Jurnal Teknik Informatika (JUTIF)
Vol. 6, No. 1, February 2025, pp. 63-74

DOI: https://doi.org/10.52436/1.jutif.2025.6.1.4170
p-ISSN: 2723-3863
e-ISSN: 2723-3871

DYNAMIC WEIGHT ALLOCATION IN MODIFIED MULTI-ATRIBUTIVE IDEAL-REAL COMPARATIVE ANALYSIS WITH SYMMETRY POINT FOR REAL-TIME DECISION SUPPORT

Sitna Hajar Hadad[1], Iryanto Chandra[2], Junhai Wang[3], Dyah Ayu Megawaty[4], Setiawansyah[*5], Aditia Yudhistira[6]

[1]Institut Teknologi Gamalama di Ternate, Ternate, Indonesia
[2]UIN Sunan Kalijaga, Yogyakarta, Indonesia
[3]Department of Commerce and Circulation, Zhejiang Technical Institute of Economics, Zhejiang, China
[4,5,6]Faculty Engineering and Computer Science, Universitas Teknokrat Indonesia, Lampung, Indonesia
Email: [1]sitnahajar18@gmail.com, [2]iryanto.chandra@uin-suka.ac.id, [3]340017@zjtie.edu.cn, [4]dyahayumegawaty@teknokrat.ac.id, [5*]setiawansyah@teknokrat.ac.id, [6]aditiayudhistira@teknokrat.ac.id

(Article received: December 4, 2024; Revision: January 7, 2025; published: February 20, 2025)

Abstract

Decision Support Systems (DSS) have a crucial role in real-time decision-making, especially in the digital era that demands high speed and accuracy. Managing criterion weights in a dynamic environment presents significant challenges due to rapid and unpredictable changes in conditions. However, determining an accurate weight becomes difficult due to uncertainty, incomplete data, and subjective factors from decision-makers. In addition, changes in the external environment, such as market trends, regulations, or customer preferences, can affect the relevance of each criterion, thus requiring a real-time weight adjustment mechanism. The purpose of this study is to develop and explore the dynamic weight allocation method in symmetry point- multi-attributive ideal-real comparative analysis (S-MAIRCA) to support more accurate and responsive real-time decision-making in a dynamic environment. This research contributes to the understanding of how the weights of criteria can be adjusted automatically and responsively to changing conditions or new data, which increases the relevance and accuracy of decisions in a dynamic environment. The urgency of S-MAIRCA research is important because it often involves real-time, dynamic, and complex data. This development not only improves the adaptability of the S-MAIRCA method, but also contributes significantly to creating computer science-based applications that are more intelligent, flexible, and relevant to the evolving needs of the system. The results of the alternative ranking comparison using the CRITIC-MAIRCA, LOPCOW-MAIRCA, ROC-MAIRCA, and S-MAIRCA methods showed variations in the ranking order generated for each alternative using spearman correlation. The results of the correlation value of CRITIC-MAIRCA and LOPCOW-MAIRCA have a very high correlation of 0.993, which shows that these two methods provide almost identical rankings in alternative evaluation. Likewise, CRITIC-MAIRCA and S-MAIRCA had a high correlation of 0.979, signaling a strong similarity in ranking results despite slight differences in the approaches used by the two methods. The results of the application of the MAIRCA-S method in the development of DSS based on real-time data have a significant impact on improving the speed, accuracy, and adaptability of decisions. MAIRCA-S strengthens the validity of decision results by considering a variety of attributes on a more comprehensive scale, providing added value in the development of DSS for various industrial sectors.

Keywords: *Decision Support System, Dynamic Weighting, S-MAIRCA, Spearman Correlation, Symmetry-Point*

1. INTRODUCING

Decision Support Systems (DSS) have a crucial role in real-time decision-making, especially in the digital era that demands high speed and accuracy[1]. DSS helps process complex and large data quickly to produce relevant and reliable information for decision-makers. With advanced analytical capabilities, such as data modeling, simulation, and criteria weighting, DSS enables organizations to respond to critical situations in a timely manner, reduce the risk of errors, and improve process efficiency[2]. The implementation of DSS also supports more objective decision-making because it is data-based and algorithmic[3], making it an irreplaceable tool in various sectors, to deal with the dynamics of rapid change. Managing criterion weights in a dynamic environment presents significant challenges due to rapid and unpredictable changes in conditions. In this context, the weight of the criteria must be able to reflect the ever-changing priorities according to the current needs or situation. However, determining an accurate weight becomes difficult due to uncertainty, incomplete data, and subjective factors from decision-makers[4]. In addition, changes in the external environment, such as market trends, regulations, or customer preferences, can affect the relevance of each criterion, thus requiring a real-time weight adjustment mechanism. Without adaptive and data-driven methods, the risk of ineffective decision-making increases, which can have an impact on operational efficiency and the achievement of organizational goals.

Multi-attributive ideal-real comparative analysis (MAIRCA) is a multi-criteria decision-making method that aims to assist in determining the best alternative based on predetermined criteria[5]–[8]. This method integrates a comparison approach between the ideal value (ideal solution) and the actual value (real solution) of each alternative to obtain objective and accurate results. The MAIRCA method has a number of advantages that make it superior in the multi-criteria decision-making process[9]. One of its advantages is its objective nature, as this method minimizes the influence of subjectivity by focusing on data analysis based on ideal and actual solutions. In addition, MAIRCA is adaptive to various types of criteria, both benefits and costs, making it suitable for use in a dynamic environment and various sectors. Its relatively simple and structured process makes it easy for users to understand and implement this method without the need for complex tools or technical expertise. Another advantage is MAIRCA ability to produce more precise and transparent decisions, as it takes into account direct deviations from the ideal solution, resulting in more reliable end results[10]. In the context of criterion weighting, the MAIRCA method has several weaknesses that need to be considered. One of them is the dependence on the weight of pre-determined criteria, so if the weight is inaccurate or does not reflect the actual priority, the results of the decision can be biased. In addition, this method is less flexible in handling weight changes dynamically[11], especially in complex and uncertain environments, where the priority of criteria can change over time[12]. Sensitivity to weight is also a weakness, as small changes in weight can result in significant differences in the final result. This makes the reliability of decisions highly dependent on the accuracy of the weighing process, which often involves the subjectivity of the decision-maker or expert.

