INTEGRATION OF CRISUS WEIGHTING AND ROV METHOD FOR DIVISION HEAD PERFORMANCE EVALUATION IN A MANUFACTURING COMPANY

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Abstract- *The performance evaluation of division heads in manufacturing companies often faces various problems, such as high subjectivity in assessment, the absence of clear criteria weighting standards, and instability in ranking results due to data variation. This situation causes the evaluation results to be less consistent and less able to accurately represent performance. Therefore, this study aims to develop a more objective performance evaluation model by integrating the CRISUS and ROV methods. The CRISUS method is used to determine the criteria weights objectively based on the characteristics of data distribution, while the ROV method is used to rank alternatives by considering variations in performance values through upper and lower bound approaches. The criteria used include leadership, productivity, innovation, operational costs, and error rates. The research results indicate that the proposed model is able to produce more stable and consistent preference values in representing candidate performance. Based on the calculation results, CDT-03 obtained a preference value of 0.4316 and ranked first, followed by CDT-06 with a value of 0.4212 in second place, and CDT-01 in third place with a value of 0.3180. Meanwhile, CDT-02 was in the last position with a value of 0.0739. These findings show that the integration of the CRISUS and ROV methods is able to provide a more objective, comprehensive, and reliable evaluation in supporting managerial decision-making. This research provides several important contributions; this combination is able to overcome the weaknesses of conventional methods by presenting objective criteria weighting as well as a ranking mechanism that takes into account variations in performance conditions.*
Keywords: *CRISUS, ROV, performance evaluation, decision support system, ranking methods*

INTRODUCTION

The performance evaluation of division heads plays a very important role in improving the efficiency and competitiveness of manufacturing companies because this position serves as the main link between top management strategy and operational implementation in the field(Junhai Wang & Setiawansyah, 2025). Through structured evaluations, companies can assess the extent to which division heads are able to manage resources, optimize production processes, and achieve the targets that have been set. Performance assessments also help identify strengths and weaknesses in leadership, which can serve as a basis for more targeted competency development. In addition, objective evaluations encourage accountability and transparency, which ultimately impact the improvement of work discipline and team productivity. In the increasingly competitive manufacturing industry, the ability of division heads to make quick and accurate decisions becomes a key factor that must continue to be monitored and improved. Therefore, performance evaluation not only serves as a measurement tool, but also as a continuous strategy to ensure the company is able to adapt, innovate, and maintain its competitive advantage(Dündar, 2025b).

The complexity of assessing the performance of division heads is increasing because it involves various interrelated criteria, such as leadership, productivity, innovation, communication skills, and strategic decision-making. Each criterion has different characteristics and levels of importance, making it difficult to evaluate simply without a systematic approach. Furthermore, some aspects, such as leadership and innovation, tend to be qualitative and subjective, which can cause bias in the evaluation process if not supported by the appropriate methods. On the other hand, criteria such as productivity are easier to measure quantitatively, but still need to be integrated with other aspects to produce a comprehensive assessment. This situation requires a multi-criteria evaluation model that is able to accommodate various types of data and give proportional weight to each indicator. With the right approach, that complexity can actually be processed into more accurate information and support more objective and effective decision-making.

Conventional methods in performance assessment often have limitations because they tend to rely on the subjectivity of the evaluator, personal experience, and perceptions that are not always consistent. This can lead to biased evaluation results, lack of transparency, and difficulty in accountability, especially when involving many complex criteria. Furthermore, traditional approaches generally have not been able to systematically integrate various assessment indicators, making the resulting decisions less optimal and potentially causing injustice. In such conditions, the application of Decision Support Systems (DSS) becomes a relevant solution to improve objectivity and accuracy in the evaluation process(Dündar, 2025b; Simic et al., 2023). DSS can process data in a structured manner by utilizing multi-criteria-based methods, allowing each assessment aspect to be analyzed proportionally according to its weight(Yiğit, 2025). With the support of DSS, the decision-making process becomes more transparent, consistent, and reproducible, thus minimizing the influence of individual subjectivity. Therefore, the use of DSS not only helps improve the quality of evaluation results but also strengthens the foundation for more rational and data-based decision-making(Stanković et al., 2024).

