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The Combination of WENSLO and MUNRA Method in Selecting the Best Employees Based on Multiple Criteria

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Abstract−This study examines the application of a combination of the WENSLO and MUNRA methods in selecting the best employees based on various criteria to address issues of subjectivity and instability in employee rankings that often arise when data is heterogeneous and criteria are conflicting. The WENSLO method is used to assess and prioritize criteria through structured and preference-based weighting, while MUNRA plays a role in consistently normalizing data and calculating weighted scores for each alternative. The integration of these two methods allows for a more objective evaluation, reduces subjective bias, and produces stable employee rankings even in the presence of data variations or conflicting criteria. The Employee Ranking results show that the top-performing employee is Lestari with a score of 1.3092, followed by Susilo with a score of 1.3080 and Maharani with a score of 1.3003, indicating superior and relatively balanced performance. These findings confirm that the combination of WENSLO and MUNRA can produce clear, objective, and effective employee rankings, as well as provide an adaptive framework to support strategic human resource management.

Keywords: Employee Ranking; MUNRA Method; WENSLO method; Decision-Making; Human Resource Management.

1. INTRODUCTION

The selection of the best employees within an organization is driven by the need to ensure that human resource decisions are made objectively, fairly, and in alignment with the organization's strategic goals[1]–[3]. In an increasingly competitive and dynamic work environment, individual performance is not determined by a single aspect, but is the result of the interaction of various criteria such as performance achievements, competencies, work attitude, and adaptability. Therefore, the process of selecting the best employees becomes crucial as a basis for awarding recognition, promotions, and career development based on actual performance. A systematic and measurable approach in this selection helps organizations minimize subjectivity, enhance work motivation, and foster a work culture that is oriented towards achievement and continuous performance improvement. The process of selecting the best employees often faces issues of subjective assessment because it still relies on the evaluator's perception without measurable indicators. In addition, using one or two dominant criteria has not been able to fully represent employee performance[4]–[6]. This condition has the potential to result in inconsistent decisions and does not fully reflect the employees' real contributions to the organization.

Multicriteria decision-making in employee performance evaluation faces complex challenges because individual performance cannot be accurately assessed based on a single aspect, but must consider various criteria[7]–[9]. Each criterion has different characteristics, measurement scales, and levels of importance, making it difficult to combine information fairly and consistently. In addition, reliance on subjective assessments, imbalanced criterion weights, and variations in data quality often cause evaluation results to be unstable and difficult to reproduce. Conventional methods also tend to be less sensitive to changes in organizational conditions and the dynamics of employee performance over time. As a result, the decisions made may not reflect actual performance and can lead to dissatisfaction and decreased work motivation[10]–[12]. Therefore, a more structured, objective multicriteria decision-making approach is needed, one that can comprehensively handle the complexity of performance data.

Multiple Normalization Rating Analysis (MUNRA) is a multi-criteria decision-making method designed to improve the reliability of ranking results by utilizing more than one normalization technique in the evaluation of alternatives[13]. The main concept of MUNRA is based on the assumption that no single normalization method is universally superior for all data characteristics, as each normalization technique has different sensitivities to scale, distribution, and extreme values of criteria. Therefore, MUNRA combines several relevant normalization approaches according to the type of benefit and cost criteria, so that the information contained in the data can be represented more evenly. The MUNRA method can reduce bias arising from reliance on a single normalization technique, increase the consistency of results, and provide a more robust and representative ranking of alternatives in the face of heterogeneous multi-criteria data. The MUNRA method has a major advantage in improving the stability of ranking results because it does not rely on a single normalization technique. The multi-normalization approach allows for a more balanced data representation, especially when dealing with differences in scale and value distribution across criteria. In addition, the aggregation mechanism in MUNRA can reduce the bias of a single method and produce more objective and consistent decisions. The weakness of MUNRA in terms of criterion weights lies in its dependence on the weighting method used,

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making the final results still sensitive to the determination of initial weights. If the criterion weights do not reflect the actual level of importance, the multi-normalization process cannot fully correct this bias. Furthermore, the use of static weights makes MUNRA less adaptable to changes in data characteristics and the performance dynamics of criteria in different evaluation contexts.

Weights by Envelope and Slope (WENSLO) is an objective weighting method in multicriteria decision-making designed to determine the importance level of criteria based on the characteristics of data distribution and the pattern of value changes[14]–[16]. The basic concept of WENSLO combines two main components: the envelope, which represents the range of maximum and minimum values for each criterion, and the slope, which illustrates the rate of change or gradient of criterion values across alternatives. The envelope is used to capture the global variation of the data, so criteria with a larger value range are considered to have a more significant influence on differentiating alternatives. Meanwhile, the slope functions to measure the sensitivity of criteria to data changes, reflecting the ability of the criteria to distinguish the performance of alternatives in more detail. The WENSLO method is capable of providing criterion weights that are more adaptive to the data structure, improving assessment consistency, and supporting more rational and empirically informed multi-criteria decision-making[16]–[18]. The WENSLO method has the advantage of producing more objective criterion weights because it is based on the data structure and the differences in value slopes between criteria. This approach is able to capture the level of discrimination of each criterion more accurately, so criteria that truly have an impact will receive proportional weights. In addition, the WENSLO mechanism is relatively systematic and consistent, thereby reducing reliance on the decision-maker's subjective judgments in the weighting process.