Developing a dynamic weight allocation method for MAIRCA aims to improve flexibility and accuracy in decision-making, especially in a rapidly changing environment. This approach involves the integration of real-time data-based weight adjustment techniques, the criteria weights can be updated automatically based on changing needs or priorities[13], allowing MAIRCA to generate more relevant and responsive decisions. This step also involves validating the results through simulation and comparing performance with static weighting methods, ensuring that the dynamic approach provides real benefits in complex dynamic contexts. The modification of the MAIRCA method with the concept of symmetry points aims to create a more balanced approach in multi-criteria decision-making[14], [15]. This modification involves calculating the symmetry points for each criterion, which is the average value between the ideal solution and the anti-ideal solution. Alternatives are then evaluated based on deviations from these points of symmetry, taking into account the weights of relevant criteria. This approach combines the power of MAIRCA in comparing actual values with ideal solutions, while adding a new dimension with a balance point to reduce the bias that may occur if only ideal or anti-ideal solutions are considered. The end result is an alternative ranking based on the total deviation to the point of symmetry, with the best alternative being the one with the lowest deviation value. These modifications improve the accuracy and relevance of MAIRCA, making it more effective in dynamic and complex environments.

Symmetry point-MAIRCA (S-MAIRCA) is a development of the MAIRCA method that integrates the concept of symmetry point to improve accuracy and balance in multi-criteria decision-making[16]–[18]. This method not only compares alternatives to ideal and anti-ideal solutions, but also adds a point of symmetry as an additional reference to assess the performance balance of each alternative. By considering the point of symmetry, S-MAIRCA is able to reduce the bias that may arise from traditional approaches and provide a more comprehensive evaluation of alternatives[19]. This approach is particularly suitable for use in complex and dynamic situations, where it is important to consider the balance between best and worst scenarios in order to make more objective and relevant decisions. The advantage of S-MAIRCA in generating dynamic criterion weights lies in its ability to accommodate changing conditions or priorities more flexibly. Using the symmetry point concept, the S-MAIRCA allows for more adaptive weighting, as the symmetry point is calculated based on the balance between the ideal and anti-ideal solutions[20]. This allows the criterion weights to automatically adjust for changes in values that arise from new data or external factors, without the need for complicated manual updates. This approach ensures that the criteria weights are not fixed or rigid, but rather can be updated in real-time to reflect changes in priorities or needs[21]. This advantage makes S-MAIRCA particularly useful in dynamic environments, where conditions and preferences change frequently, and decision-making requires speed and precision in responding to these changes.

Previous research on criterion weighting in multi-criteria decision-making methods has mostly focused on the static weighting approach, where criterion weighting is determined based on initial preference or a specific weighting method. This approach has weaknesses in dealing with dynamic conditions, such as changes in stakeholder preferences, fluctuations in real-time data, or changes in the priority of criteria due to the development of the situation. In addition, existing research often pays little attention to the incorporation of historical data, trend analysis, and real-time feedback holistically in dynamic weighting. Therefore, it is necessary to develop a more adaptive and comprehensive method in the application of dynamic criterion weights, especially in the S-MAIRCA method, to improve the accuracy and relevance of decision-making in changing situations.

The purpose of this study is to develop and explore the dynamic weight allocation method in S-MAIRCA to support more accurate and responsive real-time decision-making in a dynamic environment. This study integrates the mechanism of automatic adjustment of criterion weights, based on changes in external conditions and the latest data, by utilizing the concept of symmetry points. The contribution of this research lies in the development of an innovative dynamic weight allocation method within S-MAIRCA to support real-time decision-making. This research contributes to the understanding of how the weights of criteria can be adjusted automatically and responsively to changing conditions or new data, which increases the relevance and accuracy of decisions in a dynamic environment. Implementation of a more adaptive decision support system, which can be implemented in various sectors, to provide more objective, transparent, and real-time data-driven decisions using S-MAIRCA.

2. RELATED WORK

The MAIRCA method has been used in various studies to solve decision-making problems involving multiple criteria. In several previous studies, MAIRCA was used to evaluate and select the best alternatives in various contexts, ranging from supplier selection, performance assessment, to product selection. In contrast to other conventional methods, MAIRCA offers a more structured approach by comparing alternatives based on their proximity to ideal and realistic solutions. Related studies show the advantages of MAIRCA in producing more objective and transparent decisions, as this method is able to consider various criteria simultaneously and give weight according to the importance of each criterion. In addition, MAIRCA is also applied in several fields such as project management, decision support systems, and policy evaluation, proving its flexibility in solving complex problems involving many factors.

Research from [22] the combination of the criteria importance through intercriteria correlation (CRITIC) and MAIRCA weighting methods provides a robust framework for solving complex multi-criteria decision-making (MCDM) problems. By combining these two methods, the decision-making process becomes more reliable and systematic, as CRITIC ensures the weights are based on the nature of the data at hand, while MAIRCA provides a robust evaluation framework for selecting the best alternatives. This combination is especially useful in situations where the decision-making process involves many conflicting criteria and requires an objective and comprehensive analysis.

Research from [23] the combination of logarithmic percentage change-driven objective weighting (LOPCOW) and MAIRCA methods offers an innovative and effective approach to solving problems. The combination of LOPCOW and MAIRCA allows for more objective and transparent decision-making, as the weighting process is carried out based on existing data without the influence of subjectivity, while alternative evaluations are carried out comprehensively and thoroughly. This approach is very effective in situations that involve various conflicting and complex criteria, and requires in-depth and systematic analysis.

Research from [24] a combination of the rank order centroid (ROC) and (MAIRCA) methods is a powerful approach to dealing with MCDM problems. This combination of ROC and MAIRCA allows for a more transparent and objective decision-making process, as the ROC ensures the weight given to each criterion is based on the available data, while MAIRCA provides a thorough evaluation that considers all criteria simultaneously. This approach is particularly beneficial in situations that involve a variety of complex and conflicting criteria, and require accurate and comprehensive solutions.

The MAIRCA method uses a hands-on approach to determining the weighting of criteria, which is often subjective. This weighting can affect the outcome of a decision, especially if the decision-maker has certain biases or incomplete information. This gap opens up opportunities to integrate more objective weighting methods. Modification of the S-MAIRCA method. The modification of the S-MAIRCA method with a dynamic criterion weight approach aims to increase flexibility and adaptability in decision-making. The dynamic approach of criterion weighting in S-MAIRCA, where the criterion weights are dynamically adjusted based on preferences, real-time data, or changes in the decision-making environment.

Based on previous research, the results of the application of the CRITIC-MAIRCA, LOPCOW-MAIRCA, ROC-MAIRCA and S-MAIRCA methods will be compared from the alternative rankings obtained from each method.

3. RESEARCH METHOD

3.1. Research Stages

The research stage is a series of systematic steps carried out to achieve the research objectives, ranging from planning to analysis and preparation of research results[25]. Each stage has specific functions that are interconnected to produce valid and actionable findings. Figure 1 is the stage carried out in this study.

Figure 1. Research Stage

Data collection is the first stage in research that is very important to obtain the necessary information to support analysis and decision-making. In this stage, data is collected through various methods relevant to the research. The data collected should include information related to the alternatives and criteria to be analyzed in the study. The data collection process must be carried out systematically to ensure the accuracy, completeness, and consistency of the data that will be used in the next stage.

