Volume 1 Number 3 July 2027, Available online: July 20, 2027.

Journal of Decision Support Systems and Multi-Criteria Decision Making
ISSN: 3164-7022
Page 321-348
Journal Homepage: https://research.pilar.or.id/index.php/jodesma

Development of the Range of Value (ROV) Method Based on Dynamic Weighting for Decision Support Systems

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Keywords:
Dynamic-ROV;
Rank Order Value;
Multi-Criteria Decision Making;
Criterion Weighting;
Sensitivity Analysis;

ABSTRACT

Decision-making in complex environments requires an evaluation framework capable of integrating multiple criteria with different levels of importance and performance. This study proposes Dynamic-ROV, a modified Rank Order Value approach designed to evaluate alternatives through data-driven criterion weighting and utility-based assessment. The proposed procedure consists of decision matrix normalization, standard deviation-based criterion weighting, best and worst utility evaluation, final utility calculation, and ranking. The approach was applied to the selection of nine manager candidates using seven evaluation criteria. Its robustness was assessed through 28 sensitivity scenarios involving positive and negative changes in individual criterion weights, while its ranking consistency was further examined against SAW, MOORA, GRA, and SMART. The results show that Candidate M-02 achieves the highest final utility value of 0.3862 and obtains the first rank, whereas Candidate M-08 records the lowest utility value of 0.1179 and ranks ninth. The sensitivity analysis indicates that the principal ranking structure remains stable across all tested scenarios, with M-02 consistently occupying the first position and M-08 remaining in the last position. Comparative evaluation also demonstrates that Dynamic-ROV produces ranking patterns that are broadly consistent with the established MCDM methods. These findings indicate that Dynamic-ROV provides a reliable and stable framework for multi-criteria evaluation while offering a data-oriented mechanism for determining criterion importance and assessing alternative performance. The proposed approach can therefore serve as an alternative decision-support method for selection problems in organizational settings.

DOI: https://doi.org/10.67449/jodesma.v1i3.12

Article Link: https://research.pilar.or.id/index.php/jodesma/article/view/12

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Journal of Decision Support Systems and Multi-Criteria Decision Making

ISSN: 3164-7022

Page 321-348

Journal Homepage: https://research.pilar.or.id/index.php/jodesma

Publication Dates:
Online First Date:
December 3, 2026
Published Date:
July 20, 2027

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I. Introduction

Decision Support Systems (DSS) play an important role in supporting complex decision-making processes by providing systematic, structured, and data-driven analyses to assist decision-makers in evaluating alternatives and selecting the most appropriate solution[1], [2]. In particular, DSS is highly relevant to Multi-Criteria Decision-Making (MCDM) problems, where decisions involve numerous alternatives that must be assessed simultaneously according to multiple criteria. Such decision-making situations often present challenges because each alternative may exhibit different performance levels across criteria, while the criteria themselves may have varying degrees of importance and potentially conflicting priorities. Without an appropriate analytical framework, the evaluation process may become subjective, inconsistent, and difficult to manage, particularly when the number of alternatives and criteria increases. Therefore, the integration of DSS and MCDM methods provides a systematic approach for organizing decision data[3], [4], determining criteria priorities, evaluating alternative performance, and generating rankings that support more objective, transparent, and reliable decision-making.

Conventional MCDM methods have limitations in handling differences in the importance of criteria, particularly when the weighting process relies on fixed, subjective, or predetermined values[5], [6]. In many applications, criteria weights are assigned based on expert judgment or assumed to remain constant throughout the evaluation process, which may not fully reflect the actual contribution of each criterion to the decision. This limitation becomes more significant when criteria exhibit different levels of variability, interrelationships, or discriminatory power in distinguishing alternatives. As a result, criteria with substantial differences in data characteristics may receive insufficient or excessive influence, potentially affecting the accuracy and reliability of the resulting rankings. Furthermore, conventional weighting approaches may be less responsive to changes in alternative performance and decision contexts, reducing the adaptability of the evaluation process[7]-[10]. Therefore, an objective and data-driven weighting approach is needed to better capture the relative importance of criteria and improve the reliability of MCDM-based decision-making.

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The use of fixed or static weights in MCDM presents a limitation because the importance of each criterion is determined once and subsequently applied uniformly throughout the evaluation process, regardless of changes in data characteristics or the performance of the alternatives. This approach may not adequately reflect the actual contribution of each criterion, particularly when the criteria have different levels of variation, discriminatory power, or relationships with other criteria. As a result, the resulting alternative rankings may be influenced by predetermined weights that do not fully represent the characteristics of the evaluated data. Therefore, dynamic weighting is important to provide a more adaptive weighting mechanism in which the contribution of each criterion can be adjusted according to the characteristics of the data and the performance of the alternatives. By incorporating dynamic weighting, the decision-making process can better capture changes in the relative importance of criteria, resulting in evaluations that are more objective, adaptive, and representative of the actual decision context.

Range of Value (ROV) is one of the MCDM methods that employs the concept of minimum and maximum values, or range, to evaluate the relative performance of alternatives across multiple criteria[11], [12]. The method provides a systematic mechanism for transforming criterion values into comparable measures by considering the distribution and range of observed data. Through this approach, differences in alternative performance can be represented more clearly, allowing the decision-maker to identify the relative position of each alternative within the observed minimum–maximum interval[13]. The use of the range concept makes ROV relevant for decision-making problems involving heterogeneous criteria, as it facilitates the comparison of alternatives despite differences in measurement scales. Consequently, ROV can serve as an effective approach for evaluating and ranking alternatives in MCDM problems while utilizing the information contained in the observed range of criterion values.

The development of ROV can be further enhanced through the implementation of a dynamic weighting mechanism that allows the importance of each criterion to adapt to the characteristics of the decision data. In the conventional ROV approach, the evaluation process may rely on predetermined criterion weights, which can limit its ability to represent variations in criterion importance across different decision contexts. By incorporating dynamic weighting, the contribution of each criterion can be adjusted based on factors such as data variability, the distribution of alternative performance, and the relative information provided by each criterion[14]–[16]. This mechanism enables ROV to become more responsive to the actual characteristics of the evaluated alternatives rather than depending solely on fixed assumptions regarding criterion importance. Therefore, the integration of dynamic weighting into ROV has the potential to improve the adaptability, objectivity, and reliability of the evaluation and ranking process in complex MCDM problems.

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1.1. Problem Statement

The use of static criterion weights can limit the ability of an MCDM model to accurately represent the actual variation contained in the decision data[17], [18]. When the weights are determined in advance and maintained throughout the evaluation process, the contribution of each criterion remains unchanged even when the distribution, variability, or performance of the alternatives differs significantly. Consequently, criteria with substantial variation in the observed data may not receive an influence proportional to their actual discriminatory capacity, while criteria with relatively limited variation may have an influence that is greater than warranted. This condition can affect the evaluation process and reduce the objectivity of the resulting decision.

In the conventional ROV approach, the evaluation and ranking process still depends on criterion weights that are predetermined before the alternatives are assessed. Such a mechanism may become less effective when the distribution or characteristics of the decision data change, as the fixed weights may no longer represent the relative contribution of each criterion under the new conditions. Changes in alternative performance can therefore lead to ranking variations that are not fully captured by the weighting mechanism[19]–[21]. This indicates the need for a more adaptive ROV approach that can adjust criterion contributions according to the characteristics and distribution of the available data, thereby improving the flexibility, objectivity, and reliability of the resulting rankings.

1.2. Research Gap

The conventional ROV method has limited ability to adapt to dynamically changing criterion importance. In practical decision-making environments, the relative importance of criteria may vary depending on the characteristics of the alternatives and the distribution of the decision data[22], [23]. However, when criterion weights remain fixed throughout the evaluation process, ROV may not fully capture these changes. This limitation can reduce the flexibility of ROV when applied to decision-making problems with varying data conditions.

Another limitation concerns the integration of ROV with objective and dynamic weighting mechanisms. Existing ROV applications commonly rely on weights that are determined prior to the ranking process, either through expert judgment or another predetermined weighting procedure. Such an approach may not sufficiently reflect the actual information contained in the data, particularly differences in variability and the ability of each criterion to distinguish between alternatives. Therefore, integrating ROV with an objective weighting mechanism may provide an opportunity to determine criterion importance based on measurable characteristics of the decision data.

In addition, there is still limited investigation into ranking stability under variations in criterion weights. Changes in weights may alter the contribution of individual criteria and consequently affect the ranking positions of alternatives[24], [25]. Without sensitivity

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analysis, it can be difficult to determine whether the resulting ranking is robust or highly dependent on a particular weighting configuration. Evaluating ranking changes under different weight scenarios is therefore important for assessing the reliability and stability of ROV-based decision outcomes.

These limitations indicate the need for further development of an adaptive ROV-based DSS framework. Such a framework should be capable of dynamically determining criterion contributions based on the characteristics of the available data while maintaining the ROV mechanism for evaluating and ranking alternatives. Furthermore, the framework can incorporate sensitivity analysis to examine ranking stability under different weighting scenarios. This combination has the potential to produce a more flexible, objective, and reliable DSS for complex multi-criteria decision-making problems.