The urgency of research on the WENSLO–MUNRA hybrid model is driven by the need for a multi-criteria decision-making framework capable of producing alternative rankings that are more stable, objective, and representative of real data conditions. The WENSLO method excels in systematically determining criteria weights through the envelope approach and value slopes, but its final results are still heavily influenced by the aggregation and normalization methods used in the ranking stage. On the other hand, MUNRA offers an effective multi-normalization mechanism to reduce bias caused by differences in data scale and distribution, but it still depends on the quality and accuracy of the given criteria weights. The integration of WENSLO and MUNRA becomes relevant because it combines the strengths of adaptive objective weighting with a ranking mechanism that is robust to data heterogeneity. This hybrid model is expected to address issues of ranking instability, sensitivity to data changes, and result inconsistencies that often arise in single-method approaches. Thus, the development of the WENSLO–MUNRA model not only strengthens the methodological foundation of multi-criteria decision making but also enhances the reliability of decision support systems in the context of performance evaluation and the selection of complex alternatives.

Previous studies that serve as references include, the research by[19] showed that the Simple Additive Weighting (SAW) method is capable of systematically producing the best employee rankings based on the weighted sum of criteria scores, but it is still sensitive to the determination of weights and the rating scale. The research by [20] demonstrated that the Analytical Hierarchy Process (AHP) method is effective in structuring criteria weights hierarchically and enhancing decision consistency, although the pairwise comparison process requires time and evaluator subjectivity. Research by [21] revealed that the WASPAS method produces more stable rankings because it combines summation and multiplication approaches, but the computational complexity increases with the number of criteria. Meanwhile, research by [5] concluded that the Multi-Attribute Utility Theory (MAUT) method is capable of accurately representing decision-makers' preferences, although the accuracy of the results heavily depends on the utility function and the criteria weights used. Based on previous research, employee performance evaluations still tend to produce rankings that are sensitive to changes in data and assessment configurations. Existing approaches have not been able to integrate adaptive criteria weighting with a stable ranking mechanism within a unified framework. This research gap is addressed through the Combination of WENSLO and MUNRA Method, which aims to enhance the objectivity, consistency, and resilience of decision results in selecting the best employees based on multiple criteria.

This study aims to integrate the WENSLO and MUNRA methods in the process of selecting the best employees based on multiple criteria to produce more objective and consistent decisions. This combination contributes to strengthening the determination of criteria weights systematically while improving the stability of alternative rankings through a multi-normalization mechanism. The proposed model can reduce subjectivity in assessments as well as biases arising from reliance on a single method. This study provides conceptual and practical contributions to the development of a more accurate and accountable decision support system for employee performance evaluation.

2. RESEARCH METHODOLOGY

2.1 Research Stages

This research begins with the design of a systematic workflow to ensure that each process in the development of a multi-criteria decision-making model runs in a structured and interconnected manner. With a clear framework of stages, the research is expected to produce a decision model that can be implemented rationally, measurably, and scientifically accountable. The research stages begin with problem identification and formulation of research objectives, namely addressing ranking instability and subjectivity in employee performance evaluation based on multiple criteria. Next, employee performance data is collected based on relevant and measurable criteria to accurately represent the assessment conditions. The data is then processed in the criteria weighting stage using the WENSLO method to obtain objective

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weights by considering the importance structure and data characteristics. The next stage is ranking employee alternatives using the MUNRA method, which utilizes multi-normalization to produce more stable and consistent performance scores. The final stage involves analysis and evaluation of the results to assess the quality of the ranking, decision consistency, and the contribution of the proposed combination model in improving the accuracy and reliability of selecting the best employees. Figure 1 shows the stages in the research process conducted.

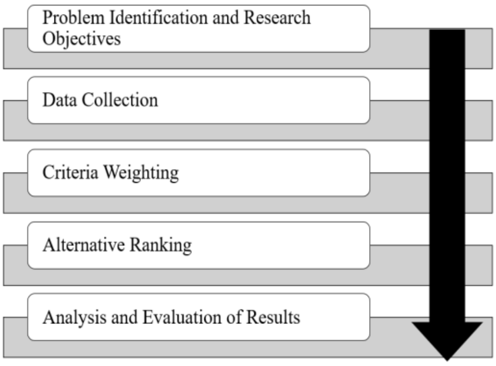

Figure 1. Research Stage

2.2 Weights by Envelope and Slope (WENSLO) Method

WENSLO is an objective weighting method designed to determine the level of importance of criteria based on the characteristics of data distribution and the pattern of value changes between criteria. The WENSLO concept relies on forming upper and lower envelopes of the criteria data to capture the range of value variation, then analyzing the slope of changes as an indicator of the sensitivity of the criteria to differences in alternative performance. Criteria with a more contrasting range of values and sharper changes will receive a higher weight because they are considered to have a high discriminatory power in the evaluation process. Through this mechanism, WENSLO is able to reduce dependence on subjective judgment and produce weights that are more adaptive to the actual data structure. This approach makes WENSLO relevant for multi-criteria decision support systems that demand objectivity, consistency, and the ability to represent the real contribution of each criterion in the decision-making process.

The stages in the WENSLO method begin with the preparation of a decision matrix, which is a representation of the performance data of each alternative against all the criteria used as the basis for calculation.