The main problem in the performance evaluation process lies in the inconsistency in determining the weight of criteria, which is often influenced by subjectivity and differences in perception among decision-makers. This condition causes the assessment results to be less stable and difficult to use as a reliable reference in strategic decision-making. In addition, there are difficulties in producing a ranking of alternatives that truly reflects the actual conditions, especially when the data used has diverse characteristics and involves many criteria(Muravev et al., 2020). The conventionally used methods are often unable to maintain the consistency of ranking results when there are small changes in data or criteria weights(Rani et al., 2025). This indicates a need for a more robust and systematic approach to managing the evaluation process. Therefore, a method is required that can objectively integrate criteria weighting while producing rankings that are effective, stable, and accurate. With this approach, the decision-making process is expected to become more consistent, transparent, and scientifically accountable.

In multi-criteria decision making, objective weighting plays an important role in ensuring that the importance level of each criterion is determined based on data characteristics, rather than the subjective preferences of the assessor(Do, 2024; Kousar et al., 2025). This approach generally utilizes statistical information such as the level of variation, value distribution, and relationships between criteria to produce proportional weights. Criteria with high data variation are usually considered more informative because they can distinguish alternatives more clearly(Sahin et al., 2024). The criterion importance based on sum of squares (CRISUS) method offers a simpler yet effective objective weighting approach based on the concept of the sum of squares of data values. This method assesses the level of importance of criteria based on the magnitude of the squared value contributions to the overall variation, so that criteria with more significant value dispersion will receive higher weights(Adalar & IŞIK, 2025; Bektaş, 2026). With a relatively easy-to-implement mechanism and the ability to accommodate diverse data, CRISUS becomes a promising alternative in enhancing the objectivity and reliability of the weighting process in multi-criteria decision support systems.

In multi-criteria decision making, ranking methods are used to determine the order of the best alternatives based on performance values that have been evaluated against various criteria(Dündar, 2025a; Roszkowska & Wachowicz, 2024). In general, ranking approaches work by aggregating the values of each criterion that have been normalized and weighted, resulting in a final score that can be compared among alternatives. Some approaches emphasize closeness to the ideal solution, while others use the concept of utility or relative dominance among alternatives. One interesting approach in the ranking process is the range of value (ROV) method, which combines the concept of minimum and maximum values to evaluate the performance of alternatives. This approach provides a more comprehensive picture of the position of alternatives, especially under conditions of uncertain data or high variability(Aytekin, 2021; Ersoy & Taslak, 2023). The main advantage of ROV lies in its ability to represent uncertainty and reduce bias due to data fluctuations, making the ranking results more stable and robust. In addition, this method is relatively simple in calculation yet still capable of providing informative and easily interpretable results. The ROV method becomes one of the alternative ranking methods that is effective in supporting more accurate decision-making and adaptive to data dynamics.

The research gap that can be identified lies in the still limited studies that integrate the CRISUS method with the ROV approach, particularly in the context of managerial performance evaluation. Most previous research tends to use weighting and ranking methods separately or combine common approaches without exploring the potential of newer methods. In fact, CRISUS has the advantage of producing objective and stable criteria weights based on data distribution, while ROV is able to provide ranking results that take into account value ranges and uncertainty. The lack of integration of these two methods results in the opportunity to obtain more comprehensive and robust evaluation results not being optimally utilized. Furthermore, in the context of managerial performance that involves many complex and dynamic indicators, an approach is needed that can accommodate data variations while maintaining the consistency of results. Therefore, the combination of CRISUS and ROV becomes relevant to be further studied as an effort to improve accuracy, objectivity, and stability in the managerial performance evaluation process. Research in this area is expected to provide both methodological and practical contributions in the development of multi-criteria decision support systems.

This study aims to develop a managerial performance evaluation model that is more objective, accurate, and stable through the integration of the CRISUS method as a criterion weighting approach and the ROV method as an alternative ranking technique. By combining these two methods, this study seeks to address the problems of weight inconsistency and ranking result instability that often arise in conventional approaches. The main contribution of this study lies in providing a new framework in a multi-criteria decision support system that can accommodate the characteristics of complex and dynamic data. In addition, this study also provides a methodological contribution by introducing a combination of methods that has not been widely explored in the literature, particularly in the context of managerial performance evaluation. From a practical perspective, the research results are expected to help organizations generate more transparent, consistent, and data-driven decisions. Thus, this study not only enriches the development of MCDM methods, but also provides practical solutions to improve the quality of decision-making in organizational environments.

