based Analysis

This sub-section presents a comprehensive simulation-based comparison of ARIE with other MCDM methods. To rigorously validate ARIE's stability, MATLAB was used to generate four distinct sets of decision matrices, each with corresponding criteria weights and types. Criteria were classified as benefit or cost for all methods, with ARIE additionally handling target-type criteria. Each technique was implemented using its native MATLAB commands; because VIKOR normally identifies the best alternative by the lowest score, its code was adjusted to produce a descending order ranking for consistency with the others. Category I comprised four alternatives and four criteria, Category II eight of each, Category III ten of each, and Category IV twelve of each. Figure 7 shows the resulting ranking scores for all methods across these four categories.

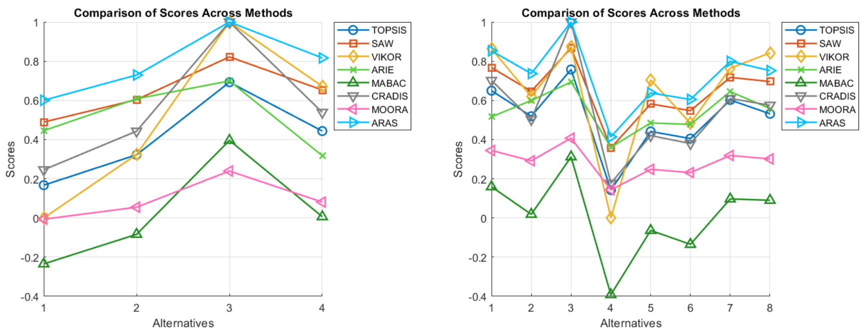

Figure 7: Comparison of Score Values across MCDM Methods for Category I and II.

Significant differences in the ranking behavior as the number of alternatives increases are shown in Figure 8. Most of the approaches in Category I show an upward trend from Alternative 1 to Alternative 3 with a minor downturn at Alternative 4. Among all the methods, Alternative 3 has the highest ranking, while Alternative 1 has the lowest. All methods continue to show steady trends with consistent ranking order, Alternatives 3 $\prec$ 4 $\prec$ 2 $\prec$ 1. At the lowest point value, ARAS and ARIE's scores are still slightly better than MABAC and MOORA. Although MABAC continues to produce negative results, it shows a noticeable improvement compared other methods, TOPSIS, SAW, and CRADIS. The majority of approaches in Category II show a trend of instability. With a discernible decrease at Alternative 4 and a high at Alternative 3, where all methods sharply increases before falling once more. Similar steady trends are followed by TOPSIS, SAW, VIKOR, and ARAS, although ARIE and VIKOR show only slight variations. Out of all the options, MABAC has the lowest score as the method allows negative values. MOORA has the smallest vertical range around 0.20–0.35, suggesting it's a very conservative method it never gives extreme highs or lows. ARIE on the other hand shows the largest variance, so it's highly sensitive to small changes in the data or the way target-type criteria are specified.

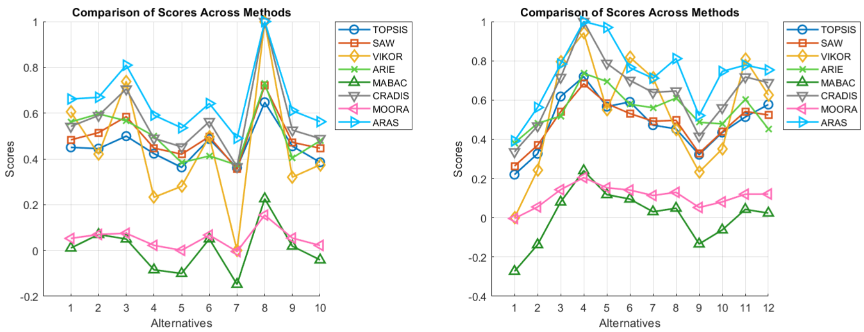

Figure 8: Comparison of Score Values across MCDM Methods for Category III and IV.