1.3. Research Objectives

This study aims to develop a dynamic weighting mechanism for the ROV method to address the limitations of predetermined or static criterion weights. The proposed mechanism will determine the contribution of each criterion dynamically based on the characteristics of the decision data and the performance of the evaluated alternatives. The resulting weighting mechanism will then be integrated directly into the ROV calculation process to produce an enhanced Dynamic-ROV method that can be implemented within a DSS framework. This integration is expected to make the evaluation process more adaptive to variations in data characteristics and criterion importance.

The performance of the proposed Dynamic-ROV method will be evaluated through the ranking of alternatives based on multiple decision criteria. The resulting rankings will be analyzed to determine the ability of the proposed method to distinguish and prioritize alternatives effectively. Furthermore, the results obtained using Dynamic-ROV will be compared with those produced by conventional ROV and other relevant MCDM methods. This comparison is intended to identify differences in ranking results and assess whether the proposed approach provides improvements in terms of evaluation consistency and decision-making effectiveness.

Finally, the study will examine the stability and robustness of alternative rankings under changes in criterion weights. Sensitivity analysis will be conducted by applying different weight variation scenarios to observe how changes in criterion importance influence the resulting rankings. The stability of the rankings across these scenarios will provide an indication of the robustness of the proposed Dynamic-ROV method. Through this evaluation, the study is expected to demonstrate whether Dynamic-ROV can provide more adaptive, stable, and reliable decision support compared with conventional ROV and other MCDM approaches.

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1.4. Research Contributions

The study is expected to contribute a new dynamic weighting mechanism for the ROV that enables the importance of each criterion to be determined adaptively based on the characteristics of the decision data. This mechanism will be integrated into an extended ROV method for DSS, resulting in an adaptive framework capable of supporting both criterion-weight determination and alternative ranking. Through this integration, the proposed method is expected to provide a more flexible and data-responsive decision-making process compared with the conventional ROV approach, particularly in situations where the relative importance of criteria varies according to the evaluated data.

Furthermore, the proposed method will be evaluated through a comparative analysis against conventional MCDM methods to assess its effectiveness in producing alternative rankings. The evaluation will include comparisons with conventional ROV and other relevant MCDM approaches to identify differences in ranking outcomes and decision performance. In addition, sensitivity and robustness analyses will be conducted by applying variations in criterion weights to examine the stability of the resulting rankings. These analyses are intended to determine whether the proposed method remains consistent and reliable under different weighting conditions, thereby demonstrating its potential as a robust and adaptive approach for MCDM-based DSS.

II. Methodology

2.1. Research Framework

The research framework provides a structured representation of the stages, relationships, and methodological procedures followed throughout a study[26], [27]. It serves as a conceptual guide that connects the research problem with the objectives, methodological approach, data processing procedures, analytical techniques, and expected outcomes. In this study, the research framework illustrates the overall workflow, beginning with problem identification and data preparation, followed by the application of the proposed method, comparative analysis, and performance evaluation. The complete research framework is presented in Figure 1.

Figure 1. Research Framework

The research framework of this study consists of five main stages, beginning with the Research Problem, which identifies the need to improve the conventional ROV method in supporting multi-criteria decision-making. The second stage, ROV Limitation Analysis, examines the

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characteristics and limitations of the conventional ROV, particularly its weighting mechanism and ability to represent varying criterion importance. The third stage focuses on the Modification of ROV into Dynamic-ROV, where a dynamic weighting mechanism is incorporated into the ROV procedure to develop a more adaptive ranking approach. The fourth stage, Experimental Testing, applies the proposed Dynamic-ROV method to decision-making datasets to evaluate its computational performance and ranking results. Finally, Comparative and Sensitivity Analysis evaluates Dynamic-ROV against the conventional ROV and other relevant MCDM methods, while sensitivity analysis examines the stability of the resulting rankings under changes in criterion weights.

2.2. Modification of ROV

The modification of the ROV method is undertaken to address the limitations of the conventional ROV framework in handling changes in criterion importance during the decision-making process. Although ROV provides a simple mechanism for evaluating alternatives through normalized criterion values and utility aggregation, its performance is influenced by the weighting scheme applied to the criteria. To improve this aspect, the proposed approach introduces a dynamic weighting mechanism that adjusts criterion weights according to the characteristics of the decision matrix. This modification retains the fundamental ranking structure of ROV while extending its weighting procedure to produce more adaptive and data-responsive preference values. Through this development, the conventional ROV is transformed into Dynamic-ROV, which is subsequently evaluated to determine its effectiveness and ranking stability in multi-criteria decision-making problems.

The modification of the ROV method into Dynamic-ROV consists of a sequential process that begins with the preparation of the decision matrix containing the performance of each alternative across the evaluation criteria. The performance data are then normalized to obtain comparable values across criteria with different measurement scales and preference directions. The normalized data are subsequently analyzed using standard deviation to determine the degree of variation and discriminatory information provided by each criterion. This information is used to generate criterion weights dynamically, allowing the importance of each criterion to be determined according to the characteristics of the decision data rather than relying solely on predetermined weights. The resulting weights are then incorporated into the best and worst utility functions to evaluate each alternative from both favorable and unfavorable performance perspectives. Finally, the utility values are aggregated into a final utility score, which is used to establish the ranking of alternatives. Through this modification, the conventional ROV procedure is extended with a dynamic weighting mechanism, resulting in the proposed Dynamic-ROV method for adaptive multi-criteria decision making.

The first stage is the construction of the decision matrix, which contains the performance values of all alternatives across the selected

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criteria[28]. This matrix represents the initial decision information and serves as the basis for the subsequent stages of the Dynamic-ROV procedure. Each performance value reflects the condition of an alternative with respect to a particular criterion. The decision matrix is formulated as follows:

$$X = [x_{ij}]_{mxn} \tag{1}$$

The normalization stage converts the original performance values into comparable values because the criteria may use different measurement scales and units[29], [30]. The normalization process also considers the characteristics of each criterion, distinguishing between criteria where higher values are preferred and criteria where lower values are preferred. Through this process, the performance values are transformed into a common scale while preserving their relative decision-making information. The normalization procedure is expressed as:

$$r_{ij}{}^{+} = \frac{x_{ij} - \min_j x_{ij}}{\max_j x_{ij} - \min_j x_{ij}}; benefit; \tag{2}$$

$$r_{ij}{}^{-} = \frac{\max_j x_{ij} - x_{ij}}{\max_j x_{ij} - \min_j x_{ij}}; cost \tag{3}$$

The standard deviation stage measures the degree of variation in the normalized performance values for each criterion[31], [32]. This measure indicates how strongly a criterion differentiates the alternatives within the decision matrix. A criterion with greater variation provides more discriminatory information because the performance of the alternatives differs more substantially. The standard deviation is calculated using:

$$SD_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(r_{ij} - \bar{r}_j)^2} \tag{5}$$

The criterion weighting stage determines the relative importance of each criterion based on the variation identified in the previous stage. The proposed Dynamic-ROV uses the standard deviation information to assign greater importance to criteria that provide stronger differentiation among alternatives. The resulting weights are normalized so that their total value equals one. The criterion weights are determined using:

$$w_j = \frac{SD_j}{\sum_{j=1}^{n} SD_j} \tag{6}$$

The best and worst utility functions evaluate the performance of each alternative from two complementary perspectives. The first function measures the contribution of the normalized performance toward the favorable decision condition, while the second represents the contribution associated with the unfavorable condition. The two utility functions allow the proposed Dynamic-ROV to retain the fundamental principle of ROV while incorporating the dynamically determined criterion weights. The utility functions are calculated as follows:

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$$U_i^{+} = \sum_{j=1}^{n} r_{ij}^{+} * w_j \quad (7)$$

$$U_i^{-} = \sum_{j=1}^{n} r_{ij}^{-} * w_j \quad (8)$$

The final utility stage combines the best and worst utility values into a single preference value for each alternative. This value represents the overall relative performance of an alternative by considering both favorable and unfavorable utility conditions. Alternatives with higher final utility values are considered more preferable and are placed in higher ranking positions. The final utility is obtained using:

$$A_i = \frac{U_i^{-} + U_i^{+}}{2} \quad (9)$$

The proposed Dynamic-ROV method provides an extended formulation of the conventional ROV by incorporating a data-driven weighting mechanism into the decision-making process. The integration of dynamic weighting enables the method to respond to the distribution and variation of criterion values while maintaining the fundamental utility-based structure of ROV. The resulting final utility values provide a basis for ranking alternatives according to their overall performance across the evaluated criteria. The effectiveness of Dynamic-ROV is subsequently assessed through experimental testing, comparative analysis with established MCDM methods, and sensitivity analysis to examine the consistency and stability of the resulting rankings.

2.3. Dataset and Case Study

The dataset and case study provide the empirical foundation for evaluating the proposed method and examining its applicability to multi-criteria decision-making problems. The dataset represents a set of decision alternatives evaluated according to several criteria that reflect the relevant characteristics of the decision context. The case study is selected to demonstrate how the proposed approach processes heterogeneous criterion information, determines the relative importance of each criterion, and produces a final ranking of alternatives. By applying the method to a realistic decision environment, the analysis not only illustrates the computational procedure but also enables the resulting rankings to be compared with established decision-making methods. This case study therefore serves as a practical basis for assessing the effectiveness, consistency, and reliability of the proposed method under actual decision conditions.