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

The next step is to calculate the normalization values to equalize the scale of values between criteria so that they can be compared fairly.

$$z_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{2}$$

After that, the class intervals of the criteria are determined, which function to group the normalized values into certain ranges so that the data distribution pattern can be analyzed more systematically.

$$\Delta Z_j = \frac{\max_j z_{ij} - \min_j z_{ij}}{1+3.322*\log(m)} \tag{3}$$

Based on these intervals, the slope of the criteria is calculated, reflecting the rate of change or sensitivity of the criteria values to differences between alternatives.

$$\varphi_j = \frac{\sum_{i=1}^{m} z_{ij}}{(m-1)*\Delta Z_j} \tag{4}$$

The next stage is the formation of the criteria envelope, which consists of the upper and lower limits representing the overall range of variation of the criteria values.

$$E_j = \sum_{i=1}^{m-1} \sqrt{\left(z_{i+1j} - z_{ij}\right)^2 + \Delta Z_j^{\,2}} \tag{5}$$

From this envelope, the proportion of the criteria envelope is then calculated, which shows the relative contribution of each criterion compared to the others.

$$q_j = \frac{E_j}{\varphi_j} \tag{6}$$

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The final stage is determining the criteria weights, which are obtained from the envelope proportions and the slope of the criteria, so that the resulting weights are objective, reflect the characteristics of the data, and quantitatively represent the importance level of the criteria.

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \quad (7)$$

The WENSLO method offers a systematic and objective approach to weighting criteria by considering the data structure comprehensively. Through the stages of class interval formation, skewness analysis, and criteria envelope construction, WENSLO is able to capture variations and the influence level of each criterion more proportionally. This approach not only reduces reliance on subjective judgments but also improves the consistency of weights in response to data changes.

2.3 Multiple Normalization Rating Analysis (MUNRA) Method

The MUNRA method is a multi-criteria decision-making method developed to produce more stable and representative alternative rankings through the simultaneous application of several normalization techniques. This method is based on the understanding that each normalization technique has advantages and limitations in representing data characteristics, so reliance on a single normalization approach can cause the ranking results to become sensitive to changes in scale and the distribution of criterion values. MUNRA works by constructing a decision matrix that is then normalized using more than one normalization formula suitable for the type of criteria, whether benefit or cost. The normalized results are subsequently integrated through an aggregation process to obtain a composite rating value that reflects the performance of alternatives in a more balanced manner. With this mechanism, MUNRA is able to reduce the bias of a single method, improve the consistency of results, and provide a stronger basis for ranking in multi-criteria decision-making, particularly in employee performance evaluation with heterogeneous data.

The first step in the MUNRA method is the preparation of the decision matrix, which represents the performance values of each alternative against all established assessment criteria using (1).

The second stage in the MUNRA method is the normalization of the decision matrix using several approaches, namely linear normalization to equalize data scales, vector normalization to consider the proportion of relative values between alternatives, and non-linear normalization to accommodate disproportionate data distribution.

$$r_{ij} = \frac{x_{ij}}{\max(x_{ij})}; if\ j \epsilon B \quad (8)$$

$$r_{ij} = \frac{\min(x_{ij})}{x_{ij}}; if\ j \epsilon C \quad (9)$$

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}}; if\ j \epsilon B \quad (10)$$

$$y_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}}; if\ j \epsilon C \quad (11)$$

$$p_{ij} = \left(\frac{x_{ij}}{\max(x_{ij})}\right)^2; if\ j \epsilon B \quad (12)$$

$$p_{ij} = \left(\frac{\min(x_{ij})}{x_{ij}}\right)^3; if\ j \epsilon C \quad (13)$$

The third stage in the MUNRA method is to perform weighted arithmetic operations, where each normalization result is multiplied by the criterion weight to reflect the importance level of each criterion in decision-making.

$$r_i' = \sum_{j \epsilon B} w_j * r_{ij} + \sum_{j \epsilon C} w_j * r_{ij} \quad (14)$$

$$y_i' = \sum_{j \epsilon B} w_j * y_{ij} + \sum_{j \epsilon C} w_j * y_{ij} \quad (15)$$

$$p_i' = \sum_{j \epsilon B} w_j * p_{ij} + \sum_{j \epsilon C} w_j * p_{ij} \quad (16)$$

The final stage in the MUNRA method is the integration of all the calculation results to obtain the final score of the alternatives, which is then used as a basis for ranking the best employees in a more stable and accountable manner.

$$v_i = \propto r_i' + \beta y_i' + \gamma p_i' \quad (17)$$

The MUNRA method offers a more robust ranking mechanism compared to conventional approaches because it can minimize dependence on a single normalization technique. The use of multi-normalization integrated with weighted arithmetic operations allows decision results that are more stable, objective, and accountable.

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Hal 451−463
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3. RESULT AND DISCUSSION

This study proposes a multi-criteria decision-making model that integrates the WENSLO and MUNRA method to improve the accuracy and stability of ranking top employees. In the context of employee performance evaluation, organizations are often faced with many heterogeneous and conflicting criteria, making the use of a single method often insufficient to optimally represent the relative importance of each criterion. The WENSLO method is used to determine the weights of criteria objectively by considering the importance level and sensitivity of the criteria to data changes, while the MUNRA method is used to normalize data using more than one approach to minimize bias that arises from differences in scale and data characteristics. The integration of these two methods produces a hybrid model capable of providing evaluations that are fairer, more consistent, and adaptive to variations in employee assessment data. The resulting ranking is expected to help management make more accurate and transparent strategic decisions regarding the determination of the best employees, while also strengthening the role of decision support systems in data-based human resource management.

3.1 Data Collection

Data collection in the process of Selecting the Best Employees is a crucial stage that determines the quality and validity of employee ranking results, as all multi-criteria analysis depends on the accuracy and completeness of the data used. At this stage, data is collected systematically from various relevant sources. Each assessment criterion is formulated operationally so that it can be measured objectively and consistently across candidates, thereby minimizing subjectivity and evaluator bias. Additionally, the data collection process is carried out with attention to the uniformity of the rating scales and the suitability of data formats to support further processing in multi-criteria decision-making methods. Data validation also becomes an important part, whether through checking for completeness, consistency, or clarification of data that is extreme or unusual. With this approach, the data collection stage not only serves as an administrative process but also as an analytical foundation that ensures decisions in Selecting the Best Employees are based on empirical, structured, and scientifically accountable information. The assessment data for candidates is presented in Table 1.