In Category III, VIKOR, MOORA and MABAC exhibits extreme fluctuations and drop sharply to its lowest value at Alternative 7. CRADIS and ARAS show a strong preference for these alternatives as the consistent peaks of the method in Alternatives 3 and 8. TOPSIS and SAW maintain moderate variations, while ARIE remain relatively stable with smaller deviations across the alternatives. The lower score in MOORA and MABAC highlight significant methodological differences where Alternatives 8 becomes a common evaluation tendency among most methods. In Category IV, all methods start at the lowest values at Alternative 1. With regular peaks at Alternative 4, all method remain steady progressions. The pattern of ARAS varies slightly greater than the structure of CRADIS. Due to their consistency and comparatively smaller scores, ARIE, SAW and TOPSIS exhibit more stable ranking behavior. Minimal fluctuations shown by ARIE across all categories compared to other MCDM approaches. Therefore, ARIE is found to be consistently stable for all categories. The score values across different iterations and MCDM method are illustrated in Figure 9, 10, 11, and 12.

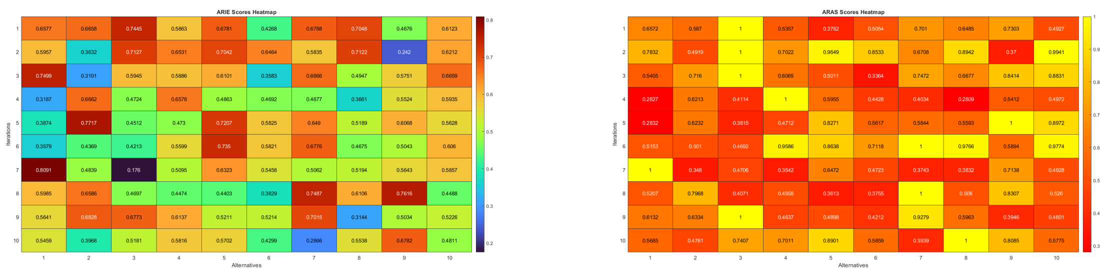

Figure 9: ARIE and ARAS Score Performance.

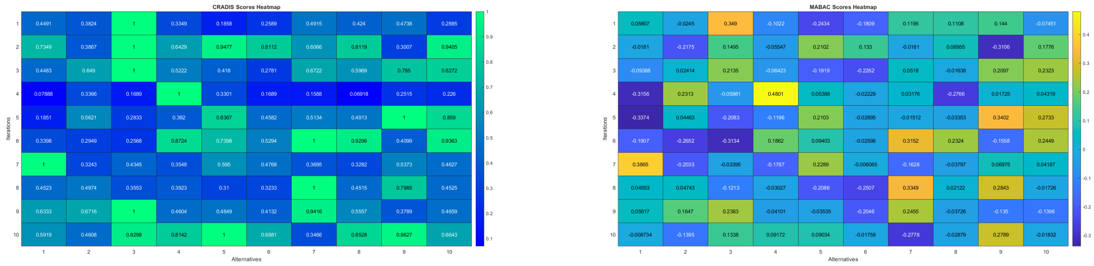

Figure 10: CRADIS and MABAC Score Performance.

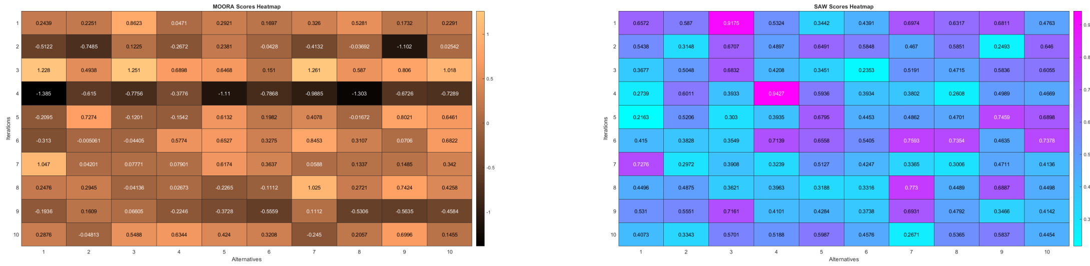

Figure 11: MOORA and SAW Score Performance.