The application of MAIRCA modification is the core stage in this study, where the MAIRCA method is modified with the concept of symmetry point to improve accuracy and flexibility in decision-making. Dynamic criterion weights are calculated by taking into account changes in conditions or recent data, which allows the model to provide more adaptive and relevant decisions in a dynamic environment.

Result validation is the last important stage to ensure that the results obtained from the implementation of MAIRCA modifications are valid and reliable. At this stage, the results of decision-making using dynamic criterion weights are compared with the results obtained using the traditional MAIRCA method with static weights. This analysis aims to test whether the dynamic approach provides an advantage in terms of accuracy and relevance of decisions. In addition, simulations and validity tests are conducted to ensure that the model can be applied in a real context and provide results that are consistent with the research objectives. If the validation results show success, the study can proceed to practical application or provide recommendations for further research.

3.2. Modification MAIRCA Method

The MAIRCA method is a multi-criteria analysis approach used to compare various alternatives based on a number of relevant attributes or criteria. This method focuses on assessing the comparison between the ideal conditions and the real conditions of the evaluated alternatives, to determine the best alternative based on predetermined preferences. The MAIRCA modification aims to improve the accuracy and flexibility of the analysis by introducing adjustments in criterion weights, calculation of preference values, or adjustments to uncertainties in the data. With this modification, it is hoped that the MAIRCA method can provide more accurate and relevant results, which are more in accordance with the complexity and dynamics of the decision-making situation faced.

The symmetric point multi-attributive ideal-real comparative analysis (S-MAIRCA) method is a development of the MAIRCA method which aims to improve accuracy in alternative evaluation by adding symmetrical points in calculations. This approach focuses on the comparison between the ideal point and the real point of various alternatives, but with adjustments so that the comparison results are more balanced and reflect the distribution of criteria more fairly. In S-MAIRCA, symmetrical points are used to correct imbalances between one criterion and another, allowing for more objective and efficient assessments. These modifications aim to reduce the bias that can arise from differences in scale or weights between criteria and improve the quality of decisions taken in complex multi-criteria situations.

The S-MAIRCA method has several advantages that make it excel in multi-criteria decision-making. The first advantage of this method integrates the concept of symmetrical point evaluation, which ensures a balanced assessment between ideal alternatives and reality. This approach minimizes bias and encourages fair comparisons across criteria. The further advantages of the S-MAIRCA method emphasize positive and negative deviations, thus providing a comprehensive evaluation framework to capture the advantages and disadvantages of each alternative. Another advantage is the simplicity of calculations and clarity in generating rankings, which allows decision-makers to easily understand the results and make more informed decisions. Finally, its robustness in handling complex datasets as well as its sensitivity to small variations in criterion values make it an excellent choice for decision-making processes that require a high level of precision.

The framework of the S-MAIRCA method is designed to provide a more balanced and objective approach in evaluating alternatives based on several criteria. This framework ensures that the analysis is carried out in a systematic and structured manner, with the aim of generating more precise and reliable decisions in a complex multi-criteria context. Figure 1 is the framework of the S-MAIRCA method.

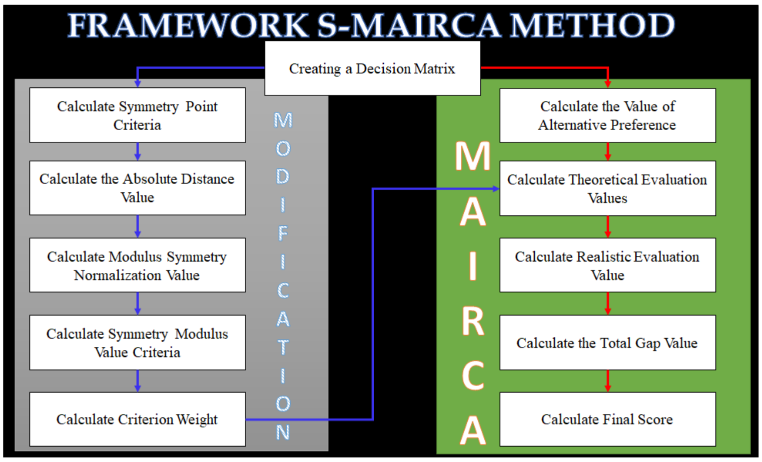

Figure 2. Framework S-MAIRCA Method

The first stage of the S-MAIRCA method framework is to create a decision matrix containing alternative data and relevant criteria. This matrix is used to map the value or performance of each alternative based on each of the predetermined criteria created with the following equation.

$$X = \begin{bmatrix} x_{11} & x_{21} & x_{2n} \\ x_{12} & x_{22} & x_{2n} \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix} \quad (1)$$

Once the decision matrix is composed, the next step is to calculate the symmetry point values for each criterion. This point of symmetry is used to balance the difference between the ideal value and the real value of the alternative based on the existing criteria calculated by the following equation.

$$SPJ_i = \frac{\min\{x_i\}+\max\{x_i\}}{2} \quad (2)$$

At this stage, the absolute distance value between the evaluated alternative and the ideal point and the real point for each criterion is calculated. This distance describes how far each alternative is from the expected ideal and real conditions calculated by the following equation.

$$d_{ij} = \left|x_{ij} - SPJ_i\right| \quad (3)$$

The normalized value of the symmetry modulus is calculated to convert the calculated values into a uniform scale, thus allowing comparison between alternatives and criteria. This normalization process reduces the potential for injustice that can arise due to scale differences between criteria calculated by the following equation.

$$r_{ij} = \frac{\frac{d_{ij}}{m}}{x_{ij}} \quad (4)$$

In this stage, the value of the symmetry modulus is calculated for each criterion based on the results of the previous calculation. This value shows how balanced or symmetrical each criterion in the alternative assessment is calculated by the following equation.

$$q_i = \frac{\sum_{i=1}^{n} r_{ij}}{m} \quad (5)$$

The weight of the criteria is calculated to reflect the importance of each criterion in decision-making calculated by the following equation.

$$w_i = \frac{q_i}{\sum_{i=1}^{n} q_i} \quad (6)$$

At this stage, the preference value for each alternative indicates how well it meets the set preferences or needs calculated by the following equation.

$$P_{ai} = \frac{1}{m} \quad (7)$$

A theoretical evaluation is carried out to determine the expected ideal value of each alternative if all criteria can be met perfectly. This value is calculated by combining the preference value and criterion weights in a theoretical model calculated by the following equation.

$$t_{pij} = P_{ai} * w_i \quad (8)$$

Realistic evaluation is carried out to calculate the actual or real value of the calculated alternative based on the available data. This value takes into account the limitations and real-world conditions that affect the evaluated alternative calculated by the following equation.

$$t_{rij} = t_{pij} * \left(\frac{x_{ij}-x_i^-}{x_i^+-x_i^-}\right) \quad (9)$$

$$t_{rij} = t_{pij} * \left(\frac{x_{ij}-x_i^+}{x_i^--x_i^+}\right) \quad (10)$$

Equation (9) is for the benefit criterion, while equation (10) is for the cost criterion.