RESEARCH METHOD

Research stages are a series of systematic steps designed to ensure that the research process proceeds in a directed, structured manner and produces findings that can be accounted for. Each stage reflects a sequence of activities ranging from problem identification, goal formulation, data collection and processing, to analysis and drawing conclusions. In the context of scientific research, these stages serve as a work guide so that researchers can manage the process effectively and minimize errors. In addition, having clear stages also facilitates the evaluation and replication process by other researchers. Research stages are usually arranged based on the approach or method used, so they may differ from one study to another. Thus, research stages become an important element in ensuring the quality, consistency, and validity of research results.

2.1 Research Stage

The research stages in the division head performance evaluation in a manufacturing company are a series of systematic steps designed to assess the performance of division heads objectively and in a structured manner based on various relevant criteria. With these systematic stages, the research not only produces more accurate and consistent assessments but also provides a strong foundation for managerial decision-making in improving organizational performance. All of these research stages are presented concisely and in a structured manner in Figure 1.

Figure 1. Research Stage

The stages of this research begin with problem identification, which is identifying issues related to the evaluation of division head performance that still faces subjectivity and inconsistency in results. Next, data collection is carried out by gathering performance data based on predetermined criteria, both in quantitative and qualitative forms, from the manufacturing company environment. The next stage is weight determination using the CRISUS method, where each criterion is given a weight objectively based on the data distribution characteristics using the sum of squares approach. Once the weights are obtained, the process continues with alternative ranking using the ROV method to determine the ranking of division heads by considering the range of values that reflect the best and worst conditions of each alternative.

2.2 CRISUS Weighting

The CRISUS method is one of the objective weighting approaches in multi-criteria decision making that determines the importance level of each criterion based on the magnitude of the sum of the squares of data values(Adalar & IŞIK, 2025). The basic concept of this method is that criteria with greater value dispersion will contribute more significantly to differentiating alternatives, thus deserve higher weights. By using the sum of squares approach, CRISUS is able to capture the intensity of data variation more clearly compared to methods that rely only on the average or simple dispersion measures. The calculation process is relatively simple yet still effective in producing proportional and consistent weights. Additionally, this method also has the advantage of maintaining result stability against data changes, making it suitable for use under dynamic and complex data conditions. Determination of the criteria weights using the CRISUS method as in the following equation.

$$X = [x_{ij}]_{mxn} \quad \text{..} (1)$$

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}; benefit\ criteria \\ 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}; cost\ criteria \end{cases} \text{..........} (2)$$

$$s_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \text{..} (3)$$

$$\rho_j = \sum_{i=1}^{m} s_{ij}^2 \text{...} (4)$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(s_{ij} - \bar{s_j})^2}{m}} \text{....................................} (5)$$

$$w_j = \frac{\rho_j * \sigma_j}{\sum_{j=1}^{n} \rho_j * \sigma_j} \text{...} (6)$$

Equation (1) represents the decision matrix X where x_{ij} indicates the value of the i^th alternative for the j^th criterion, with m as the number of alternatives and n as the number of criteria. This matrix serves as the main basis in the calculation process because it contains all the evaluation data that will be processed in the next stage.

Equation (2) is used to normalize the values in the decision matrix by taking into account the type of criteria, which are benefit and cost. For benefit criteria, the values are normalized by comparing them to the square root of the sum of squares, whereas for cost criteria, an adjustment is made by subtracting the normalization result from one. This process aims to equalize the data scale so that all criteria can be compared proportionally.

Equation (3) shows the process of forming the proportion value s_{ij}, which is done by dividing the normalized value by the total value for each criterion. This stage aims to illustrate the relative contribution of each alternative within a specific criterion, so that it can reflect the distribution of values more evenly.

Equation (4) is used to calculate the value ρ_j, which is the sum of the squares of each proportion value within a criterion. This value represents the level of dominance or strength of data distribution in that criterion, where the higher the value, the greater the influence of the criterion in differentiating the alternatives.