Manager selection is a strategic decision-making problem because the quality of managerial personnel can directly influence organizational performance, team effectiveness, and the achievement of business objectives. In this case study, the decision problem involves selecting the most suitable manager from a set of qualified candidates based on multiple managerial and professional attributes. The evaluation considers both benefit criteria, where higher values indicate better candidate performance, and cost criteria, where lower values represent more desirable outcomes for the organization. The selected criteria cover

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leadership competency, professional experience, decision-making ability, communication skill, team management, problem-solving ability, salary expectation, and training requirement. Each candidate is evaluated using a predefined assessment scale for all criteria, producing a decision matrix that represents the relative performance of the alternatives. The resulting assessment data for the manager selection problem are presented in Table 1.

Table 1. Dataset Manager Selection

Candidate	CSM-1	CSM-2	CSM-3	CSM-4	CSM-5	CSM-6	CSM-7
Candidate M-01	8	9	4	6	4	9	18500000
Candidate M-02	9	8	5	8	5	8	16500000
Candidate M-03	7	7	4	8	3	8	14000000
Candidate M-04	8	8	3	9	4	7	20000000
Candidate M-05	9	7	5	6	5	8	22000000
Candidate M-06	7	8	3	7	4	8	15000000
Candidate M-07	8	7	4	7	4	7	13500000
Candidate M-08	6	6	3	8	2	7	12000000
Candidate M-09	8	9	4	8	3	8	19000000

The manager selection dataset consists of nine candidates evaluated using seven criteria, namely CSM-1 Leadership, CSM-2 Experience, CSM-3 Decision-Making, CSM-4 Communication, CSM-5 Team Management, CSM-6 Problem-Solving, and CSM-7 Salary Expectation (IDR/month). The first six criteria represent candidate competencies and professional attributes, where higher assessment values indicate stronger managerial capabilities and are therefore treated as benefit criteria. Leadership reflects the candidate's ability to direct and motivate others, while Experience represents relevant professional background. Decision-Making measures the ability to select appropriate actions under different conditions, Communication assesses the effectiveness of information exchange, Team Management evaluates the ability to coordinate and manage team members, and Problem-Solving reflects the capability to identify and resolve managerial problems. In contrast, Salary Expectation represents the monthly compensation expected by each candidate and is treated as a cost criterion, where a lower value is considered more favorable from the organizational perspective. The assessment data provide the decision matrix required for the subsequent normalization, weighting, utility calculation, and ranking stages.

III. Result

3.1. Implementation of Dynamic-ROV

The Dynamic-ROV method is implemented to evaluate and rank the manager candidates by integrating criterion weights with their corresponding performance values in a structured decision-making process. The implementation begins with the decision matrix containing the assessment of each candidate across the selected criteria, followed

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by normalization to transform the criteria into comparable scales. The normalized values are then combined with the determined criterion weights to construct the best and worst utility functions, which represent the relative performance of each candidate from both favorable and unfavorable perspectives. The resulting utility values are subsequently aggregated to obtain the final utility score for each candidate, which serves as the basis for establishing the priority ranking. Through these stages, Dynamic-ROV provides a systematic mechanism for handling benefit and cost criteria while producing a comprehensive ranking of the alternatives.

The first stage of the Dynamic-ROV implementation is the construction of the decision matrix, which contains the performance values of all manager candidates with respect to the selected criteria. The decision matrix is constructed using (1), and the resulting matrix for the manager selection case study is presented as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} & x_{17} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} & x_{27} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} & x_{37} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} & x_{47} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} & x_{57} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} & x_{67} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} & x_{77} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} & x_{87} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} & x_{97} \end{bmatrix}$$

The results of the candidate evaluation decision matrix are shown as follows.

$$X = \begin{bmatrix} 8 & 9 & 4 & 6 & 4 & 9 & 18500000 \\ 9 & 8 & 5 & 8 & 5 & 8 & 16500000 \\ 7 & 7 & 4 & 8 & 3 & 8 & 14000000 \\ 8 & 8 & 3 & 9 & 4 & 7 & 20000000 \\ 9 & 7 & 5 & 6 & 5 & 8 & 22000000 \\ 7 & 8 & 3 & 7 & 4 & 8 & 15000000 \\ 8 & 7 & 4 & 7 & 4 & 7 & 13500000 \\ 6 & 6 & 3 & 8 & 2 & 7 & 12000000 \\ 8 & 9 & 4 & 8 & 3 & 8 & 19000000 \end{bmatrix}$$

The normalization stage transforms the original performance values into comparable values to accommodate differences in measurement scales and units among the selected criteria. The normalization procedure is performed using (3) for criteria CSM-7 and using (2) for the other criteria, and the resulting normalized decision matrix is presented as follows:

$$r_{11}{}^{+} = \frac{x_{11} - \min\limits_{1} x_{ij}}{\max\limits_{1} x_{ij} - \min\limits_{1} x_{ij}} = \frac{8-6}{9-6} = \frac{2}{3} = 0.6667$$

The overall normalization results of the Dynamic-ROV method are shown in Table 2.

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Table 2. Normalization Results of the Dynamic-ROV method

Candidate	CSM-1	CSM-2	CSM-3	CSM-4	CSM-5	CSM-6	CSM-7
Candidate M-01	0.6667	1.0000	0.5000	0.0000	0.6667	1.0000	0.3500
Candidate M-02	1.0000	0.6667	1.0000	0.6667	1.0000	0.5000	0.5500
Candidate M-03	0.3333	0.3333	0.5000	0.6667	0.3333	0.5000	0.8000
Candidate M-04	0.6667	0.6667	0.0000	1.0000	0.6667	0.0000	0.2000
Candidate M-05	1.0000	0.3333	1.0000	0.0000	1.0000	0.5000	0.0000
Candidate M-06	0.3333	0.6667	0.0000	0.3333	0.6667	0.5000	0.7000
Candidate M-07	0.6667	0.3333	0.5000	0.3333	0.6667	0.0000	0.8500
Candidate M-08	0.0000	0.0000	0.0000	0.6667	0.0000	0.0000	1.0000
Candidate M-09	0.6667	1.0000	0.5000	0.6667	0.3333	0.5000	0.3000

The standard deviation stage measures the variation in normalized performance values for each criterion. A higher value indicates greater differences among manager candidates and stronger discriminatory information, while a lower value indicates more similar performance. The standard deviation is calculated using (5), with the resulting values presented as follows:

$$SD_1 = \sqrt{\frac{1}{9}\sum_{i=1}^{9}(r_{i1} - \bar{r}_1)^2} = \sqrt{\frac{1}{9}(0.8395)} = \sqrt{0.0933} = 0.3054$$

The overall standard deviation results of the Dynamic-ROV method are shown in Table 3.

Table 3. Standard Deviation Results of the Dynamic-ROV method

CSM-1	CSM-2	CSM-3	CSM-4	CSM-5	CSM-6	CSM-7
0.3054	0.3143	0.3685	0.3186	0.3054	0.3143	0.3163

The criterion weighting stage determines the relative importance of each criterion based on the standard deviation obtained in the previous stage. The criterion weights are determined using (6), with the resulting weights presented as follows:

$$w_1 = \frac{SD_1}{\sum_{j=1}^{6} SD_j} = \frac{0.3054}{2.2428} = 0.1362$$

The overall criteria weight results of the Dynamic-ROV method are shown in Table 4.

Table 4. Criteria Weight Results of the Dynamic-ROV method

CSM-1	CSM-2	CSM-3	CSM-4	CSM-5	CSM-6	CSM-7
0.1362	0.1401	0.1643	0.1421	0.1362	0.1401	0.1410

The best and worst utility functions evaluate each alternative from favorable and unfavorable perspectives. These functions preserve the fundamental ROV principle while incorporating the dynamically determined criterion weights. The best and worst utility values are calculated using (7) and (8), respectively, with the resulting values presented as follows:

$$U_1^+ = (r_{ij}^+ * w_j) + (r_{ij}^+ * w_j) + (r_{ij}^+ * w_j) + (r_{ij}^+ * w_j) + (r_{ij}^+ * w_j) + (r_{ij}^+ * w_j)$$

DOI: https://doi.org/10.67449/jodesma.v1i3.12

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$$U_1^{-} = r_{17}^{+} * w_7 = 0.3500 * 0.1410 = 0.0494$$

The overall best and worst utility results of the Dynamic-ROV method are shown in Table 5.

Table 5. Best and Worst Utility of the Dynamic-ROV method

Candidate	Best Utility	Worst Utility
Candidate M-01	0.5440	0.0494
Candidate M-02	0.6948	0.0776
Candidate M-03	0.3844	0.1128
Candidate M-04	0.4170	0.0282
Candidate M-05	0.5534	0.0000
Candidate M-06	0.3470	0.0987
Candidate M-07	0.3578	0.1199
Candidate M-08	0.0947	0.1410
Candidate M-09	0.5232	0.0423

The final utility stage combines the best and worst utility values to obtain a single preference value for each alternative. This value represents the overall performance of each manager candidate by considering both favorable and unfavorable conditions. The final utility is calculated using (9), with the resulting values presented as follows:

$$A_1 = \frac{U_1^{-} + U_1^{+}}{2} = \frac{0.494 + 0.5440}{2} = \frac{0.5993}{2} = 0.2967$$

The overall final utility results of the Dynamic-ROV method are shown in Table 6.