The total gap value calculates the difference between the theoretical evaluation and the realistic evaluation of the alternative. This gap provides information about how much the difference between theoretical expectations and reality exists in each alternative calculated by the following equation.

$$G_{ij} = t_{pij} - t_{rij} \quad (11)$$

The final step is to calculate the final value of each alternative based on the difference between the total gap and the previous calculation. This final value is used to determine the best alternative based on the criteria and preferences that have been determined calculated by the following equation.

$$V_i = \sum_{i=1}^{n} G_{ij} \quad (12)$$

Each of these stages in the S-MAIRCA method aims to optimize the evaluation process in multi-criteria decision-making by providing a more balanced consideration between the ideal and real conditions of each alternative.

4. RESULT AND DISCUSSION

Implementation of dynamic weight allocation in the S-MAIRCA method to improve the accuracy and flexibility of real-time decision-making. This approach integrates dynamic weight changes based on the relevance and contribution of each criterion in an ever-evolving situation. The modified S-MAIRCA method is able to automatically adjust the weight of the criteria according to changes in the input data, thereby providing more adaptive and relevant ranking results.

4.1. Data Collection

Collecting data on the best supplier assessment is an important step in the process of selecting suppliers that can support the company's operational success. This assessment data is collected by setting relevant criteria, such as price (C1) which is cost, product quality (C2) which is benefit, product availability (C3) which is benefit, delivery time (C4) which is benefit, and flexibility in ordering (C5) which is benefit. Each criterion is evaluated based on quantitative data, such as scores or numbers, as well as qualitative data, such as feedback or direct observations from parties involved with suppliers.

Table 1. Supplier Assessment Data

Alternative	C1	C2	C3	C4	C5
A1	7.5	9.0	8.5	8.0	9.0
A2	8.0	8.5	8.0	8.5	8.5
A3	7.0	8.0	8.5	7.5	7.5
A4	9.0	9.0	9.0	9.5	8.5
A5	8.0	8.5	7.5	8.0	7.0
A6	9.0	7.5	8.0	9.0	8.5
A7	7.5	8.0	8.5	7.5	7.5
A8	8.5	9.5	9.0	9.0	9.5
A9	8.0	8.0	8.0	8.0	8.0

Data collection is carried out through surveys or questionnaires filled out by internal teams that are directly related to suppliers, as well as historical data related to supplier performance, for example regarding delivery or product quality. In addition, data can be obtained from various sources within the company, such as purchasing, logistics, and quality teams, to ensure a comprehensive and objective evaluation. Once the data is collected, analysis is carried out using appropriate methods, such as the multi-criteria decision making (MCDM) technique, to compare the performance of various suppliers and determine the best one. In this way, companies can make more informed decisions in choosing suppliers who not only meet quality and cost needs, but also have on-time delivery capabilities and flexibility in meeting demand. The assessment data of table 1 will be used by the S-MAIRCA method in the selection of the best alternative.

4.2. Implementation of the S-MAIRCA Method

The implementation of the S-MAIRCA method by identifying relevant alternatives and criteria, where the alternatives represent the options evaluated, and the criteria reflect important assessment factors. The resulting criterion weights are the result of calculations by considering the balance between ideal, real, and symmetry conditions for each criterion. The point of symmetry for each criterion is the average value between the ideal (best) and the real (worst) value, thus representing a neutral position or balance between the two extremes. The weight of the criteria generated based on this approach reflects the relative contribution level of each criterion to the final result, taking into account how the criterion values are in the context of the distance from the ideal, real, and point of symmetry conditions. The results of alternative values using this method are obtained through a process that measures the proximity of each alternative to the ideal condition (the best value for each criterion) and the distance from the real condition (the worst value for each criterion). The S-MAIRCA approach not only considers proximity to ideal conditions, but also balance with real conditions and points of symmetry, making it a flexible and effective method in complex multi-criteria decision-making.

The first stage of the S-MAIRCA method framework is to create a decision matrix containing alternative data and relevant criteria using equation (1) based on the assessment data of table 1.

$$X = \begin{bmatrix} 7.5 & 9.0 & 8.5 & 8.0 & 9.0 \\ 8.0 & 8.5 & 8.0 & 8.5 & 8.5 \\ 7.0 & 8.0 & 8.5 & 7.5 & 7.5 \\ 9.0 & 9.0 & 9.0 & 9.5 & 8.0 \\ 8.0 & 8.5 & 7.5 & 8.0 & 7.5 \\ 9.0 & 7.5 & 8.0 & 9.0 & 8.5 \\ 7.5 & 8.0 & 8.5 & 7.5 & 7.5 \\ 8.5 & 9.5 & 9.0 & 9.0 & 9.5 \\ 8.0 & 8.0 & 8.0 & 8.0 & 8.0 \end{bmatrix}$$

Once the decision matrix is composed, the next step is to calculate the symmetry point values for each criterion using equation (2).

$$SPJ_1 = \frac{\min\{x_1\} + \max\{x_1\}}{2} = \frac{9.0 + 7.0}{2} = 8.0$$

$$SPJ_2 = \frac{\min\{x_2\} + \max\{x_2\}}{2} = \frac{9.5 + 7.5}{2} = 8.5$$

$$SPJ_3 = \frac{\min\{x_3\} + \max\{x_3\}}{2} = \frac{9.0 + 7.5}{2} = 8.25$$

$$SPJ_4 = \frac{\min\{x_4\} + \max\{x_4\}}{2} = \frac{9.5 + 7.5}{2} = 8.5$$

$$SPJ_5 = \frac{\min\{x_5\} + \max\{x_5\}}{2} = \frac{9.5 + 7.0}{2} = 8.25$$

At this stage, the value of the absolute distance between the evaluated alternative with the ideal point and the real point for each criterion is calculated using equation (3).

$$d_{11} = |x_{11} - SPJ_1| = |7.5 - 8.0| = 0.5$$

The entire result of the calculation of the value of the absolute distance is shown in table 2.

Table 2. The Result of the Calculation of the Absolute Distance

Alternative	C1	C2	C3	C4	C5
A1	0.500	0.500	0.250	0.500	0.750
A2	0.000	0.000	0.250	0.000	0.250
A3	1.000	0.500	0.250	1.000	0.750
A4	1.000	0.500	0.750	1.000	0.250
A5	0.000	0.000	0.750	0.500	1.250
A6	1.000	1.000	0.250	0.500	0.250
A7	0.500	0.500	0.250	1.000	0.750
A8	0.500	1.000	0.750	0.500	1.250
A9	0.000	0.500	0.250	0.500	0.250

The normalized value of the symmetry modulus is calculated to convert the calculated value into a uniform scale, thus allowing comparison between the alternative and the criterion using equations (4).

$$r_{11} = \frac{\frac{d_{11}}{9}}{x_{11}} = \frac{\frac{0.500}{9}}{7.0} = 0.00741$$

The entire result of the calculation of the normalized value of the symmetry modulus is shown in table 3.