Equation (5) calculates the standard deviation σ_j of the proportion values, which indicates the level of data dispersion relative to its mean. The larger the standard deviation value, the higher the data variation in that criterion, which means the criterion has a stronger discriminative ability.

Equation (6) represents the final stage in determining the criterion weight w_j, which is obtained from the multiplication of the value ρ_j and σ_j, then normalized against the total of all criteria. This result reflects the final weight that considers both the intensity of distribution and the level of data variation, thus producing a weight that is objective, proportional, and stable.

2.3 ROV Method

The ROV method is one approach in multi-criteria decision-making used to determine the ranking of alternatives based on the range of values that can be obtained from each alternative. Unlike conventional ranking methods that produce a single value, ROV considers the lower bound (minimum) and upper bound (maximum) of each criterion's contribution, thereby producing an evaluation interval. This approach provides a more comprehensive view of the position of alternatives, especially under conditions where data contains uncertainty or high variation. By considering the range of values, ROV can reduce bias due to data fluctuations and improve the stability of ranking results. In addition, this method is relatively simple to apply yet remains effective in producing more robust and informative decisions. The determination of alternative rankings using the ROV method is as shown in the following equation.

$$x_{ij}^{-} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}}; benefit \text{..........................} (7)$$

$$x_{ij}^{+} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}}; cost \text{...............................} (8)$$

$$u_i^{+} = \sum_{i=1}^{m} x_{ij}^{+} * w_j \text{....................................} (9)$$

$$u_i^{-} = \sum_{i=1}^{m} x_{ij}^{-} * w_j \text{....................................} (10)$$

$$u_i = \frac{u_i^{+} + u_i^{-}}{2} \text{..} (11)$$

Equation (7) is used to calculate the normalization value of the lower bound x_{ij}^{-}, which is done by measuring the position of an alternative's value relative to the minimum and maximum values for each criterion. This process aims to convert the data into a uniform scale while representing the lowest possible contribution of an alternative in the context of evaluation.

Equation (8) is used to obtain the normalization value of the upper bound x_{ij}^{+}, which indicates the closeness of an alternative's value to the best condition for each criterion. With this approach, higher values reflect better performance, thereby representing the maximum potential of the alternative being evaluated.

Equation (9) calculates the optimistic utility value u_i^{+}, which is by summing the results of multiplying the upper bound values by the criteria weights. This value reflects the best-case scenario that an alternative can achieve based on the maximum contribution of each considered criterion.

Equation (10) is used to calculate the pessimistic utility value u_i^{-}, which is by summing the results of multiplying the lower bound values by the criteria weights. This value represents the lowest possible condition, thus providing a cautious perspective in evaluating the performance of alternatives.

Equation (11) is the final stage in the ROV method, which is to calculate the final utility value u_i by taking the average of the optimistic and pessimistic values. This result reflects a balance between the best and worst conditions, thereby providing a more stable, fair, and representative assessment in determining the ranking of alternatives.

RESULTS AND DISCUSSION

Integration of CRISUS Weighting and the ROV Method provides a structured and objective framework for evaluating division head performance in a manufacturing company. In this approach, CRISUS is first applied to determine the weights of evaluation criteria based on the distribution and intensity of data, ensuring that each criterion reflects its true importance without subjective bias. These objective weights are then incorporated into the ROV method, which ranks division heads by considering both the best and worst possible performance scenarios through value ranges. This combination allows the evaluation process to capture not only the relative importance of criteria but also the uncertainty and variability in performance data. As a result, the integrated model produces rankings that are more stable, consistent, and reflective of real conditions in a dynamic manufacturing environment. Moreover, this integration enhances decision-making by providing a more comprehensive and balanced assessment, supporting management in identifying high-performing division heads and areas that require improvement.

3.1 Problem Identification

Problem identification in the performance evaluation of division heads in manufacturing companies becomes a very crucial initial stage because it is directly related to the accuracy and relevance of the assessment results. In practice, the evaluation process often faces various obstacles, such as the use of conventional methods that still rely on the subjectivity of the assessor and the absence of clear standards in determining the weight of each criterion. Furthermore, many organizations have not been able to systematically integrate various performance indicators such as leadership, productivity, and innovation, resulting in evaluation outcomes that tend to be inconsistent. This problem becomes even more complex when the data used have diverse characteristics, both in terms of measurement scale and level of variation, which ultimately complicates the process of comprehensive processing and analysis.