Table 6. Final Utility of the Dynamic-ROV method

Candidate	Final Utility
Candidate M-01	0.2967
Candidate M-02	0.3862
Candidate M-03	0.2486
Candidate M-04	0.2226
Candidate M-05	0.2767
Candidate M-06	0.2229
Candidate M-07	0.2388
Candidate M-08	0.1179
Candidate M-09	0.2828

The final utility values obtained from the Dynamic-ROV calculation are used to determine the ranking of the manager candidates. Candidates are ranked in descending order of their final utility values, where a higher value indicates a stronger overall preference and a more favorable position in the selection process. The resulting ranking provides a clear basis for identifying the most suitable manager candidate, with the complete ranking presented in Figure 2.

DOI: https://doi.org/10.67449/jodesma.v1i3.12

Article Link: https://research.pilar.or.id/index.php/jodesma/article/view/12

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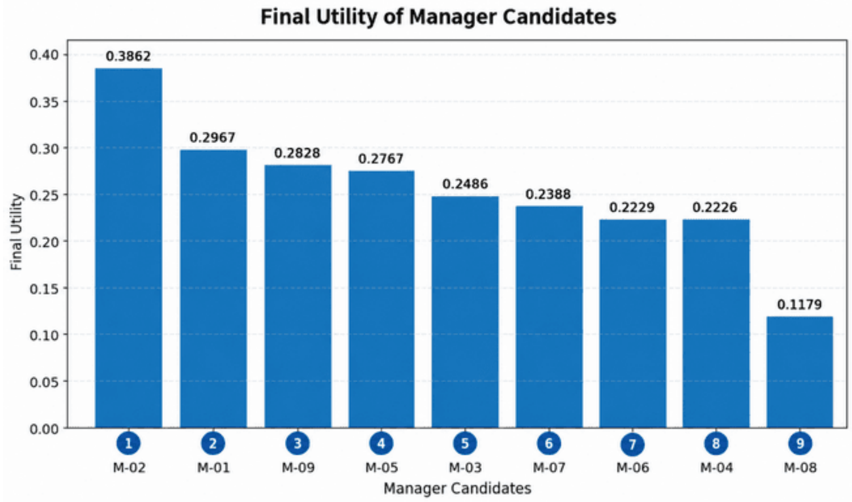

Figure 2. Alternative Ranking Using the Dynamic-ROV Method

The final utility values indicate that Candidate M-02 achieved the highest preference value of 0.3862, placing it first in the manager selection ranking, as presented in Figure 2. Candidate M-01 followed with a final utility of 0.2967, while Candidate M-09 and Candidate M-05 occupied the third and fourth positions with values of 0.2828 and 0.2767, respectively. Candidate M-03 ranked fifth with a value of 0.2486, followed by Candidate M-07 with 0.2388. The lower positions were obtained by Candidate M-06 and Candidate M-04, with final utility values of 0.2229 and 0.2226, respectively. Meanwhile, Candidate M-08 recorded the lowest final utility value of 0.1179 and ranked ninth. These results show that Candidate M-02 provides the strongest overall preference among the evaluated candidates and can therefore be considered the most suitable candidate for the manager position based on the Dynamic-ROV assessment.

3.2. Sensitivity Analysis

Sensitivity analysis is conducted to assess the robustness, stability, and reliability of the proposed decision-making method under variations in criterion weights[33], [34]. In multi-criteria decision-making, the assignment of weights plays an important role in determining the relative importance of each criterion and can influence the final ranking of alternatives. Therefore, evaluating the effects of weight changes is necessary to determine whether the ranking results remain consistent or experience significant shifts when different weighting conditions are applied. This analysis examines the relationship between changes in criterion weights and the resulting ranking of alternatives by comparing the outcomes obtained under different weighting conditions. The findings provide an assessment of the method’s sensitivity to weight variations and offer further evidence of its reliability in supporting consistent decision-making.

The sensitivity analysis is performed by modifying the criterion weights to evaluate the stability of the alternative rankings under different weighting conditions[35], [36]. The scenarios are designed by

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increasing and decreasing the criterion weights by 0.05 and 0.1 from their initial values. These adjustments are intended to examine the extent to which changes in the relative importance of criteria affect the final ranking of alternatives. The results obtained from each weighting scenario are compared with the initial ranking to identify changes in alternative positions and assess the robustness of the proposed method.

The sensitivity analysis is conducted by modifying the criterion weights to evaluate the stability of the decision-making results. In the first scenario, the weight of each criterion is increased by 0.05 individually, while the weights of the other criteria remain unchanged. After the adjustment, the resulting weights are normalized to ensure that the total weight remains equal to 1.0000. This process is applied sequentially to all seven criteria to observe the effect of each weight increase on the decision-making model. The results of the sensitivity analysis with a weight increase of 0.05 are presented in Table 7.

Table 7. Test Changes with Weight Increased by 0.05

Test	Scenario	CSM-1	CSM-2	CSM-3	CSM-4	CSM-5	CSM-6	CSM-7
Test 1	CSM-1+0.05	0.1773	0.1334	0.1565	0.1353	0.1297	0.1334	0.1343
Test 2	CSM-2+0.05	0.1297	0.181	0.1565	0.1353	0.1297	0.1334	0.1343
Test 3	CSM-3+0.05	0.1297	0.1334	0.2041	0.1353	0.1297	0.1334	0.1343
Test 4	CSM-4+0.05	0.1297	0.1334	0.1565	0.183	0.1297	0.1334	0.1343
Test 5	CSM-5+0.05	0.1297	0.1334	0.1565	0.1353	0.1773	0.1334	0.1343
Test 6	CSM-6+0.05	0.1297	0.1334	0.1565	0.1353	0.1297	0.181	0.1343
Test 7	CSM-7+0.05	0.1297	0.1334	0.1565	0.1353	0.1297	0.1334	0.181

Based on the weight changes in the sensitivity analysis scenario, the alternatives are ranked to determine the effect of criterion-weight adjustments on their ranking positions. The ranking results show the order of alternatives according to their preference values under the weight-change scenario. The comparison of ranking positions is used to evaluate the stability of the decision-making results against changes in criterion weights. The ranking results for the scenario with a weight increase of 0.05 are presented in Figure 3.

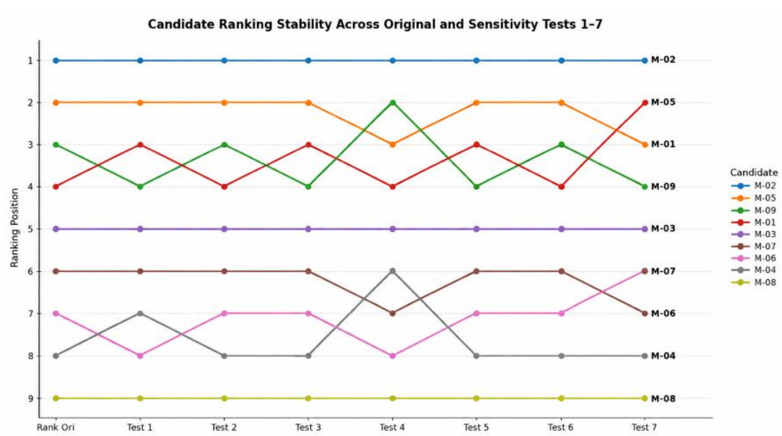

Figure 3. Ranking Results from the Weight Change Increased by 0.05

DOI: https://doi.org/10.67449/jodesma.v1i3.12

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The ranking results across the original condition and Tests 1–7 indicate a generally stable ordering, with Candidate M-02 consistently maintaining the first position throughout all scenarios, while Candidate M-08 remains in ninth position without any change. Candidate M-03 also demonstrates complete stability by retaining fifth place in every test. Moderate ranking fluctuations are observed among Candidates M-01, M-09, and M-05, with M-01 shifting between second and third positions, M-09 varying between second and fourth positions, and M-05 moving between second and fourth positions. The lower-ranked candidates also exhibit several changes, particularly M-07, M-06, and M-04. M-07 changes from sixth to seventh position, M-06 moves between sixth, seventh, and eighth positions, while M-04 improves from eighth to sixth position in Test 4 and Test 7. Overall, the ranking pattern shows that the leading and lowest-ranked candidates are highly stable, whereas the middle-ranked candidates experience limited positional changes under the sensitivity tests.

In the second sensitivity analysis scenario, the weight of each criterion is individually decreased by 0.05, while the weights of the remaining criteria are kept unchanged. The adjusted weights are subsequently normalized to ensure that the total weight remains equal to 1.0000. This procedure is applied sequentially to all seven criteria to examine the effect of increasing each criterion's weight on the decision-making results. The resulting criterion weights are presented in Table 8.