Table 3. The Result of the Calculation of the Normalized Value

Alternative	C1	C2	C3	C4	C5
A1	0.00741	0.00617	0.00327	0.00694	0.00926
A2	0.00000	0.00000	0.00347	0.00000	0.00327
A3	0.01587	0.00694	0.00327	0.01481	0.01111
A4	0.01235	0.00617	0.00926	0.01170	0.00327
A5	0.00000	0.00000	0.01111	0.00694	0.01984
A6	0.01235	0.01481	0.00347	0.00617	0.00327
A7	0.00741	0.00694	0.00327	0.01481	0.01111
A8	0.00654	0.01170	0.00926	0.00617	0.01462
A9	0.00000	0.00694	0.00347	0.00694	0.00347

At this stage, the value of the symmetry modulus is calculated for each criterion indicating how balanced or symmetrical each criterion is in the alternative assessment using equation (5).

$$q_1 = \frac{\sum_{i=1}^{n} r_{11,19}}{9} = \frac{0.06192}{9} = 0.00688$$

$$q_2 = \frac{\sum_{i=1}^{n} r_{21,29}}{9} = \frac{0.05969}{9} = 0.00663$$

$$q_3 = \frac{\sum_{i=1}^{n} r_{31,39}}{9} = \frac{0.04985}{9} = 0.00554$$

$$q_4 = \frac{\sum_{i=1}^{n} r_{41,49}}{9} = \frac{0.07450}{9} = 0.00828$$

$$q_5 = \frac{\sum_{i=1}^{n} r_{51,59}}{9} = \frac{0.07922}{9} = 0.00880$$

The criterion weights are calculated to reflect the importance of each criterion in decision-making calculated using equation (6).

$$w_1 = \frac{q_1}{\sum_{i=1}^{n} q_{1,5}} = \frac{0.00688}{0.03613} = 0.19040$$

$$w_2 = \frac{q_2}{\sum_{i=1}^{n} q_{1,5}} = \frac{0.00663}{0.03613} = 0.18356$$

$$w_3 = \frac{q_3}{\sum_{i=1}^{n} q_{1,5}} = \frac{0.00554}{0.03613} = 0.15330$$

$$w_4 = \frac{q_4}{\sum_{i=1}^{n} q_{1,5}} = \frac{0.00828}{0.03613} = 0.22912$$

$$w_5 = \frac{q_5}{\sum_{i=1}^{n} q_{1,5}} = \frac{0.00880}{0.03613} = 0.24362$$

At this stage, the preference value for each alternative indicates how well it meets the established preferences or needs calculated using equation (7).

$$P_{11,59} = \frac{1}{9} = 0.1111$$

Theoretical evaluations are carried out to determine the ideal value expected from each alternative if all criteria can be met perfectly. This value is calculated by combining the preference value and criterion weights in a theoretical model calculated using equation (8).

$$t_{p11} = P_{11} * w_1 = 0.1111 * 0.19040 = 0.02116$$

The entire result of the calculation of the theoretical evaluations value is shown in table 4.

Table 4. The Result of the Calculation of the Theoretical Evaluations value

Alternative	C1	C2	C3	C4	C5
A1	0.02116	0.02040	0.01703	0.02546	0.02707
A2	0.02116	0.02040	0.01703	0.02546	0.02707
A3	0.02116	0.02040	0.01703	0.02546	0.02707
A4	0.02116	0.02040	0.01703	0.02546	0.02707
A5	0.02116	0.02040	0.01703	0.02546	0.02707
A6	0.02116	0.02040	0.01703	0.02546	0.02707
A7	0.02116	0.02040	0.01703	0.02546	0.02707
A8	0.02116	0.02040	0.01703	0.02546	0.02707
A9	0.02116	0.02040	0.01703	0.02546	0.02707

Realistic evaluation is carried out to calculate the actual or real value of the calculated alternative based on the available data. This value takes into account the limitations and real-world conditions that affect the evaluated alternative calculated using equation (9).

$$t_{r11} = t_{p11} * \left(\frac{x_{11} - x_1^+}{x_1^- - x_1^+}\right) = 0.02116 * (0.75) = 0.01587$$

The entire result of the calculation of the realistic evaluations value is shown in table 5.

Table 5. The Result of the Calculation of the Realistic Evaluations value

Alternative	C1	C2	C3	C4	C5
A1	0.01587	0.01530	0.01136	0.00636	0.02165
A2	0.01058	0.01020	0.00568	0.01273	0.01624
A3	0.02116	0.00510	0.01136	0.00000	0.00541
A4	0.00000	0.01530	0.01703	0.02546	0.01624
A5	0.01058	0.01020	0.00000	0.00636	0.00000
A6	0.00000	0.00000	0.00568	0.01909	0.01624
A7	0.01587	0.00510	0.01136	0.00000	0.00541
A8	0.00529	0.02040	0.01703	0.01909	0.02707
A9	0.01058	0.00510	0.00568	0.00636	0.01083

The total gap value calculates the difference between the theoretical evaluation and the alternative realistic evaluation calculated using equation (11).

$$G_{11} = t_{p11} - t_{r11} = 0.02116 - 0.01587 = 0.00529$$

The entire result of the calculation of the total gap value is shown in table 6.

Table 6. The Result of the Calculation of the Total Gap value

Alternative	C1	C2	C3	C4	C5
A1	0.00529	0.00510	0.00568	0.01909	0.00541
A2	0.01058	0.01020	0.01136	0.01273	0.01083
A3	0.00000	0.01530	0.00568	0.02546	0.02165
A4	0.02116	0.00510	0.00000	0.00000	0.01083
A5	0.01058	0.01020	0.01703	0.01909	0.02707
A6	0.02116	0.02040	0.01136	0.00636	0.01083
A7	0.00529	0.01530	0.00568	0.02546	0.02165
A8	0.01587	0.00000	0.00000	0.00636	0.00000
A9	0.01058	0.01530	0.01136	0.01909	0.01624

The final step is to calculate the final value of each alternative based on the difference between the total gap and the previous calculation. This final value is used to determine the best alternative based on predetermined criteria and preferences calculated using equations (12).

$$V_1 = \sum_{i=1}^{n} G_{11,51} = 0.04057$$

The entire result of the calculation of the total value is shown in table 7.