Furthermore, instability in ranking results also becomes a major issue that frequently arises in managerial performance evaluation. Small changes in data or criteria weighting can result in significantly different rankings, thereby raising doubts about the validity of the decisions made. On the other hand, there is still limited research that adopts an integrated approach between objective weighting methods and ranking techniques capable of effectively handling data uncertainty. This condition indicates a need for a more robust, adaptive evaluation model that can provide consistent results. Therefore, the identification of problems not only focuses on the weaknesses of existing methods but also highlights the importance of developing new approaches that can improve objectivity, stability, and reliability in the division head performance evaluation process.

3.2 Data Collection

Data collection in this study was carried out systematically to obtain accurate and relevant information related to the performance of division heads in manufacturing companies. The data used includes various assessment indicators such as leadership, productivity, innovation, communication skills, and target achievement, obtained from internal company sources such as performance reports, management assessments, and operational documentation. In addition, the data can also be supplemented through observation and interviews to capture qualitative aspects that are not fully reflected in numbers. The data collection process is conducted by ensuring consistency, completeness, and validity so that it can be optimally used in the subsequent analysis stage. With structured and representative data, the performance evaluation process can be carried out more objectively and be able to reflect the actual conditions in the field. The results of this data collection are presented in detail in Table 1.

Table 1. Data Collection

Candidate	Leadership (C1)	Productivity (C2)	Innovation (C3)	Operational Cost (C4)	Error Rate (C5)
CDT-01	85	90	80	70	5
CDT-02	78	85	75	65	7
CDT-03	88	92	85	75	4
CDT-04	82	88	78	68	6
CDT-05	80	86	82	72	5
CDT-06	87	91	84	74	4
CDT-07	79	84	77	66	6
CDT-08	83	89	81	69	5
CDT-09	81	87	79	71	5

Table 1 presents the results of data collection assessments of nine division head candidates based on five criteria, namely leadership (C1), productivity (C2), innovation (C3), operational costs (C4), and error rate (C5). The criteria of leadership, productivity, and innovation fall into the benefit category, where higher values indicate better performance, as they reflect managerial ability, target achievement, and creativity at work. Meanwhile, operational costs and error rate are cost criteria, where lower values are preferred because they indicate efficient use of resources and minimal errors in operations. The data shows a variation in performance among candidates, where CDT-03 and CDT-06 have relatively high scores in benefit criteria and low scores in cost criteria, thus reflecting superior performance.

Conversely, some candidates such as CDT-02 and CDT-07 have lower scores in benefit criteria and higher scores in cost criteria, which can affect the overall evaluation results. This data variation provides a strong basis for further analysis in determining the criteria weights and objectively ranking the candidates.

3.3 Weight Determination using the CRISUS Method

The determination of criteria weights using the CRISUS method is carried out to obtain the level of importance of each criterion objectively based on the characteristics of the available data. This approach allows each criterion to be given a weight proportionally without being influenced by the subjectivity of the assessor. The CRISUS method is capable of producing weights that are more stable, consistent, and representative in supporting an accurate performance evaluation process.

The first stage begins with forming a decision matrix as shown in (1), which contains the values of each alternative for each criterion. This matrix serves as the main basis in the calculation process because it represents all the evaluation data that will be analysis.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} \end{bmatrix}$$

The results of the assessment data matrix from Table 1 are as follows.

$$X = \begin{bmatrix} 85 & 90 & 80 & 70 & 5 \\ 78 & 85 & 75 & 65 & 7 \\ 88 & 92 & 85 & 75 & 4 \\ 82 & 88 & 78 & 68 & 6 \\ 80 & 86 & 82 & 72 & 5 \\ 87 & 91 & 84 & 74 & 4 \\ 79 & 84 & 77 & 66 & 6 \\ 83 & 89 & 81 & 69 & 5 \\ 81 & 87 & 79 & 71 & 5 \end{bmatrix}$$

The second stage is the normalization process calculated using (2), taking into account the type of criteria, whether benefit or cost. This normalization aims to equalize the data scales so that values across criteria can be compared fairly.

$$r_{11} = \frac{x_{11}}{\sqrt{\sum_{i=1}^{9} x_{1j}^{2}}} = \frac{85}{\sqrt{61437}} = \frac{85}{247.865} = 0.343$$

The results of the normalization value calculations using the CRISUS method are displayed in Table 2.