Table 8. Test Changes with Weight Decreased by 0.05

Test	Scenario	CSM-1	CSM-2	CSM-3	CSM-4	CSM-5	CSM-6	CSM-7
Test 8	CSM-1-0.05	0.0907	0.1475	0.1729	0.1496	0.1434	0.1475	0.1484
Test 9	CSM-2-0.05	0.1434	0.0948	0.1729	0.1496	0.1434	0.1475	0.1484
Test 10	CSM-3-0.05	0.1434	0.1475	0.1203	0.1496	0.1434	0.1475	0.1484
Test 11	CSM-4-0.05	0.1434	0.1475	0.1729	0.0969	0.1434	0.1475	0.1484
Test 12	CSM-5-0.05	0.1434	0.1475	0.1729	0.1496	0.0907	0.1475	0.1484
Test 13	CSM-6-0.05	0.1434	0.1475	0.1729	0.1496	0.1434	0.0948	0.1484
Test 14	CSM-7-0.05	0.1434	0.1475	0.1729	0.1496	0.1434	0.1475	0.0958

Based on the weight changes in the sensitivity analysis scenario, the alternatives are ranked to determine the effect of criterion-weight adjustments on their ranking positions. The ranking results show the order of alternatives according to their preference values under the weight-change scenario. The comparison of ranking positions is used to evaluate the stability of the decision-making results against changes in criterion weights. The ranking results for the scenario with a weight decrease of 0.05 are presented in Figure 4.

DOI: https://doi.org/10.67449/jodesma.v1i3.12

Article Link: https://research.pilar.or.id/index.php/jodesma/article/view/12

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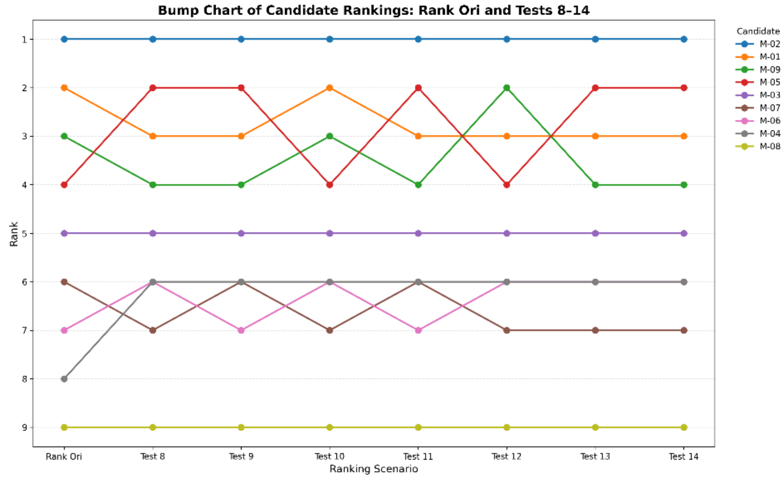

Figure 4. Ranking Results from the Weight Change Decreased by 0.05

The ranking pattern across the original condition and Tests 8–14 shows a high degree of stability, particularly for the top- and bottom-ranked candidates. Candidate M-02 consistently maintains Rank 1 in every scenario, while M-03 remains at Rank 5 and M-08 remains at Rank 9 throughout all tests. Candidate M-01 experiences only minor variation, moving between second and third positions, whereas M-09 fluctuates between second and fourth positions, including an improvement to Rank 2 in Test 12. Candidate M-05 shows more noticeable movement within the upper group, alternating between second and fourth positions and achieving Rank 2 in Tests 8, 9, 11, 13, and 14. Among the lower-ranked candidates, M-07 alternates between sixth and seventh positions, while M-06 varies between sixth and seventh positions. Candidate M-04 shows the most consistent improvement from its original Rank 8, remaining at Rank 6 across all sensitivity tests. Overall, the results indicate that the sensitivity tests produce only limited changes in candidate ordering, with M-02, M-03, M-04, and M-08 demonstrating particularly strong ranking stability.

In the third sensitivity analysis scenario, the weight of each criterion is individually increased by 0.10, while the weights of the other criteria remain unchanged. The resulting weights are then normalized to ensure that the total weight remains equal to 1.0000. This procedure is applied sequentially to all seven criteria to evaluate the effect of a larger increase in criterion importance on the decision-making results. The resulting criterion weights are presented in Table 9.

Table 9. Test Changes with Weight Increased by 0.1

Test	Scenario	CSM-1	CSM-2	CSM-3	CSM-4	CSM-5	CSM-6	CSM-7
Test 15	CSM-1+0.1	0.2147	0.1274	0.1494	0.1292	0.1238	0.1274	0.1282
Test 16	CSM-2+0.1	0.1238	0.2183	0.1494	0.1292	0.1238	0.1274	0.1282
Test 17	CSM-3+0.1	0.1238	0.1274	0.2403	0.1292	0.1238	0.1274	0.1282
Test 18	CSM-4+0.1	0.1238	0.1274	0.1494	0.2201	0.1238	0.1274	0.1282
Test 19	CSM-5+0.1	0.1238	0.1274	0.1494	0.1292	0.2147	0.1274	0.1282
Test 20	CSM-6+0.1	0.1238	0.1274	0.1494	0.1292	0.1238	0.2183	0.1282

DOI: https://doi.org/10.67449/jodesma.v1i3.12

Article Link: https://research.pilar.or.id/index.php/jodesma/article/view/12

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Test 21	CSM-7+0.1	0.1238	0.1274	0.1494	0.1292	0.1238	0.1274	0.2191

Based on the weight changes in the sensitivity analysis scenario, the alternatives are ranked to determine the effect of criterion-weight adjustments on their ranking positions. The ranking results show the order of alternatives according to their preference values under the weight-change scenario. The comparison of ranking positions is used to evaluate the stability of the decision-making results against changes in criterion weights. The ranking results for the scenario with a weight increase of 0.10 are presented in Figure 5.

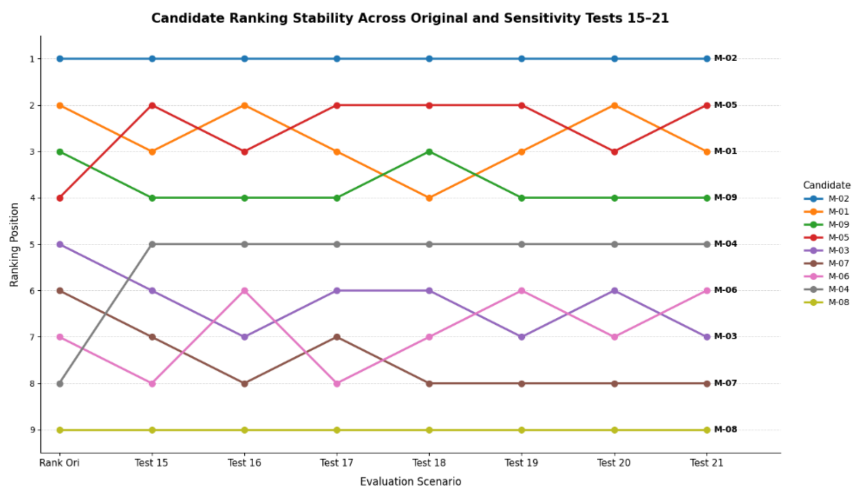

Figure 5. Ranking Results from the Weight Change Increased by 0.1

The ranking results across Tests 15–21 indicate a high level of stability, particularly for the leading and lowest-ranked candidates. Candidate M-02 consistently maintains Rank 1 across all sensitivity scenarios, confirming its dominant position under different weight configurations. Candidate M-08 also remains unchanged at Rank 9, while Candidate M-04 consistently improves from its original Rank 8 to Rank 5 throughout all tests. Among the upper-ranked candidates, M-01 fluctuates between Ranks 2 and 4, with its lowest position occurring in Test 18, whereas M-05 varies between Ranks 2 and 3 and generally remains within the top four positions. Candidate M-09 shows limited variation between Ranks 3 and 4, indicating relatively stable performance despite minor changes in ranking. In the middle and lower positions, M-03 varies between Ranks 6 and 7, M-07 shifts between Ranks 7 and 8, and M-06 fluctuates between Ranks 6 and 8. Overall, the sensitivity analysis demonstrates that the ranking structure remains relatively stable, with M-02 and M-08 completely unaffected by the tested changes and the remaining candidates experiencing only moderate movements in their positions.

In the fourth sensitivity analysis scenario, the weight of each criterion is individually decreased by 0.10, while the weights of the remaining criteria are kept unchanged. The adjusted weights are subsequently normalized to ensure that the total weight remains equal

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to 1.0000. This procedure is applied sequentially to all seven criteria to examine the effect of a larger reduction in criterion importance on the decision-making results. The resulting criterion weights presented in Table 10.

Table 10. Test Changes with Weight Decreased by 0.1

Test	Scenario	CSM-1	CSM-2	CSM-3	CSM-4	CSM-5	CSM-6	CSM-7
Test 22	CSM-1-0.1	0.0402	0.1557	0.1826	0.1579	0.1513	0.1557	0.1567
Test 23	CSM-2-0.1	0.1513	0.0446	0.1826	0.1579	0.1513	0.1557	0.1567
Test 24	CSM-3-0.1	0.1513	0.1557	0.0714	0.1579	0.1513	0.1557	0.1567
Test 25	CSM-4-0.1	0.1513	0.1557	0.1826	0.0468	0.1513	0.1557	0.1567
Test 26	CSM-5-0.1	0.1513	0.1557	0.1826	0.1579	0.0402	0.1557	0.1567
Test 27	CSM-6-0.1	0.1513	0.1557	0.1826	0.1579	0.1513	0.0446	0.1567
Test 28	CSM-7-0.1	0.1513	0.1557	0.1826	0.1579	0.1513	0.1557	0.0456

Based on the weight changes in the sensitivity analysis scenario, the alternatives are ranked to determine the effect of criterion-weight adjustments on their ranking positions. The ranking results show the order of alternatives according to their preference values under the weight-change scenario. The comparison of ranking positions is used to evaluate the stability of the decision-making results against changes in criterion weights. The ranking results for the scenario with a weight decrease of 0.10 are presented in Figure 6.