Table 7. The Result of the Calculation of the Total value

Alternative	Final Value (V_i)
A1	0.04057
A2	0.05569
A3	0.06809
A4	0.03708
A5	0.08397
A6	0.07010
A7	0.07338
A8	0.02223
A9	0.07256

The results of the ranking of the best suppliers using the S-MAIRCA method show a ranking based on a thorough evaluation of the performance of each supplier on five predetermined criteria. In the S-MAIRCA method, the criterion weights are calculated objectively using a point of symmetry approach, which ensures that the more important criteria get greater attention in the evaluation. Based on this analysis, each supplier is compared to an ideal solution and a realistic solution to calculate their distance from the point of symmetry, which then translates into an overall score. The ranking results show that the supplier with the lowest score at the ideal distance has the best performance, reflecting its ability to optimally meet the desired needs. The ranking results are shown in table 8.

Table 8. Supplier Ranking Results

Alternative	Final Value (V_i)	Rank
A8	0.02223	1
A4	0.03708	2
A1	0.04057	3
A2	0.05569	4
A3	0.06809	5
A6	0.0701	6
A9	0.07256	7
A7	0.07338	8
A5	0.08397	9

The ranking results based on the final score show that Alternative A8 has the best performance with a value of 0.02223, thus occupying the first position in the ranking. Followed by Alternative A4 in second place with a value of 0.03708, and Alternative A1 in third place with a value of 0.04057. Meanwhile, Alternative A2, A3, A6, A9, A7, and A5 each occupy the fourth to ninth positions with higher scores, namely 0.05569, 0.06809, 0.0701, 0.07256, 0.07338, and 0.08397. This ranking reflects that alternatives with lower scores show more optimal performance in meeting the criteria that have been set, while alternatives with higher scores are at the bottom. Thus, Alternative A8 can be considered the best option based on the evaluation conducted with the S-MAIRCA method.

4.3. Result Validation

Result validation is an important step in ensuring the reliability and accuracy of the results obtained from an evaluation or analysis method. This process aims to verify that the results obtained are in accordance with real conditions and reliable in decision-making. Validation of the results was carried out to evaluate the consistency and objectivity of the decisions produced by the S-MAIRCA method. The validation process is carried out by comparing the results produced by the MAIRCA method with the results obtained using other relevant methods, to assess the consistency and accuracy of the decisions taken. This comparison helps to identify whether the MAIRCA method can produce more objective and accurate results in the selection of the best alternative, especially in the face of complex data with various criteria. Validation of these results is important to increase credibility and confidence in the decisions made, as well as to ensure that the alternatives chosen are the most optimal based on a thorough and measurable evaluation.

The ranking comparison results obtained from the CRITIC-MAIRCA method from research [22], LOPCOW-MAIRCA from research [23], ROC-MAIRCA from research [24], and S-MAIRCA provide an in-depth understanding of how each approach in criterion weighting and alternative evaluation affects the final outcome in multi-criteria decision-making. Table 9 is the result of a comparison of the ratings of the methods used.

Table 9. The Result of the Ranking Comparison

Alternative	Rank			
	CRITIC-MAIRCA	LOPCOW-MAIRCA	ROC-MAIRCA	S-MAIRCA
A8	1	1	2	1
A4	2	2	6	2
A1	3	3	1	3
A2	4	4	5	4
A3	5	5	3	5
A6	7	8	9	6
A9	8	7	7	7
A7	6	6	4	8
A5	9	9	8	9

The results of the alternative ranking comparison using the CRITIC-MAIRCA, LOPCOW-MAIRCA, ROC-MAIRCA, and S-MAIRCA methods showed variations in the ranking order generated for each alternative. Although some alternatives obtain the same rating in some methods, there are significant differences, especially in the lower performing alternatives. For example, the A8 alternative is ranked first on CRITIC-MAIRCA, LOPCOW-MAIRCA, and S-MAIRCA, while on ROC-MAIRCA, the A8 alternative is ranked second. Alternative A1, which consistently ranks third across all methods, shows stability in its performance evaluation. In contrast, the A6 alternative received the highest rating in S-MAIRCA (ranked 6th), but ranked 7th and 8th in CRITIC-MAIRCA and LOPCOW-MAIRCA. Other alternative ratings, such as A4 and A7, show clear fluctuations between methods, highlighting how differences in the way weights are calculated and evaluated can affect decision-making outcomes. Overall, despite the differences in the rankings produced, all methods provide a fairly consistent picture of the best and worst alternatives, which can help decision-makers choose the alternative that best fits the criteria.

5. DICUSSION

The results of the comparison between four multi-criteria decision-making methods, namely CRITIC-MAIRCA method from research [22], LOPCOW-MAIRCA from research [23], ROC-MAIRCA from research [24], and S-MAIRCA. These four methods use different approaches in determining criterion weights and evaluating alternatives, but aim to produce objective and consistent rankings based on relevant criteria. CRITIC-MAIRCA relies on correlations between criteria to calculate weights, while LOPCOW-MAIRCA uses logarithmic percentage changes, ROC-MAIRCA focuses on ranking sequences, and

S-MAIRCA utilizes a point of symmetry approach for weighting. Despite using different methods, the comparative results obtained through correlation and ranking analysis showed that most of the methods gave fairly consistent results, although there were differences in the order of the rankings produced. Therefore, it is important to explore the differences and similarities between these methods in order to understand the advantages and disadvantages of each, as well as to determine the most appropriate method for decision-making based on the existing context.

Spearman correlation is a non-parametric statistical method used to measure the strength and direction of the relationship between two variables based on the order of data ranking, not their absolute values. Unlike Pearson correlation, which assumes a linear relationship and normal distribution of data, Spearman correlation is more flexible because it can be used for data that is not normally distributed or has a non-linear relationship. In the context of multi-criteria decision analysis, Spearman correlation is often used to assess how consistent two methods are in assigning ratings to different alternatives. The use of Spearman correlation is very useful in evaluating the ranking results of various methods to understand the extent of differences or similarities between the approaches used. The results of the comparison between four multi-criteria decision-making methods, namely CRITIC-MAIRCA, LOPCOW-MAIRCA, ROC-MAIRCA, and S-MAIRCA, were analyzed using Spearman correlation. Spearman correlation is used to measure the extent to which the alternative ranking sequences are similar to each method. By understanding the correlation between methods through this approach, we can evaluate how sensitive each method is to changes in weights and rankings, as well as the extent to which differences in the approaches affect the results obtained. Table 10 is the comparison of the spearman correlation of each method.