Table 1. Assessment data

Employees Name	Benefit Criteria				Cost Criteria	
	Performance (CE-1)	Technical Competence (CE-2)	Work Discipline (CE-3)	Communication Skills (CE-4)	Error Rate (CE-5)	Disciplinary Violations (CE-6)
Pratama	85	88	90	82	6	5
Budi	78	80	85	79	7	6
Lestari	92	91	93	88	5	5
Dedi	70	75	78	74	8	7
Eka	88	86	89	85	6	5
Hidayat	83	82	84	80	7	6
Maharani	90	89	92	87	5	5
Wijaya	76	78	80	77	8	6
Intan	84	85	87	83	6	5
Susilo	91	90	94	89	5	5
Oktaviani	79	81	83	78	7	6

The explanation of each criterion in the selection of the best employees based on the evaluation data in Table 1 is presented as follows

Performance: This criterion measures the level of an employee's achievement against the set work targets, both in terms of the quantity and quality of work results. Performance reflects the effectiveness of an employee in carrying out tasks, consistency of performance, and tangible contributions to achieving organizational goals.

Technical Competence: Technical Competence assesses the level of mastery of knowledge, skills, and technical abilities relevant to the employee's field of work or position. This criterion reflects the employee's ability to operate technology, understand work procedures, and complete tasks professionally and accurately.

Work Discipline: Work Discipline measures the level of employee compliance with the rules, operational standards, and work ethics in the organization. The aspects assessed include punctuality, attendance, adherence to work schedules, and consistency in performing tasks according to regulations.

Communication Skills: This criterion evaluates an employee's ability to convey information, ideas, and opinions clearly, effectively, and professionally, both verbally and in writing. Communication Skills also include the ability to interact with colleagues, supervisors, and external parties to support smooth workflow and team collaboration.

Error Rate: Error Rate measures the frequency of errors occurring in the processes or work results carried out by employees. This criterion falls under the cost category, where a lower value indicates higher work accuracy and precision as well as a lower risk of operational errors.

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Hal 451−463
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Disciplinary Violations: Disciplinary Violations assess the number and severity of violations committed by employees against organizational rules and policies. This criterion reflects the level of employee compliance and integrity, and is also categorized under cost, where a lower number of violations indicates better work behavior.

The data sources in Selecting the Best Employees are obtained from a combination of primary and secondary data designed to provide a comprehensive overview of the performance and competence of each employee. Primary data comes directly from the internal assessment process, namely the results of supervisor evaluations, while secondary data is obtained from official company documents recorded in the human resource information system. The use of various data sources aims to increase the objectivity and reliability of the assessment by reducing dependence on a single perspective. By integrating diverse and complementary data sources, the Selecting the Best Employees process can produce evaluations that are more accurate, fair, and accountable as a basis for managerial decision-making.

3.2 Calculation of Criteria Weights Using the WENSLO Method

The calculation of criteria weights using the WENSLO method is carried out to obtain the level of importance of each criterion objectively based on data characteristics and its contribution to the decision-making process. The WENSLO method is able to produce rational, consistent, and data-based criteria weights, thereby supporting the Selecting the Best Employees process more accurately and reliably. The first stage of calculating criteria weights using the WENSLO method begins with creating a decision matrix using (1) based on the assessment data in Table 1. The results of the WENSLO method decision matrix are as follows.

$$X = \begin{bmatrix} 85 & 88 & 90 & 82 & 6 & 5 \\ 78 & 80 & 85 & 79 & 7 & 6 \\ 92 & 91 & 93 & 88 & 5 & 5 \\ 70 & 75 & 78 & 74 & 8 & 7 \\ 88 & 86 & 89 & 85 & 6 & 5 \\ 83 & 82 & 84 & 80 & 7 & 6 \\ 90 & 89 & 92 & 87 & 5 & 5 \\ 76 & 78 & 80 & 77 & 8 & 6 \\ 84 & 85 & 87 & 83 & 6 & 5 \\ 91 & 90 & 94 & 89 & 7 & 5 \\ 79 & 81 & 83 & 78 & 5 & 6 \end{bmatrix}$$

Normalization calculations in the WENSLO method aim to equalize the value scale among criteria so that they can be compared fairly. This process is carried out by converting the values in the decision matrix into relative values based on the characteristics of each criterion. The normalization results in the WENSLO method are as follows, calculated using (2).

$$z_{11} = \frac{85}{85 + 78 + 92 + 70 + 88 + 83 + 90 + 76 + 84 + 91 + 79} = \frac{85}{916} = 0.0928$$

The overall result of the calculations from the normalization values in the WENSLO method is presented in the following Table 2.