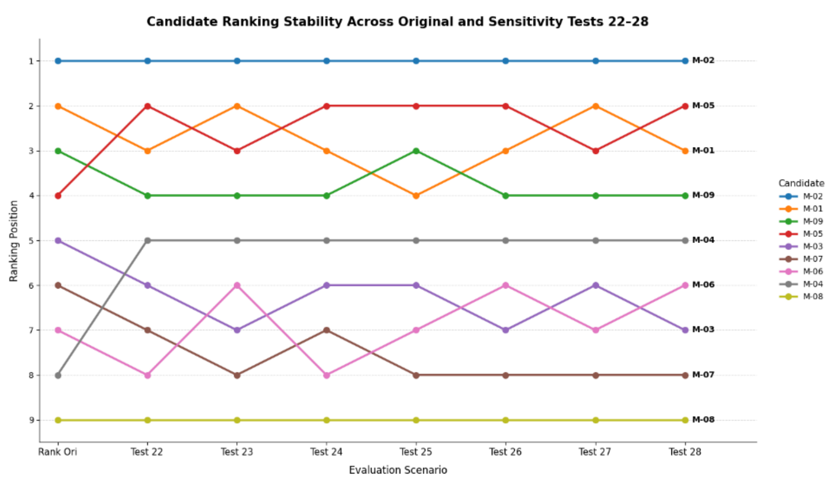

Figure 6. Ranking Results from the Weight Change Decreased by 0.1

The sensitivity analysis across Tests 22–28 demonstrates a consistent ranking pattern with only limited changes among the candidates. Candidate M-02 remains firmly at Rank 1 in all scenarios, while Candidate M-08 consistently occupies Rank 9, indicating that their positions are unaffected by the tested variations. Candidate M-04 also shows complete stability across the sensitivity tests, maintaining Rank 5 compared with its original Rank 8. In the upper-ranked group, Candidate M-01 fluctuates between Ranks 2 and 4, while M-05 varies between Ranks 2 and 3, with M-05 generally maintaining a stronger position than its original Rank 4. Candidate M-09 changes only between Ranks 3 and 4, indicating relatively stable performance. For the remaining candidates, M-03 moves between

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Ranks 6 and 7, M-07 varies between Ranks 7 and 8, and M-06 fluctuates between Ranks 6 and 8. Overall, the results confirm that the ranking structure remains stable under the sensitivity scenarios, with the most substantial changes occurring only among candidates in the middle positions, while the first and last positions remain completely unchanged.

Overall, the sensitivity analysis conducted across Tests 1–28 demonstrates that the proposed method produces a highly stable ranking structure under variations in criterion weights. Candidate M-02 consistently maintains Rank 1 across all 28 tests, confirming its robust dominance as the most preferred candidate, while M-08 remains at Rank 9 throughout the entire sensitivity analysis. Candidate M-03 also shows strong stability, remaining around Rank 5–7, whereas M-04 generally improves from its original Rank 8 and maintains a relatively stable position under most test configurations. Candidates M-01, M-09, and M-05 exhibit moderate rank changes within the upper group, but their movements remain limited and do not substantially alter the overall ordering. Similarly, M-06 and M-07 experience minor fluctuations in the middle-to-lower positions. These findings indicate that changes in criterion weights have only a limited influence on the final ranking, particularly for the leading and lowest-ranked candidates. Therefore, the results across Tests 1–28 confirm the robustness and reliability of the proposed approach for manager selection, as the principal ranking structure remains consistent despite systematic variations in the weighting conditions.

3.3. Comparison Dynamic-ROV with Other MCDM Methods

The ranking comparison was conducted among Dynamic-ROV, Simple Additive Weighting (SAW), Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), Grey Relational Analysis (GRA), and Simple Multi-Attribute Rating Technique (SMART) to evaluate the consistency of the alternative rankings generated by each method. ROV was considered the primary method, while SAW, MOORA, GRA, and SMART were employed as comparative approaches to identify similarities in ranking patterns and assess the extent to which the results obtained by ROV are consistent with other MCDM methods. Overall, the methods exhibit relatively consistent ranking patterns, although several differences can be observed in the positions of particular alternatives. The similarities among the rankings indicate that ROV provides decision outcomes that are generally consistent with the comparative MCDM approaches, thereby supporting the reliability of its ranking results. The ranking comparison among Dynamic-ROV, SAW, MOORA, GRA, and SMART is presented in Figure 7.

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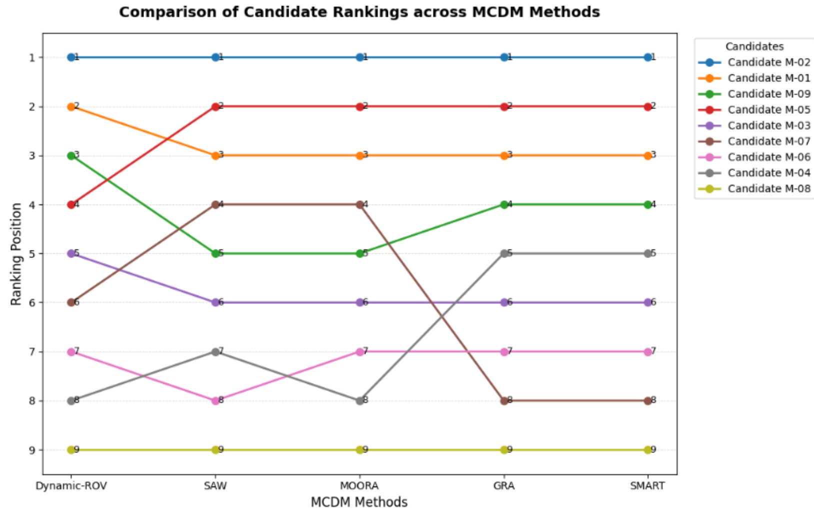

Figure 7. Comparison of Alternative Rankings

The ranking comparison shows that Dynamic-ROV produces a ranking pattern that is generally consistent with SAW, MOORA, GRA, and SMART. Candidate M-02 consistently occupies the first position across all methods, while Candidate M-08 remains in the ninth position. Several differences appear in the middle-ranked candidates, particularly Candidates M-01, M-09, M-05, M-07, and M-04, indicating that although the methods produce similar overall rankings, their evaluation mechanisms can affect the relative positions of certain alternatives. To further assess the consistency of the ranking results, rank correlation analysis is subsequently performed among Dynamic-ROV and the comparative MCDM methods, providing a quantitative measure of the similarity between the generated rankings. The correlation results are presented in Figure 8.

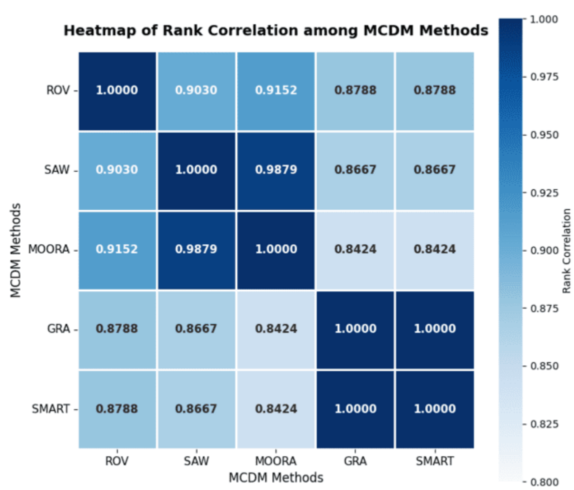

Figure 8. Comparison of Correlation Values

The rank correlation analysis indicates that Dynamic-ROV has a strong positive relationship with all comparative methods, namely SAW, MOORA, GRA, and SMART. The strongest relationship involving ROV is observed

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with MOORA, followed by SAW, while the relationships with GRA and SMART remain consistently strong. Among the comparative methods, SAW and MOORA exhibit the highest degree of ranking agreement, whereas GRA and SMART produce identical ranking patterns. Overall, the correlation matrix demonstrates that the ranking generated by ROV is highly consistent with the results obtained from the other MCDM methods, particularly SAW and MOORA, supporting the reliability and stability of ROV in producing alternative rankings.

IV. Discussion

The findings of this study provide broader evidence on the applicability of Dynamic-ROV for multi-criteria manager selection. The proposed approach addresses the need to evaluate candidates whose performance differs across several criteria while maintaining a consistent basis for aggregation and ranking. The resulting decision structure demonstrates that the evaluation process can distinguish candidates with different performance profiles without producing excessive dependence on a single criterion. This characteristic is important in managerial selection because candidate suitability is generally determined by a combination of competencies and performance dimensions rather than by one dominant attribute. The obtained results therefore provide a basis for examining Dynamic-ROV not only from the perspective of the final ranking, but also in terms of its methodological value and relevance to actual organizational decision processes.