Table 10. Results of Spearman Correlation Comparison

	CRITIC-MAIRCA	LOPCOW-MAIRCA	ROC-MAIRCA	S-MAIRCA
CRITIC-MAIRCA	1	0.993	0.8741	0.979
LOPCOW-MAIRCA	0.993	1	0.8881	0.972
ROC-MAIRCA	0.8741	0.8881	1	0.8882
S-MAIRCA	0.979	0.972	0.8882	1

From the data provided, it can be seen that CRITIC-MAIRCA and LOPCOW-MAIRCA have a very high correlation (0.993), which shows that these two methods provide almost identical ratings in alternative evaluation. Likewise, CRITIC-MAIRCA and S-MAIRCA had a high correlation (0.979), signaling a strong similarity in ranking results despite slight differences in the approaches used by the two methods. In contrast, comparisons with ROC-MAIRCA showed lower correlations, such as in CRITIC-MAIRCA and ROC-MAIRCA (0.8741) and LOPCOW-MAIRCA and ROC-MAIRCA (0.8881), which showed greater differences in the ranking order given by ROC-MAIRCA compared to other methods. The correlation between ROC-MAIRCA and S-MAIRCA was also relatively lower (0.8882), although it still showed a significant relationship. Overall, the results of Spearman's correlation show that despite differences in their respective methodologies, most methods (notably CRITIC-MAIRCA, LOPCOW-MAIRCA, and S-MAIRCA) produce very similar ranking sequences, whereas ROC-MAIRCA has slight differences compared to other methods in terms of alternative rankings.

The results of Spearman's correlation show that the largest correlation value is 0.979 obtained from the S-MAIRCA method. This indicates that the alternative ratings resulting from the S-MAIRCA approach have a very high degree of alignment. The S-MAIRCA method shows that the symmetrical approach used is highly compatible in analyzing multi-criteria alternatives.

The results of the application of the MAIRCA-S method in the development of DSS based on real-time data have a significant impact on improving the speed, accuracy, and adaptability of decisions. By integrating this approach, DSS is able to handle real-time data more efficiently through a more standardized normalization and attribute comparison process, resulting in more objective rankings even as the data continues to change. This impact is particularly relevant in dynamic environmental contexts, such as supply chain management, financial monitoring systems, and human resource management, where timely and data-driven decision-making is crucial. In addition, MAIRCA-S strengthens the validity of decision results by considering a variety of attributes on a more comprehensive scale, providing added value in the development of DSS for various industrial sectors.

6. CONCLUSION

The purpose of this study is to develop and explore the dynamic weight allocation method in S-MAIRCA to support more accurate and responsive real-time decision-making in a dynamic environment. This study integrates the mechanism of automatic adjustment of criterion weights, based on changes in external conditions and the latest data, by utilizing the concept of symmetry points. The results of the alternative ranking comparison using the CRITIC-MAIRCA, LOPCOW-MAIRCA, ROC-MAIRCA, and S-MAIRCA methods showed variations in the ranking order generated for each alternative. Although some alternatives obtain the same rating in some methods, there are significant differences, especially in the lower performing alternatives. For example, the A8 alternative is ranked first on CRITIC-MAIRCA, LOPCOW-MAIRCA, and S-MAIRCA, while on ROC-MAIRCA, the A8 alternative is ranked second. Alternative A1, which consistently ranks third across all methods, shows stability in its performance evaluation. In contrast, the A6 alternative received the highest rating in S-MAIRCA (ranked 6th), but ranked 7th and 8th in CRITIC-MAIRCA and LOPCOW-MAIRCA. Other alternative ratings, such as A4 and A7, show clear fluctuations between methods, highlighting how differences in the way weights are calculated and evaluated can affect decision-making outcomes. Overall, despite the differences in the rankings produced, all methods provide a fairly consistent picture of the best and worst alternatives, which can help decision-makers choose the alternative that best fits the criteria,

The results of the alternative ranking comparison using the CRITIC-MAIRCA, LOPCOW-MAIRCA, ROC-MAIRCA, and S-MAIRCA methods showed variations in the ranking order generated for each alternative using spearman correlation. The results of the correlation value of CRITIC-MAIRCA and LOPCOW-MAIRCA have a very high correlation of 0.993, which shows that these two methods provide almost identical rankings in alternative evaluation. Likewise, CRITIC-MAIRCA and S-MAIRCA had a high correlation of 0.979, signaling a strong similarity in ranking results despite slight differences in the approaches used by the two methods. This emphasizes the importance of dynamic weighting as an innovative approach in supporting real-time data-based decision-making systems. This research contributes to the understanding of how the weights of criteria can be adjusted automatically and responsively to changing conditions or new data, which increases the relevance and accuracy of decisions in a dynamic environment. Implementation of a more adaptive decision support system, which can be implemented in various sectors, to provide more objective, transparent, and real-time data-driven decisions using S-MAIRCA.

REFERENCES

[1] A. R. Mishra, P. Rani, F. Cavallaro, I. M. Hezam, and J. Lakshmi, "An Integrated Intuitionistic Fuzzy Closeness Coefficient-Based OCRA Method for Sustainable Urban Transportation Options Selection," *Axioms*, vol. 12, no. 2, p. 144, Jan. 2023, doi: 10.3390/axioms12020144.

[2] I. Granado, L. Hernando, Z. Uriondo, and J. A. Fernandes-Salvador, "A fishing route optimization decision support system: The case of the tuna purse seiner," *Eur. J. Oper. Res.*, vol. 312, no. 2, pp. 718–732, 2024, doi: https://doi.org/10.1016/j.ejor.2023.07.009.

[3] L. Siciliani, V. Taccardi, P. Basile, M. Di Ciano, and P. Lops, "AI-based decision support system for public procurement," *Inf. Syst.*, vol. 119, p. 102284, Oct. 2023, doi: 10.1016/j.is.2023.102284.

[4] H. Sulistiani, S. Setiawansyah, A. F. O. Pasaribu, P. Palupiningsih, K. Anwar, and V. H. Saputra, "New TOPSIS: Modification of the TOPSIS Method for Objective Determination of Weighting," *Int. J. Intell. Eng. Syst.*, vol. 17, no. 5, pp. 991–1003, Oct. 2024, doi: 10.22266/ijies2024.1031.74.

[5] S. Chakraborty, P. Chatterjee, and P. P. Das, "Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) Method," in *Multi-Criteria Decision-Making Methods in Manufacturing Environments*, Apple Academic Press, 2024, pp. 289–296.

[6] F. Ecer, A. Böyükaslan, and S. Hashemkhani Zolfani, "Evaluation of Cryptocurrencies for Investment Decisions in the Era of Industry 4.0: A Borda Count-Based Intuitionistic Fuzzy Set Extensions EDAS-MAIRCA-MARCOS Multi-Criteria Methodology," *Axioms*, vol. 11, no. 8, p. 404, Aug. 2022, doi: 10.3390/axioms11080404.

[7] S. Hadian, E. Shahiri Tabarestani, and Q. B. Pham, "Multi attributive ideal-real comparative analysis (MAIRCA) method for evaluating flood susceptibility in a temperate Mediterranean climate," *Hydrol. Sci. J.*, vol. 67, no. 3, pp. 401–418, Feb. 2022, doi: 10.1080/02626667.2022.2027949.

[8] S. Riahi, A. Bahroudi, M. Abedi, and S. Aslani, "Hybrid outranking of geospatial data: Multi attributive ideal-real comparative analysis and combined compromise solution," *Geochemistry*, vol. 82, no. 3, p. 125898, Sep. 2022, doi: 10.1016/j.chemer.2022.125898.