Table 2. Normalization results using the WENSLO method

Employees Name	Benefit Criteria				Cost Criteria	
	Performance (CE-1)	Technical Competence (CE-2)	Work Discipline (CE-3)	Communication Skills (CE-4)	Error Rate (CE-5)	Disciplinary Violations (CE-6)
Pratama	0.0928	0.0951	0.0942	0.0909	0.0857	0.0820
Budi	0.0852	0.0865	0.0890	0.0876	0.1000	0.0984
Lestari	0.1004	0.0984	0.0974	0.0976	0.0714	0.0820
Dedi	0.0764	0.0811	0.0817	0.0820	0.1143	0.1148
Eka	0.0961	0.0930	0.0932	0.0942	0.0857	0.0820
Hidayat	0.0906	0.0886	0.0880	0.0887	0.1000	0.0984
Maharani	0.0983	0.0962	0.0963	0.0965	0.0714	0.0820
Wijaya	0.0830	0.0843	0.0838	0.0854	0.1143	0.0984
Intan	0.0917	0.0919	0.0911	0.0920	0.0857	0.0820
Susilo	0.0993	0.0973	0.0984	0.0987	0.0714	0.0820
Oktaviani	0.0862	0.0876	0.0869	0.0865	0.1000	0.0984

The calculation of class intervals of the criteria in the WENSLO method is carried out to group the criteria values into several class intervals based on the range and distribution of the data. This stage aims to capture the pattern of the distribution of each criterion's values so that the differences between alternatives can be represented in a more structured manner. The resulting class intervals are then used as a basis for determining the relative contribution of the criteria in

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Hal 451−463
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the WENSLO weighting process. The results of the class intervals of the criteria calculation in the WENSLO method are as follows, calculated using (3).

$$\Delta Z_1 = \frac{\max_1 z_{ij} - \min_1 z_{ij}}{1 + 3.322 * \log(11)} = \frac{0.1004 - 0.0764}{1 + 3.322 * \log(11)} = \frac{0.0240}{4.4595} = 0.0054$$

$$\Delta Z_2 = \frac{\max_2 z_{ij} - \min_2 z_{ij}}{1 + 3.322 * \log(11)} = \frac{0.0984 - 0.0811}{1 + 3.322 * \log(11)} = \frac{0.0173}{4.4595} = 0.0039$$

$$\Delta Z_3 = \frac{\max_3 z_{ij} - \min_3 z_{ij}}{1 + 3.322 * \log(11)} = \frac{0.0984 - 0.0817}{1 + 3.322 * \log(11)} = \frac{0.0168}{4.4595} = 0.0038$$

$$\Delta Z_4 = \frac{\max_4 z_{ij} - \min_4 z_{ij}}{1 + 3.322 * \log(11)} = \frac{0.0987 - 0.0820}{1 + 3.322 * \log(11)} = \frac{0.0166}{4.4595} = 0.0037$$

$$\Delta Z_5 = \frac{\max_5 z_{ij} - \min_5 z_{ij}}{1 + 3.322 * \log(11)} = \frac{0.1143 - 0.0714}{1 + 3.322 * \log(11)} = \frac{0.0429}{4.4595} = 0.0096$$

$$\Delta Z_6 = \frac{\max_6 z_{ij} - \min_6 z_{ij}}{1 + 3.322 * \log(11)} = \frac{0.1148 - 0.0820}{1 + 3.322 * \log(11)} = \frac{0.0328}{4.4595} = 0.0074$$

The calculation of the slope of the criteria in the WENSLO method is carried out to measure the rate of change in values between class intervals for each criterion. The slope value reflects the sensitivity of a criterion in distinguishing alternatives based on performance increases or decreases. The larger the resulting slope value, the stronger the role of that criterion in the weight determination process in the WENSLO method, which is calculated using (4).

$$\varphi_1 = \frac{\sum_{i=1}^{m} z_{1j}}{(m-1) * \Delta Z_1} = \frac{1.0000}{(11-1) * 0.0054} = \frac{1.0000}{0.0539} = 18.5678$$

$$\varphi_2 = \frac{\sum_{i=1}^{m} z_{2j}}{(m-1) * \Delta Z_2} = \frac{1.0000}{(11-1) * 0.0039} = \frac{1.0000}{0.0388} = 25.7815$$

$$\varphi_3 = \frac{\sum_{i=1}^{m} z_{3j}}{(m-1) * \Delta Z_3} = \frac{1.0000}{(11-1) * 0.0038} = \frac{1.0000}{0.0376} = 26.6177$$

$$\varphi_4 = \frac{\sum_{i=1}^{m} z_{4j}}{(m-1) * \Delta Z_4} = \frac{1.0000}{(11-1) * 0.0037} = \frac{1.0000}{0.0373} = 26.8165$$

$$\varphi_5 = \frac{\sum_{i=1}^{m} z_{5j}}{(m-1) * \Delta Z_5} = \frac{1.0000}{(11-1) * 0.0096} = \frac{1.0000}{0.0961} = 10.4055$$

$$\varphi_6 = \frac{\sum_{i=1}^{m} z_{6j}}{(m-1) * \Delta Z_6} = \frac{1.0000}{(11-1) * 0.0074} = \frac{1.0000}{0.0735} = 13.6015$$

The calculation of the criteria envelope in the WENSLO method is carried out to determine the upper and lower limits of each criterion's contribution based on the calculated slope values and class intervals. This envelope represents the range of variation of the criteria in quantitatively distinguishing alternatives. The results of the criteria envelope calculation are used as the basis for adjusting the weights to remain proportional and consistent in the WENSLO method, which is calculated using (5), and the results are shown in Table 3.

Table 3. Criteria envelope results using the WENSLO method

Benefit Criteria				Cost Criteria	
Performance (CE-1)	Technical Competence (CE-2)	Work Discipline (CE-3)	Communication Skills (CE-4)	Error Rate (CE-5)	Disciplinary Violations (CE-6)
0.1375	0.1047	0.1012	0.0994	0.2902	0.2003

The calculation of the proportion of the criteria envelope in the WENSLO method is carried out to determine the relative portion of each criterion in relation to the overall envelope formed. This stage aims to convert the envelope values into a contribution measure that is comparable between criteria. The resulting proportion becomes the main basis for determining the final weights of the criteria in the WENSLO method, which are calculated using (6), and the calculation results are presented in Table 4.