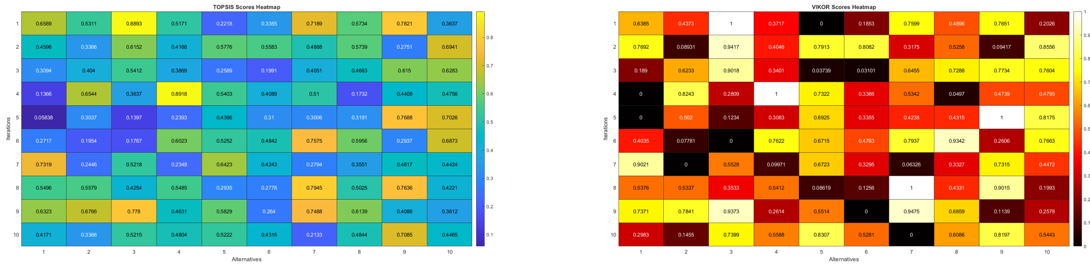

Figure 12: TOPSIS and VIKOR Score Performance.

All of the figures display color intensities that represent alternative rankings during multiple iterations of assessment. The ranking system utilizes bright colors to represent high scores while darker hues correspond to lower scores along with lower placement for alternatives across the methods. Based on the distribution of these color intensities, ARIE, MABAC, MOORA, TOPSIS and SAW methods share a similar ranking order pattern for all iterations. While ARAS, CRADIS and VIKOR have a similar color pattern especially for the Alternative 3. The ARIE, TOPSIS, and MOORA scores heatmap display a balanced and structured ranking system with scores ranging. Alternatives 4 frequently receive the highest scores as shown by warm colors, meanwhile either Alternatives 1 or 8 are the last ranked for the fourth iteration across all method. Alternative 3 consistently appears in bright tones, being a top favorable option in first until third and ninth and last iterations and being a stable ranking behavior is seen in ARAS, CRADIS and VIKOR heatmap.

The ARAS heatmap also presents a well-organized ranking structure compared to ARIE. While Alternatives 2 and 9 are consistently ranked lowest in second iteration, Alternatives 3, 4, and 7 typically receive the highest scores. The moderate range of scores indicates that ARIE offers a methodical approach to evaluation. TOPSIS, SAW and CRADIS maintain stable and balanced rankings while VIKOR demonstrates sudden aggressive ranking changes. VIKOR demonstrates better performance when alternatives have stark differences yet ARIE together with MABAC and CRADIS demonstrate superior reliability in situations demanding consistent ranking results. Overall, the heatmaps reveal that ARIE offers a well-balanced ranking approach since the method avoids extreme fluctuations while maintaining adaptability. SAW and CRADIS provide stable and structured rankings as the methods are ideal for decision-making contexts that require controlled score variations. In contrast, VIKOR exhibit highly dynamic ranking behaviours which better suited for cases where strong differentiation among alternatives is essential. Thus, ARIE becomes a preferred MCDM method especially for scenarios requiring both ranking consistency and adaptability.

One of ARIE's key innovations is its unified multi-type normalization scheme, which seamlessly integrates benefit, cost, and explicit target-based scaling alongside the usual extreme-value (maximum and minimum) adjustments. ARIE then applies a parameterized similarity based scoring function driven by a sensitivity exponent γ to tune nonlinearity and a balancing coefficient κ to trade off closeness to the ideal against distance from the anti-ideal to quantify each alternative's overall performance. The method automatically adjust its parameters γ and κ in real-time to adapt to changing between network dependencies, and varying criteria and datasets therefore delivering automatic resistance against outliers and high variability. ARIE implements a dynamic benchmarking framework which enables production of correct rankings derived from settings where rigid static methods fail to work and delivers results that adapt according to decision-making needs.

5. Conclusion

In challenging conditions, robust decision-making demands precise and trustworthy evaluation methods, and the ARIE method meets this need by combining a novel normalization technique with a similarity-to-ideal/anti-ideal solutions process to create a reliable, stable, and adaptable benchmarking framework that overcomes the limitations of traditional MCDM approaches; through comparative, sensitivity, and simulation-based analyses. ARIE method consistently outperforms established methods in stability and efficiency, confirming its practical value, yet its reliance on complete information can limit its effectiveness when data are missing. Future research should explore hybridizing ARIE with other MCDM techniques or embedding it within advanced fuzzy and neutrosophic set frameworks to broaden its applicability, with the method's inherent adaptability underscoring its robustness and laying the groundwork for next-generation decision frameworks capable of tackling today's complex challenges.

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