[9] T. ÖZTAŞ and G. Z. ÖZTAŞ, "Innovation Performance Analysis of G20 Countries: A Novel Integrated LOPCOW-MAIRCA MCDM Approach Including the COVID-19 Period," *Veriml. Derg.*, pp. 1–20, Jan. 2024, doi: 10.51551/verimlilik.1320794.

[10] M. C. Joe Anand, K. Kalaiarasi, N. Martin, B. Ranjitha, S. S. Priyadharshini, and M. Tiwari, "Fuzzy C-Means Clustering with MAIRCA -MCDM Method in Classifying Feasible Logistic Suppliers of Electrical Products," in *2023 First International Conference on Cyber Physical Systems, Power Electronics and Electric Vehicles (ICPEEV)*, Sep. 2023, pp. 1–7. doi: 10.1109/ICPEEV58650.2023.10391835.

[11] S. Hashemkhani Zolfani, F. Ecer, D. Pamučar, and S. Raslanas, "NEIGHBORHOOD SELECTION FOR A NEWCOMER VIA A NOVEL BWM-BASED REVISED MAIRCA INTEGRATED MODEL: A CASE FROM THE COQUIMBO-LA SERENA CONURBATION, CHILE," *Int. J. Strateg. Prop. Manag.*, vol. 24, no. 2, pp. 102–118, Jan. 2020, doi: 10.3846/ijspm.2020.11543.

[12] M. S. Almhanna, T. A. Murshedi, A. M. Al-Salih, and R. M. Almuttairi, "Dynamic Allocation of Weights Using the Minimally Connected Method to Augment Load Equilibrium in Distributed Systems," *Int. J. Intell. Eng. Syst.*, vol. 17, no. 1, pp. 343–356, Feb. 2024, doi: 10.22266/ijies2024.0229.31.

[13] H. Li and T. Zhao, "A dynamic similarity weighted evolving fuzzy system for concept drift of data streams," *Inf. Sci. (Ny).*, vol. 659, p. 120062, 2024, doi: https://doi.org/10.1016/j.ins.2023.120062.

[14] D. S. Maltseva and R. O. Popovych, "Point-symmetry pseudogroup, Lie reductions and exact solutions of Boiti–Leon–Pempinelli system," *Phys. D Nonlinear Phenom.*, vol. 460, p. 134081, Apr. 2024, doi: 10.1016/j.physd.2024.134081.

[15] I. M. Hezam, N. R. D. Vedala, B. R. Kumar, A. R. Mishra, and F. Cavallaro, "Assessment of Biofuel Industry Sustainability Factors Based on the Intuitionistic Fuzzy Symmetry Point of Criterion and Rank-Sum-Based MAIRCA Method," *Sustainability*, vol. 15, no. 8, p. 6749, Apr. 2023, doi: 10.3390/su15086749.

[16] P. Rani, A. R. Mishra, D. Pamucar, J. Ali, and I. M. Hezam, "Interval-valued intuitionistic fuzzy symmetric point criterion-based MULTIMOORA method for sustainable recycling partner selection in SMEs," *Soft Comput.*, 2023, doi: 10.1007/s00500-023-08189-7.

[17] A. R. Mishra, P. Rani, D. Pamucar, and V. Simic, "Evaluation and Prioritization of Sustainable Enterprise Resource Planning in SMEs Using q-Rung Orthopair Fuzzy Rough Set-Based Decision Support Model," *IEEE Trans. Fuzzy Syst.*, vol. 32, no. 5, pp. 3260–3273, 2024, doi: 10.1109/TFUZZ.2024.3374799.

[18] J. Úradníček, M. Musil, Ľ. Gašparovič, M. Páleník, and M. Bachratý, "Enhancing reliability in estimating modal parameters for automotive disk Brakes: A comprehensive approach using the Eigensystem Realization algorithm and additional criteria," *Mech. Syst. Signal Process.*, vol. 224, p. 112069, 2025, doi: https://doi.org/10.1016/j.ymssp.2024.112069.

[19] H. Ren, X. Zhuang, X. Fu, Z. Li, and T. Rabczuk, "Bond-based nonlocal models by nonlocal operator method in symmetric support domain," *Comput. Methods Appl. Mech. Eng.*, vol. 418, p. 116230, 2024, doi: https://doi.org/10.1016/j.cma.2023.116230.

[20] A. Saha *et al.*, "Fermatean Fuzzy Dombi Generalized Maclaurin Symmetric Mean Operators for Prioritizing Bulk Material Handling Technologies," *Cognit. Comput.*, vol. 16, no. 6, pp. 3096–3121, 2024, doi: 10.1007/s12559-024-10323-y.

[21] W. A. Faridi, A.-M. Wazwaz, A. M. Mostafa, R. Myrzakulov, and Z. Umurzakhova, "The Lie point symmetry criteria and formation of exact analytical solutions for Kairat-II equation: Paul-Painlevé approach," *Chaos, Solitons & Fractals*, vol. 182, p. 114745, 2024, doi: https://doi.org/10.1016/j.chaos.2024.114745.

[22] M. W. Arshad, S. Setiawansyah, R. R. Suryono, and Y. Rahmanto, "Combination of CRITIC Weighting Method and Multi-Atributive Ideal-Real Comparative Analysis in Staff Admissions," *Explorer (Hayward).*, vol. 4, no. 2, pp. 77–86, 2024, doi: 10.47065/explorer.v4i2.1428.

[23] S. H. Hadad, S. Subhan, S. Setiawansyah, M. W. Arshad, A. Yudhistira, and Y. Rahmanto, "COMBINATION OF LOGARITHMIC PERCENTAGE CHANGE-DRIVEN OBJECTIVE WEIGHTING AND MULTI-ATTRIBUTIVE IDEAL-REAL COMPARATIVE ANALYSIS IN DETERMINING THE BEST PRODUCTION EMPLOYEES," *J. Tek. Inform.*, vol. 5, no. 3, pp. 843–853, 2024, doi: 10.52436/1.jutif.2024.5.3.2057.

[24] H. T. Dung, D. T. Do, and V. T. Nguyen, "Comparison of Multi-Criteria Decision Making Methods Using The Same Data Standardization Method," *Strojnícky časopis - J. Mech. Eng.*, vol. 72, no. 2, pp. 57–72, Nov. 2022, doi: 10.2478/scjme-2022-0016.

[25] S. Setiawansyah, S. H. Hadad, A. A. Aldino, P. Palupiningsih, G. Fitri Laxmi, and D. A. Megawaty, "Employing PIPRECIA-S weighting with MABAC: a strategy for identifying organizational leadership elections," *Bull. Electr. Eng. Informatics*, vol. 13, no. 6, pp. 4273–4284, Dec. 2024, doi: 10.11591/eei.v13i6.7713.