Table 2. Normalization Results of the CRISUS Method

Candidate	CT-1	CT-2	CT-3	CT-4	CT-5
CDT-01	0.343	0.341	0.333	0.333	0.314
CDT-02	0.315	0.322	0.312	0.309	0.440
CDT-03	0.355	0.348	0.353	0.357	0.251
CDT-04	0.331	0.333	0.324	0.323	0.377
CDT-05	0.323	0.326	0.341	0.343	0.314
CDT-06	0.351	0.345	0.349	0.352	0.251
CDT-07	0.319	0.318	0.320	0.314	0.377
CDT-08	0.335	0.337	0.337	0.328	0.314
CDT-09	0.327	0.329	0.328	0.338	0.314

The third stage is carried out by calculating the proportion values using (3), which is done by dividing the normalized value by the total value for each criterion. This stage shows the relative contribution of each alternative within a particular criterion.

$$s_{11} = \frac{r_{11}}{\sum_{i=1}^{9} r_{1j}} = \frac{0.343}{2.998} = 0.114$$

The results of the proportion value calculations using the CRISUS method are displayed in Table 3.

Table 3. Proportion Results of the CRISUS Method

Candidate	CT-1	CT-2	CT-3	CT-4	CT-5
CDT-01	0.114	0.114	0.111	0.111	0.106
CDT-02	0.105	0.107	0.104	0.103	0.149
CDT-03	0.118	0.116	0.118	0.119	0.085
CDT-04	0.110	0.111	0.108	0.108	0.128
CDT-05	0.108	0.109	0.114	0.114	0.106
CDT-06	0.117	0.115	0.117	0.117	0.085
CDT-07	0.106	0.106	0.107	0.105	0.128
CDT-08	0.112	0.112	0.112	0.110	0.106
CDT-09	0.109	0.110	0.110	0.113	0.106

The fourth stage is calculating the proportion value using (4), which is obtained from the sum of the squares of the proportion values. This value reflects the level of dominance or the strength of the data distribution for each criterion.

$$\rho_1 = \sum_{i=1}^{9} {s_{1j}}^{2} = 0.111$$

The results of the sum square value calculations using the CRISUS method are displayed in Table 4.

Table 4. Sum Square Results of the CRISUS Method

CT-1	CT-2	CT-3	CT-4	CT-5
0.1113	0.1112	0.1113	0.1113	0.1145

The fifth stage is calculating the standard deviation value using (5), which is used to measure the level of data dispersion relative to its mean. The greater the value, the higher the variation of the data for that criterion.

$$\sigma_1 = \sqrt{\frac{\sum_{i=1}^{9}\left(s_{1j} - \bar{s_1}\right)^2}{m}} = 0.0010$$

The results of the standard deviation value calculations using the CRISUS method are displayed in Table 5.

Table 5. Standard Deviation Results of the CRISUS Method

CT-1	CT-2	CT-3	CT-4	CT-5
0.0010	0.0007	0.0009	0.0011	0.0045

The final stage is determining the criterion weights using (6), this result produces the final objective and proportional weights for each criterion.

$$w_1 = \frac{\rho_1 * \sigma_1}{\sum_{j=1}^{5} \rho_j * \sigma_j} = \frac{0.000111}{0.000939} = 0.1179$$

The results of the criterion weights value calculations using the CRISUS method are displayed in Table 6.

Table 6. Criterion Weights Results of the CRISUS Method

CT-1	CT-2	CT-3	CT-4	CT-5
0.1198	0.0878	0.1148	0.1368	0.5407

The weighting results show that the Error Rate criterion (C5) has the highest weight of 0.5407, indicating that the error rate is the most dominant factor in evaluating the performance of division heads. This demonstrates that the company places great emphasis on the importance of work quality and minimizing errors in operations. Furthermore, the Operational Cost criterion (C4) has a weight of 0.1368, which shows that cost efficiency is also an important consideration in the assessment. The Leadership (C1) and Innovation (C3) criteria have relatively balanced weights, at 0.1198 and 0.1148 respectively, indicating that the ability to lead and innovate is still considered even though it is not as strong as efficiency and quality aspects. Meanwhile, Productivity (C2) has the lowest weight of 0.0878, meaning its contribution in differentiating candidate performance is relatively smaller compared to the other criteria.