Table 4. Proportion of the criteria envelope results using the WENSLO method

Benefit Criteria				Cost Criteria	

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Performance (CE-1)	Technical Competence (CE-2)	Work Discipline (CE-3)	Communication Skills (CE-4)	Error Rate (CE-5)	Disciplinary Violations (CE-6)
0.0074	0.0041	0.0038	0.0037	0.0279	0.0147

The calculation of criterion weights in the WENSLO method is carried out by normalizing the envelope proportion of each criterion so that the total weight equals one. This step ensures that the resulting weights reflect the relative importance level of the criteria objectively based on the data characteristics. These final weights are then used as the main input in the process of evaluating and ranking alternatives using the multi-criteria decision-making method calculated with (7), with the calculation results presented in Table 5.

Table 5. Criteria weighting results using the WENSLO method

Benefit Criteria				Cost Criteria	
Performance (CE-1)	Technical Competence (CE-2)	Work Discipline (CE-3)	Communication Skills (CE-4)	Error Rate (CE-5)	Disciplinary Violations (CE-6)
0.1203	0.0659	0.0617	0.0602	0.4528	0.2391

The calculation results of the criteria weights using the WENSLO method show that Error Rate has the highest weight at 0.4528, indicating that the rate of work errors is the most dominant factor in the employee evaluation process because it directly affects quality and operational risk. The Disciplinary Violations criterion ranks second with a weight of 0.2391, suggesting that adherence to rules and consistent work behavior also plays an important role in determining overall performance. Meanwhile, Performance has a weight of 0.1203, followed by Technical Competence at 0.0659, Work Discipline at 0.0617, and Communication Skills at 0.0602, indicating that although aspects of ability, discipline, and communication remain relevant, their contribution is relatively smaller compared to criteria directly related to errors and work violations. Overall, this weight distribution reflects an assessment focus on risk control and compliance as the main basis for Selecting the Best Employees.

3.3 Calculation of Alternative Values Using the MUNRA Method

The calculation of alternative values using the MUNRA method is carried out to obtain comprehensive scores for each alternative based on their contribution to all established criteria. At this stage, the decision matrix, which has been normalized using various normalization techniques, is combined with the criteria weights, so that each alternative's performance value reflects the relative importance of the criteria. Next, a weighted arithmetic operation is performed to accumulate all the criteria values into a single final value for each alternative. This value reflects the overall position of the alternative in the multi-criteria decision-making system. With this approach, the MUNRA method is able to produce more stable and representative alternative evaluations, especially when the data has heterogeneous characteristics and differences in rating scales. The first stage of calculating alternative values using the MUNRA method begins by creating a decision matrix using (1) based on the evaluation data in Table 1. The results of the MUNRA method decision matrix are as follows.

$$X = \begin{bmatrix} 85 & 88 & 90 & 82 & 6 & 5 \\ 78 & 80 & 85 & 79 & 7 & 6 \\ 92 & 91 & 93 & 88 & 5 & 5 \\ 70 & 75 & 78 & 74 & 8 & 7 \\ 88 & 86 & 89 & 85 & 6 & 5 \\ 83 & 82 & 84 & 80 & 7 & 6 \\ 90 & 89 & 92 & 87 & 5 & 5 \\ 76 & 78 & 80 & 77 & 8 & 6 \\ 84 & 85 & 87 & 83 & 6 & 5 \\ 91 & 90 & 94 & 89 & 7 & 5 \\ 79 & 81 & 83 & 78 & 5 & 6 \end{bmatrix}$$

Normalization in the MUNRA method is carried out to equalize the value scales among criteria so they can be compared fairly. This process is conducted through several complementary normalization approaches to reduce bias caused by differences in data distribution and units. The normalization results produce a normalized matrix that is more representative as the basis for calculating the final alternative values. In the first stage of normalization in the MUNRA method, linear normalization is used to convert the values in the decision matrix into comparable scales. This process takes into account the type of criteria, whether benefit or cost, so that the preference direction is maintained. The results of the linear normalization are calculated using (8) and (9), and the calculation results are presented in table 6.

Table 6. Normalization linier results using the MUNRA method

Employees Name	Benefit Criteria	Cost Criteria

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Vol 5, No 2, March 2026
Hal 451−463
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	Performance (CE-1)	Technical Competence (CE-2)	Work Discipline (CE-3)	Communication Skills (CE-4)	Error Rate (CE-5)	Disciplinary Violations (CE-6)
Pratama	0.9239	0.9670	0.9574	0.9213	0.8333	1.0000
Budi	0.8478	0.8791	0.9043	0.8876	0.7143	0.8333
Lestari	1.0000	1.0000	0.9894	0.9888	1.0000	1.0000
Dedi	0.7609	0.8242	0.8298	0.8315	0.6250	0.7143
Eka	0.9565	0.9451	0.9468	0.9551	0.8333	1.0000
Hidayat	0.9022	0.9011	0.8936	0.8989	0.7143	0.8333
Maharani	0.9783	0.9780	0.9787	0.9775	1.0000	1.0000
Wijaya	0.8261	0.8571	0.8511	0.8652	0.6250	0.8333
Intan	0.9130	0.9341	0.9255	0.9326	0.8333	1.0000
Susilo	0.9891	0.9890	1.0000	1.0000	1.0000	1.0000
Oktaviani	0.8587	0.8901	0.8830	0.8764	0.7143	0.8333

In the second stage of normalization in the MUNRA method, vector normalization is used to adjust the criterion values based on the vector length of each criterion. This approach aims to maintain the relative proportions among alternatives by considering the overall data distribution. The result of vector normalization produces a more balanced matrix that is ready to be combined with the normalization results from other stages in the MUNRA method. The vector normalization results are calculated using (10) and (11), and the calculation results are shown in Table 7.