The broader assessment also highlights the importance of evaluating an MCDM method from multiple perspectives. A ranking that performs well under one configuration may not necessarily remain dependable when criterion priorities change or when compared with alternative decision-making procedures. In this study, sensitivity testing and comparative evaluation provide complementary evidence for examining the behavior of Dynamic-ROV under different decision conditions. The consistency observed across these assessments strengthens the interpretation of the proposed approach and provides a foundation for discussing its principal findings, methodological contribution, and practical implications. These three aspects are subsequently discussed to clarify what the study establishes, what it contributes to MCDM methodology, and how the approach can support managerial decision-making.

4.1. Main Findings

The study demonstrates that Dynamic-ROV is able to generate a distinct and interpretable priority structure for manager candidate selection. Among the nine evaluated candidates, M-02 obtains the highest final utility value of 0.3862 and is identified as the most preferred candidate, followed by M-01 and M-09. At the other end of the ranking, M-08 records the lowest final utility value of 0.1179. The resulting ordering provides a clear differentiation among candidates whose

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performances vary across the seven evaluation criteria. The findings also indicate that the weighting mechanism assigns importance according to the observed characteristics of the decision data, allowing criteria with greater discriminatory information to have a stronger influence on the overall evaluation.

The robustness assessment provides an additional finding regarding the behavior of the proposed ranking under alternative weighting configurations. Across 28 sensitivity tests involving positive and negative changes in individual criterion weights, the principal ranking positions remain well preserved. In particular, M-02 consistently retains the highest position, whereas M-08 remains at the lowest position throughout the tested scenarios. Differences are mainly concentrated among the intermediate candidates, where some alternatives experience moderate positional changes. The cross-method evaluation further shows that Dynamic-ROV produces ranking patterns that are broadly comparable with SAW, MOORA, GRA, and SMART. These findings collectively demonstrate that the proposed approach produces decision outcomes that remain recognizable and coherent under both internal sensitivity testing and external methodological comparison.

4.2. Methodological Contribution

The methodological contribution of this study is the development of Dynamic-ROV as a data-oriented ranking framework that combines criterion weighting and utility evaluation within a single decision-making procedure. The approach uses the variation observed in the normalized decision matrix to determine criterion weights, thereby reducing the need to establish importance levels solely through subjective judgment. The subsequent evaluation of best and worst utility conditions provides two complementary perspectives on candidate performance, allowing the final utility to reflect both the degree to which an alternative approaches favorable performance and its relationship with unfavorable performance. This structure offers a systematic mechanism for converting multi-criteria performance information into a final priority order.

The study also contributes an evaluation framework for examining the reliability of the resulting rankings rather than treating the initial ranking as the sole indicator of method performance. The use of systematic weight perturbations at multiple levels enables the response of Dynamic-ROV to changes in criterion importance to be examined in a controlled manner. This is complemented by comparisons with established MCDM methods and rank correlation analysis, which provide an external reference for evaluating ranking agreement. Therefore, the contribution of Dynamic-ROV extends beyond the formulation of its computational stages, incorporating a methodological validation strategy that can be used to assess ranking consistency, sensitivity, and comparative reliability in multi-criteria selection problems.

DOI: https://doi.org/10.67449/jodesma.v1i3.12

Article Link: https://research.pilar.or.id/index.php/jodesma/article/view/12

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ISSN: 3164-7022
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4.3. Practical Implications

The practical implications of the findings are particularly relevant for organizations that need to select managers from multiple candidates with different strengths and weaknesses. Dynamic-ROV can provide decision makers with a structured ranking that integrates several evaluation dimensions rather than relying on a single performance indicator. The resulting priority order can be used to identify the leading candidate while also maintaining a complete ordering of alternative candidates for further consideration. This is useful in situations where managerial selection involves diverse factors and where decision makers require an analytical basis for explaining why one candidate is prioritized over another.

The stability observed in the sensitivity analysis also supports the use of Dynamic-ROV in decision environments where the importance assigned to criteria may change over time or differ among organizational stakeholders. Decision makers can examine alternative weighting scenarios without necessarily having to reconstruct the entire evaluation process, while the resulting ranking can be reviewed to identify candidates whose positions are more sensitive to changes in organizational priorities. In this context, Dynamic-ROV can support recruitment, promotion, succession planning, and other managerial selection processes by providing a reproducible evaluation procedure. The combination of ranking transparency, sensitivity assessment, and comparison with established MCDM methods can further strengthen the justification of selection decisions and facilitate more consistent decision-making practices.

V. Conclusion

This study developed and evaluated Dynamic-ROV as a data-driven MCDM approach for manager candidate selection. The proposed method integrates decision matrix normalization, criterion weighting based on performance variability, and best and worst utility assessment to derive a final preference value and ranking. The empirical results identify Candidate M-02 as the most preferred alternative, while M-08 occupies the lowest position, providing a clear prioritization among the evaluated candidates. The findings demonstrate that Dynamic-ROV can effectively accommodate multiple selection criteria and distinguish candidate performance through a structured utility-based evaluation process.

The robustness of the proposed approach was further examined through 28 sensitivity scenarios involving systematic changes in individual criterion weights. The persistence of the principal ranking positions across these scenarios indicates that the decision outcome is not highly dependent on a specific weighting configuration. In addition, comparison with SAW, MOORA, GRA, and SMART shows broadly consistent ranking patterns, supporting the reliability of the proposed approach from a comparative perspective. These results suggest that Dynamic-ROV offers a useful balance between ranking discrimination and decision

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Volume 1 Number 3 July 2027, Available online: July 20, 2027.
Journal of Decision Support Systems and Multi-Criteria Decision Making
ISSN: 3164-7022
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stability, making it suitable for multi-criteria selection problems in which criterion priorities may vary.

Overall, Dynamic-ROV contributes an alternative framework for MCDM by linking data-derived criterion importance with complementary evaluations of favorable and unfavorable performance conditions. Its integration with sensitivity and comparative analyses also provides a more comprehensive basis for validating ranking reliability. Nevertheless, the present evaluation is limited to a single manager selection dataset and a specific set of criteria. Future studies should therefore examine Dynamic-ROV using larger and more diverse datasets, different decision-making contexts, and additional objective or subjective weighting techniques. Further investigation could also consider hybridization with other MCDM approaches and more extensive robustness measures to determine the generalizability of the proposed method across different types of decision-making problems.

CRediT Authorship Contribution Statement

Erlin Windia Ambarsari: Conceptualization, Writing – Original Draft Preparation. **Muhammad Waqas Arshad:** Methodology, Visualization, Writing – Review & Editing. **Gustian Rama Putra:** Investigation, Software, Writing – Original Draft Preparation. **Yuwan Jumaryadi:** Formal Analysis, Writing – Original Draft Preparation, Writing – Review & Editing. **Febryo Ponco Sulistyo:** Data Curation, Validation, Writing – Original Draft Preparation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding Statements

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Declaration of Generative AI and AI-assisted Technologies in The Writing Process

The authors used Generative AI to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and take full responsibility for the final publication.

DOI: https://doi.org/10.67449/jodesma.v1i3.12

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Journal Homepage: https://research.pilar.or.id/index.php/jodesma

References

[1] M. P. D. Schadd *et al.*, "Reinforcement Learning for decision support in defense and security: A systematic review," *Ann. Oper. Res.*, 2026, doi: 10.1007/s10479-026-07205-x.

[2] M. A. Salem, "AI-Driven Decision Support Beneath Uncertainty: A Hybrid Bayesian–PLS Model for Systemic Sustainability Innovation," *Applied System Innovation*, vol. 9, no. 5. p. 99, 2026. doi: 10.3390/asi9050099.

[3] S. Padmavathi, "AI and Fuzzy Multi-Criteria Decision-Making for Organizational Performance and Strategic Management," *J. Intell. Decis. Mak. Inf. Sci.*, vol. 3, no. 6, pp. 228–249, 2026, doi: 10.59543/jidmis.v3.1389.

[4] G. Stavrou, P. Adamidis, and J. Papathanasiou, "Balancing efficiency and robustness in project team formation: a hybrid evolutionary-MCDM approach," *Int. Trans. Oper. Res.*, vol. 1, no. 1, Sep. 2026, doi: 10.1111/itor.70262.

[5] D. A. Megawaty *et al.*, "DAM Weighting: A New Approach to Determining Criteria Weighting in Multi-Criteria Decision Making," *Evergreen*, vol. 13, no. 2, pp. 788–800, 2026, doi: 10.5109/7432655.

[6] M. Amin, M. S. Nazeer, K. Ullah, Z. Ali, and Y. Shang, "An intelligent spherical fuzzy OPARA-based MCDM framework for optimal player selection in collegiate volleyball," *Cogent Soc. Sci.*, vol. 12, no. 1, p. 2708483, Dec. 2026, doi: 10.1080/23311886.2026.2708483.

[7] S. Z. Khan, T. Alballa, M. Rahim, S. S. Alodhaibi, and H. A. E.-W. Khalifa, "A Context-aware Cognitive Decision-making Framework for Green Supplier Selection Using Quasi-rung Orthopair Diophantine Fuzzy Modeling," *Cognit. Comput.*, vol. 18, no. 1, p. 21, 2026, doi: 10.1007/s12559-025-10539-6.

[8] E. Roszkowska, "Entropy and Normalization in MCDA: A Data-Driven Perspective on Ranking Stability," *Entropy*, vol. 28, no. 1. p. 114, 2026. doi: 10.3390/e28010114.