3.4 Alternative Ranking using the ROV Method

Alternative Ranking using the ROV Method is an approach used to determine the performance ranking of division heads more comprehensively by considering the variation in values that may occur for each alternative. This method does not only focus on a single final value but also takes into account the range of performance reflecting the best and worst conditions, thereby providing a more realistic evaluation picture. By utilizing the pre-determined criterion weights, ROV generates preference values that represent the balance between the maximum and minimum potential of each candidate. This approach is very effective in reducing bias due to data fluctuations and improving the stability of ranking results. In addition, ROV is also able to capture performance differences among alternatives more clearly, especially in conditions of complex and diverse data.

The implementation of the ROV method in the ranking process begins by calculating the lower bound normalization value based on using (7), which indicates the relative position of an alternative with respect to the minimum value for each criterion. The calculation of the lower bound normalization value using the ROV method is as follows.

$$x_{11}^{-} = \frac{x_{11} - x_1^{min}}{x_1^{max} - x_1^{min}} = \frac{85 - 78}{88 - 78} = \frac{7}{10} = 0.700$$

The results of the overall calculation of the lower bound normalization values using the ROV method are presented in Table 7.

Table 7. Lower Bound Normalization Results of the ROV Method

Candidate	CT-1	CT-2	CT-3
CDT-01	0.700	0.750	0.500
CDT-02	0.000	0.125	0.000
CDT-03	1.000	1.000	1.000
CDT-04	0.400	0.500	0.300
CDT-05	0.200	0.250	0.700
CDT-06	0.900	0.875	0.900
CDT-07	0.100	0.000	0.200
CDT-08	0.500	0.625	0.600
CDT-09	0.300	0.375	0.400

Next, the upper limit value is calculated using Equation (8) to represent the closeness of alternatives to the maximum value, thereby reflecting the potential for the best performance. The calculation of the upper limit normalization value for the ROV method is as follows.

$$x_{14}^{+} = \frac{x_4^{max} - x_{14}}{x_4^{max} - x_4^{min}} = \frac{75 - 70}{75 - 65} = \frac{5}{10} = 0.500$$

The results of the overall calculation of the upper limit normalization value for the ROV method are presented in Table 8.

Table 8. Upper Bound Normalization Results of the ROV Method

Candidate	CT-4	CT-5
CDT-01	0.500	0.667
CDT-02	1.000	0.000
CDT-03	0.000	1.000
CDT-04	0.700	0.333
CDT-05	0.300	0.667
CDT-06	0.100	1.000
CDT-07	0.900	0.333
CDT-08	0.600	0.667
CDT-09	0.400	0.667

After both values are obtained, the calculation of optimistic utility is carried out using (9) by multiplying the upper limit value by the criterion weight, which represents the benefit condition of each alternative. The calculation of the normalized upper limit value using the ROV method is as follows.

$$u_1^{+} = (x_{11}^{+} * w_1) + (x_{12}^{+} * w_2) + (x_{13}^{+} * w_3)$$

$$u_1^{+} = (0.700 * 0.1198) + (0.750 * 0.0878) + (0.500 * 0.1148)$$

$$u_1^{+} = (0.0839) + (0.0659) + (0.0574)$$

$$u_1^{+} = 0.2071$$

The results of the overall calculation of the optimistic upper limit utility using the ROV method are presented in Table 9.

Table 9. Upper Utility Results of the ROV Method

Candidate	Upper Utility
CDT-01	0.2071
CDT-02	0.0110
CDT-03	0.3224
CDT-04	0.1263
CDT-05	0.1263

CDT-06	0.2880
CDT-07	0.0349
CDT-08	0.1837
CDT-09	0.1148

After both values are obtained, the calculation of optimistic utility is carried out using (10) by multiplying the lower limit value by the criterion weight, which represents the benefit condition of each alternative. The calculation of the normalized lower limit value using the ROV method is as follows.