Table 7. Normalization vector results using the MUNRA method

Employees Name	Benefit Criteria				Cost Criteria	
	Performance (CE-1)	Technical Competence (CE-2)	Work Discipline (CE-3)	Communication Skills (CE-4)	Error Rate (CE-5)	Disciplinary Violations (CE-6)
Pratama	0.3068	0.3150	0.3120	0.3010	0.7196	0.7300
Budi	0.2815	0.2863	0.2947	0.2900	0.6729	0.6760
Lestari	0.3321	0.3257	0.3224	0.3231	0.7664	0.7300
Dedi	0.2527	0.2684	0.2704	0.2717	0.6262	0.6220
Eka	0.3176	0.3078	0.3086	0.3120	0.7196	0.7300
Hidayat	0.2996	0.2935	0.2912	0.2937	0.6729	0.6760
Maharani	0.3248	0.3185	0.3190	0.3194	0.7664	0.7300
Wijaya	0.2743	0.2792	0.2774	0.2827	0.6262	0.6760
Intan	0.3032	0.3042	0.3016	0.3047	0.7196	0.7300
Susilo	0.3285	0.3221	0.3259	0.3267	0.7664	0.7300
Oktaviani	0.2851	0.2899	0.2878	0.2863	0.6729	0.6760

In the third stage of normalization in the MUNRA method, nonlinear normalization is used to capture patterns of data relationships that cannot be represented linearly. This approach allows for the adjustment of extreme values so that they do not dominate the calculation results. Thus, nonlinear normalization helps produce a more stable and realistic normalized matrix in the evaluation of alternatives. The results of the nonlinear normalization are calculated using (12) and (13), and the calculation results are presented in Table 8.

Table 8. Normalization non linier results using the MUNRA method

Employees Name	Benefit Criteria				Cost Criteria	
	Performance (CE-1)	Technical Competence (CE-2)	Work Discipline (CE-3)	Communication Skills (CE-4)	Error Rate (CE-5)	Disciplinary Violations (CE-6)
Pratama	0.8536	0.9352	0.9167	0.8489	0.5787	1.0000
Budi	0.7188	0.7729	0.8177	0.7879	0.3644	0.5787
Lestari	1.0000	1.0000	0.9788	0.9777	1.0000	1.0000
Dedi	0.5789	0.6793	0.6885	0.6913	0.2441	0.3644
Eka	0.9149	0.8931	0.8964	0.9121	0.5787	1.0000
Hidayat	0.8139	0.8120	0.7986	0.8080	0.3644	0.5787
Maharani	0.9570	0.9565	0.9579	0.9556	1.0000	1.0000
Wijaya	0.6824	0.7347	0.7243	0.7485	0.2441	0.5787
Intan	0.8336	0.8725	0.8566	0.8697	0.5787	1.0000
Susilo	0.9784	0.9781	1.0000	1.0000	1.0000	1.0000
Oktaviani	0.7374	0.7923	0.7797	0.7681	0.3644	0.5787

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Hal 451−463
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Weighted arithmetic operations in the MUNRA method are carried out to systematically integrate normalization results with criterion weights. This process produces an aggregate value that represents the relative contribution of each criterion to the performance of an alternative. The aggregate value serves as the main basis for determining the final score and ranking of alternatives in the MUNRA method. In the first stage of weighted arithmetic operations in the MUNRA method, the normalized linear values are multiplied by the weights of each criterion. This process aims to integrate the importance level of the criteria into the performance of each alternative. The calculation results in partial scores for the alternatives that reflect the contribution of the criteria based on linear normalization. The linear normalization results multiplied by the weights are calculated using (14), and the calculation results are presented in Table 9.

Table 9. Weighted linear normalization results in the MUNRA method

Employees Name	Linear Weight Results
Pratama	0.9058
Budi	0.7918
Lestari	0.9987
Dedi	0.7009
Eka	0.9097
Hidayat	0.7998
Maharani	0.9933
Wijaya	0.7427
Intan	0.9011
Susilo	0.9980
Oktaviani	0.7919

In the second stage of weighted arithmetic operations in the MUNRA method, the normalized vector values are combined with the predetermined criterion weights. This step maintains a balance of contributions among the criteria by preserving the relative proportion of alternative values. The result is a partial score that reflects the performance of the alternatives based on the vector normalization approach. The normalized vector values are multiplied by the weights calculated using (15), and the results of the calculation are presented in Table 10.

Table 10. Weighted vector normalization results in the MUNRA method

Employees Name	Vector Weight Results
Pratama	0.5955
Budi	0.5547
Lestari	0.6223
Dedi	0.5134
Eka	0.5967
Hidayat	0.5574
Maharani	0.6205
Wijaya	0.5307
Intan	0.5939
Susilo	0.6221
Oktaviani	0.5547

In the third stage of weighted arithmetic operations in the MUNRA method, the non-linear normalization results are multiplied by the weights of each criterion to produce weighted contributions. This stage serves to control the influence of extreme values so that they do not distort the evaluation results of alternatives. The partial scores obtained reflect the performance of the alternatives based on the non-linear approach in the MUNRA method. The results of the non-linear normalization multiplied by the weights are calculated using (16), and the calculation results are shown in Table 11.