[9] A. Sarkar and S. S. Goswami, "A comprehensive review: The novel weighting methods for multi-criteria decision-making (MCDM)," *Spectr. Oper. Res.*, vol. 4, no. 1, pp. 1–26, 2027, doi: 10.31181/sor202781.

[10] J. Chen, "A robust decision making algorithm for handling uncertainty in career planning via a circular intuitionistic fuzzy SWARA WASPAS method," *Sci. Rep.*, vol. 16, no. 1, p. 15953, 2026, doi: 10.1038/s41598-026-45506-0.

[11] D. D. Trung, B. Dudic, D. M. Huong, N. T. Tham, and A. Ašonja, "Evaluating Innovation Levels based on Standard Deviation of Parameters and MCDM Methods," *Spectr. Eng. Manag. Sci.*, vol. 4, no. 1, pp. 77–97, Apr. 2026, doi: 10.31181/sems41202666.

[12] N. T. Mai, "Implementation of an enhanced criterion weighting method based on standard deviation in multi -criteria decision-making," *EUREKA Phys. Eng.*, vol. 2, no. 2, pp. 129–139, Feb. 2026, doi: 10.21303/2461-4262.2026.003983.

[13] Rohit, K. Kumar, P. Kaur, and G. Kaur, "Assessment of underwater robot using hesitant q-Rung orthopair Einstein operators and BWM-based MCDM method," *Comput. Appl. Math.*, vol. 46, no. 1, p. 18, 2026, doi: 10.1007/s40314-026-03869-0.

[14] A. Alamoodi *et al.*, "Evaluating agriculture 4.0 decision support systems based on hyperbolic fuzzy-weighted zero-inconsistency combined with combinative distance-based assessment," *Comput. Electron. Agric.*, vol. 227, p. 109618, 2024, doi: 10.1016/j.compag.2024.109618.

[15] X. Zhang, "Pythagorean fuzzy MAIRCA CRITIC for energy price and demand

Journal of Decision Support Systems and Multi-Criteria Decision Making
ISSN: 3164-7022
Page 321-348
Journal Homepage: https://research.pilar.or.id/index.php/jodesma

forecasting involving eco economic factors for sustainable economy," *Sci. Rep.*, vol. 15, no. 1, p. 34340, 2025, doi: 10.1038/s41598-025-16780-1.
[16] M. Soltani, B. Barekatain, F. Hendessi, and Z. Beheshti, "PSSN: a novel cache placement method based on adapted Shannon entropy and simple additive weighting method in named data networking," *Knowl. Inf. Syst.*, vol. 67, no. 2, pp. 1507–1540, 2025, doi: 10.1007/s10115-024-02266-5.
[17] A. Sarkar, S. S. Goswami, D. K. Behera, and D. Bozanic, "Criteria Weighting Methods in Multi-Criteria Decision Making: A Comprehensive Review of Subjective, Objective, and Hybrid Approaches," *J. Contemp. Decis. Sci.*, vol. 2, no. 1, pp. 1–34, 2026, doi: 10.67334/cds202619.
[18] J. Streimikis, "Multi-criteria sustainability assessment in energy and agricultural systems: Challenges and pathways for low-carbon transition," *Energies*, vol. 19, no. 2, p. 436, 2026, doi: 10.3390/en19020436.
[19] S. Shahab, V. Simic, A. K. Dutta, D. Pamucar, and M. Anjum, "Evaluating blockchain-based waste management investments in smart cities using a multi-criteria decision support framework," *Sci. Rep.*, vol. 16, no. 1, p. 3179, 2026, doi: 10.1038/s41598-025-33085-5.
[20] R. JeddouBen Jeddou, A. Ati, and P. Bouchet, "A Data-Driven Multi-criteria Framework for Recruiting Football Forwards Using CRITIC and TOPSIS," *Oper. Res. Forum*, vol. 7, no. 3, p. 102, 2026, doi: 10.1007/s43069-026-00692-5.
[21] Y. Huang and Q. Wu, "Smart decision engine for performance optimization in enterprise management," *Sci. Rep.*, vol. 16, no. 1, p. 3034, 2026, doi: 10.1038/s41598-025-32966-z.
[22] R. M. Faisal and Z. N. Shehab, "A Spatial Decision-Support Approach to Identifying Optimal Sites for Rainwater Harvesting," *Trans. GIS*, vol. 30, no. 1, p. e70178, Feb. 2026, doi: 10.1111/tgis.70178.
[23] N. Komatina, N. Petrović, D. Pamučar, V. Simić, and D. Marinković, "Multi-Criteria Ranking of Industrial Presses with Respect to Operational Performance Using the Square-Root Based Evaluation Method (SREM)," *Facta Univ. Ser. Mech. Eng.*, vol. 25, no. 1, pp. 1–23, 2026, doi: 10.22190/FUME260305009K.
[24] C. Kampalasiri, K. Pitiruek, and P. Sureeyatanapas, "An enhanced TOPSIS method for resilient supplier selection under data uncertainty," *Int. J. Manag. Sci. Eng. Manag.*, vol. 21, no. 1, pp. 36–51, Jan. 2026, doi: 10.1080/17509653.2025.2544569.
[25] M. Öztürk, "Equipment Supplier Selection for Sustainable Hydrogen Production: A Group Decision-Making Supported Spherical Fuzzy TOPSIS Approach," *Sustainability*, vol. 18, no. 4. p. 1737, 2026. doi: 10.3390/su18041737.
[26] E. Roszkowska and T. Wachowicz, "Impact of Normalization on Entropy-Based Weights in Hellwig's Method: A Case Study on Evaluating Sustainable Development in the Education Area," *Entropy*, vol. 26, no. 5. 2024. doi: 10.3390/e26050365.
[27] J. Guliyev and M. Deveci, "A stochastic approach to criterion weighting in multi-criteria decision making: Entropy-based Monte Carlo modeling," *Meas. Digit.*, vol. 7, p. 100043, 2026, doi: 10.1016/j.meadig.2026.100043.
[28] I. Z. Mukhametzyanov, "Elimination of the Domains' Displacement of the Normalized Values in MCDM Tasks: The IZ-Method," *Int. J. Inf. Technol. Decis. Mak.*, vol. 23, no. 01, pp. 289–326, Jan. 2024, doi: 10.1142/S0219622023500037.
[29] K. Kara, E. Akagün Ergin, G. Cihan Yalçın, T. Çelik, M. Deveci, and S. Kadry, "Sustainable brand logo selection using an AI-Supported PF-WENSLO-ARLON hybrid method," *Expert Syst. Appl.*, vol. 260, p. 125382, 2025, doi: 10.1016/j.eswa.2024.125382.

DOI: https://doi.org/10.67449/jodesma.v1i3.12

Article Link: https://research.pilar.or.id/index.php/jodesma/article/view/12

Volume 1 Number 3 July 2027, Available online: July 20, 2027.
Journal of Decision Support Systems and Multi-Criteria Decision Making
ISSN: 3164-7022
Page 321-348
Journal Homepage: https://research.pilar.or.id/index.php/jodesma

[30] S. Dündar and İ. Karadağ, "Selection of a Facility Location for a Cosmetics Company by Integrated F-LBWA and I-RAWEC Methods," *Int. J. Fuzzy Syst.*, 2025, doi: 10.1007/s40815-024-01960-4.

[31] B. Zhang, P. Niu, X. Guo, and J. He, "Fuzzy PID control of permanent magnet synchronous motor electric steering engine by improved beetle antennae search algorithm," *Sci. Rep.*, vol. 14, no. 1, p. 2898, 2024, doi: 10.1038/s41598-024-52600-8.

[32] A. H. Mohammed and M. A. H. Ashour, "Enhancing Fuzzy C-Means Clustering with a Novel Standard Deviation Weighted Distance Measure," *Baghdad Sci. J.*, vol. 21, no. 9, pp. 2956–2569, 2024, doi: 10.21123/bsj.2024.9516.

[33] D. Tešić, D. Božanić, S. P. Mondal, and A. Puška, "Modification of the Ranking of Alternatives with Weights of Criterion (RAWEC) Method and Improvement with Fermatean Fuzzy numbers," *J. Soft Comput. Decis. Anal.*, vol. 3, no. 1, pp. 146–157, Aug. 2025, doi: 10.31181/jscda31202570.

[34] B. S. Mahapatra, D. Ghosh, D. Pamucar, and G. S. Mahapatra, "Dynamic group decision-making for enterprise resource planning selection using two-tuples Pythagorean fuzzy MOORA approach," *Expert Syst. Appl.*, vol. 263, p. 125675, 2025, doi: 10.1016/j.eswa.2024.125675.

[35] 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: 10.1016/j.chaos.2024.114745.

[36] A. L. Kalua, F. Indriyani, R. I. Putra, A. Asistyasari, and A. T. Priandika, "SOWA Method Framework: New Algorithm for Criteria Weight Balancing with a Hybrid Subjective and Objective Approach," *Int. J. Inf. Eng. Electron. Bus.*, vol. 18, no. 3, p. 71, 2026, doi: 10.5815/ijieeb.2026.03.05.

DOI: https://doi.org/10.67449/jodesma.v1i3.12

Article Link: https://research.pilar.or.id/index.php/jodesma/article/view/12