$u_1^- = (x_{14}^- * w_4) + (x_{15}^- * w_5)$

$u_1^- = (0.500 * 0.1368) + (0.667750 * 0.5407)$

$u_1^- = (0.0684) + (0.3605)$

$u_1^- = 0.4289$

The results of the overall calculation of the optimistic upper limit utility using the ROV method are presented in Table 10.

Table 10. Lower Utility Results of the ROV Method

Candidate	Lower Utility
CDT-01	0.4289
CDT-02	0.1368
CDT-03	0.5407
CDT-04	0.2760
CDT-05	0.4015
CDT-06	0.5544
CDT-07	0.3034
CDT-08	0.4425
CDT-09	0.4152

The final stage is carried out by calculating the final preference value using (11), which is by combining the optimistic and pessimistic values in a balanced manner. The calculation of the final preference value of the ROV method is as follows.

$$u_1 = \frac{u_1^+ + u_1^-}{2} = \frac{0.2071 + 0.4289}{2} = 0.3180$$

The results of the overall final preference calculation for the ROV method are shown in Table 11.

Table 11. Final Preference Results of the ROV Method

Candidate	Final Value
CDT-01	0.3180
CDT-02	0.0739
CDT-03	0.4316
CDT-04	0.2011
CDT-05	0.2639
CDT-06	0.4212
CDT-07	0.1691
CDT-08	0.3131
CDT-09	0.2650

Table 11 presents the final preference values from the ROV method for nine division head candidates, which reflect the relative performance levels based on the evaluation of all criteria and predefined weights. The resulting preference values show variations in performance among the candidates, where each value represents a balance between the best and worst conditions of each alternative. Some candidates have values that are close to each other, indicating a competitive performance level, while other candidates show a fairly clear difference. Overall, these results provide a comprehensive picture of the relative position of each candidate in the evaluation process. This information serves as an important basis in supporting a more objective and structured decision-making process. Based on these results, the next step will be the ranking process, as shown in Figure 2.

Figure 2. Ranking Results of Alternatives Using CRISUS and ROV

Figure 2 displays the ranking results of alternatives based on the final preference values of the ROV method visually, where each candidate is ordered according to the obtained value. Based on the graph, the ranking order begins with CDT-03 with a value of 0.4316 in first place, followed by CDT-06 with a value of 0.4212 in second place. Next, CDT-01 occupies third place with a value of 0.3180, followed by CDT-08 in fourth place with a value of 0.3131. The fifth and sixth places are occupied by CDT-09 with a value of 0.2650 and CDT-05 with a value of 0.2639, respectively. Then, CDT-04 is in seventh place with a value of 0.2011, followed by CDT-07 in eighth place with a value of 0.1691. Finally, CDT-02 is in ninth place with a value of 0.0739. This visualization provides a clear picture of the relative positions of each candidate, making it easier to understand the overall evaluation results.

CONCLUSION

The integration of the CRISUS and ROV methods is able to produce a division head performance evaluation system that is more objective, structured, and consistent. CRISUS plays a role in determining the weight of criteria objectively based on data characteristics, thereby reducing subjectivity in the assessment. Furthermore, the ROV method utilizes these weights to produce preference values that take into account variations in performance conditions, thus providing a more realistic and balanced evaluation overview. The results obtained show differences in preference values among candidates, reflecting variations in overall performance levels.

In addition, this approach has also been proven to improve the quality of decision-making in a dynamic manufacturing company environment. By considering various criteria such as leadership, productivity, innovation, operational costs, and error rates, this system can provide a more comprehensive evaluation. The final results in the form of preference scores and candidate rankings can be used as a strong basis for management in determining the most suitable division head and identifying areas that need improvement, thus supporting the overall enhancement of organizational performance.

Future work of this research can be focused on the development of an evaluation model that is more adaptive and flexible to the dynamics of the industrial environment. One direction that can be pursued is integrating the CRISUS and ROV methods with an artificial intelligence or machine learning-based approach to enhance the ability to predict performance patterns more deeply. In addition, future research can also consider adding broader evaluation criteria, such as employee satisfaction, sustainability, and strategic managerial capabilities, so that the assessment results become more comprehensive and relevant to the needs of modern companies.

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