Table 11. Weighted non linier normalization results in the MUNRA method

Employees Name	Non-Linear Weight Results
Pratama	0.7731
Budi	0.5387
Lestari	0.9973
Dedi	0.3962
Eka	0.7803
Hidayat	0.5527
Maharani	0.9867
Wijaya	0.4692
Intan	0.7641
Susilo	0.9960

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ISSN 2808-375X (Media Online)
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Hal 451−463
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Employees Name	Non-Linear Weight Results
Oktaviani	0.5386

The calculation result to obtain the final score in the MUNRA method is obtained by combining all partial scores from the three stages of weighted arithmetic operations. This process produces an aggregate value that reflects the overall performance of each alternative based on all weighted criteria. This final score is then used to rank the alternatives objectively and consistently in multi-criteria decision-making, calculated using (17). The calculation results are presented in Table 12.

Table 11. Final score results in the MUNRA method

Employees Name	Final Score
Pratama	1.1372
Budi	0.9426
Lestari	1.3092
Dedi	0.8052
Eka	1.1434
Hidayat	0.9550
Maharani	1.3003
Wijaya	0.8713
Intan	1.1295
Susilo	1.3080
Oktaviani	0.9426

The final result of the MUNRA method provides a comprehensive evaluation of each alternative by considering the contribution of all criteria proportionally. This method is capable of producing stable and representative rankings, especially when the data has heterogeneous characteristics and different scales. Thus, MUNRA becomes an effective tool to support objective and accountable multi-criteria decision-making.

3.4 Alternative Ranking

Alternative ranking is carried out after the final scores of each alternative are calculated based on the method used. Each alternative is compared with one another to determine the order based on the aggregate score obtained. The alternative with the highest score occupies the top rank as it is considered most suitable for the established criteria. This process helps decision-makers in choosing the best option systematically and transparently. With a clear ranking, the decisions made become more objective, consistent, and scientifically accountable. The ranking of alternatives using a combination of the WENSLO and MUNRA methods in Selecting the Best Employees is done by integrating the objective criteria weights from WENSLO and the comprehensive alternative scores from MUNRA. Each employee is evaluated based on the relative contribution of weighted criteria, resulting in an aggregate score that reflects overall performance. Alternatives with the highest scores occupy the top ranks, indicating that the candidate is the most suitable for the organization's needs. This combined approach allows for more accurate decision-making, as it combines the stability of WENSLO weights with the normalization flexibility of MUNRA for heterogeneous data. Thus, the ranking process becomes more objective, transparent, and accountable in determining the best employees. The ranking results of the alternatives are shown in Figure 2.

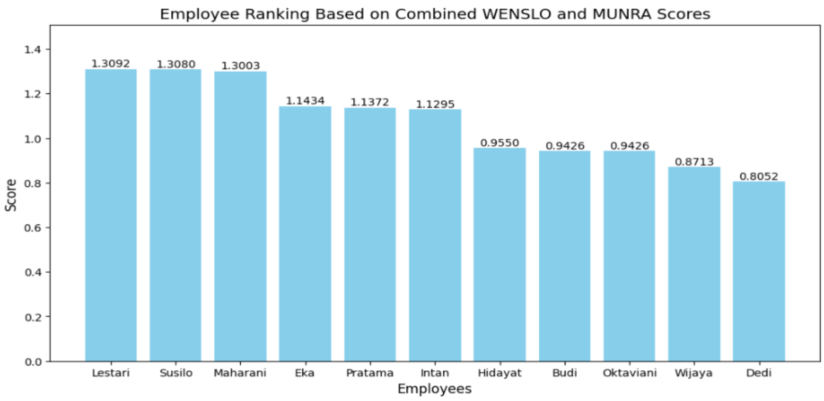

Figure 2. Alternative Ranking Results

Based on the Employee Ranking Based on Combined WENSLO and MUNRA Scores graph, it can be seen that the best-performing employee is Lestari with the highest score of 1.3092, closely followed by Susilo with a score of 1.3080 and Maharani with a score of 1.3003. These three employees occupy the top positions and demonstrate a very high and relatively balanced level of performance based on the results of the WENSLO and MUNRA integration methods. In the middle group, there are Eka with a score of 1.1434, Pratama with a score of 1.1372, and Intan with a score of 1.1295, reflecting good performance but still below the top group. Next, Hidayat with a score of 0.9550, Budi with a score of 0.9426, and Oktaviani with a score of 0.9426 are at the lower-middle performance level with closely related scores, indicating relatively similar performance. Meanwhile, Wijaya with a score of 0.8713 and Dedi with a score of 0.8052 are at the bottom ranking, which indicates the need for further attention and performance evaluation to encourage improvement in the future. Overall, this chart shows that the combination of the WENSLO and MUNRA methods is able to produce a clear, objective employee ranking and effectively differentiate performance levels among employees.

4. CONCLUSION

The results of this study indicate that the combination of the WENSLO and MUNRA methods in selecting the best employees based on various criteria provides a systematic and comprehensive approach, where WENSLO functions to assess and prioritize criteria through structured, preference-based weighting, while MUNRA ensures consistent data normalization and mathematically weighted score processing for each alternative. The integration of these two methods allows for a more objective and accurate evaluation, reduces subjective bias, and produces stable employee rankings even when facing variations in data or conflicting criteria. Through a thorough data collection process, decision matrix construction, multi-method normalization, and weighted final score calculation, organizations can identify employees with the best performance and potential in a transparent and measurable way. The Employee Ranking results based on the combined WENSLO and MUNRA scores show that the highest-performing employee is Lestari with a score of 1.3092, closely followed by Susilo with a score of 1.3080 and Maharani with a score of 1.3003, occupying the top positions and demonstrating superior and relatively balanced performance levels. Thus, the combination of WENSLO and MUNRA methods not only enhances the reliability of decision-making but also provides an adaptive academic and practical framework for human resource management, enabling clear, objective, and effective employee ranking that differentiates performance levels among individuals.

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