Modification of the Complex Proportional Assessment Method: A New Methodology for Decision Support

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Modification of the Complex Proportional Assessment Method: A New Methodology for Decision Support

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Abstract: Complex Proportional Assessment (COPRAS) is one of the methods in MCDM that is used to evaluate and rank alternatives based on several criteria. One of its main drawbacks is its sensitivity to criteria weighting, as small changes in weighting can significantly affect the final ranking results of the evaluated alternatives. This makes the method susceptible to subjective errors in weighting, which can reduce the validity of the decisions taken. The aim of this paper is to propose improvements to the COPRAS method that are more accurate and flexible in supporting the decision-making process. COPRAS's proposed method uses a root mean square called COPRAS-R. We calculated the correlation between the alternative ratings using the COPRAS method and the weights calculated by the ROC, Rank Sum, and Entropy weighting methods which had a correlation value of 0.97 compared to the original ranking. The result of the calculation of the correlation value of the COPRAS-R method is 1 which means that the results of this method ranking are exactly the same as the alternative initial rankings.

Keywords: COPRAS; COPRAS-R; Improvement; RMS; Weighting

1. Introduction

Multiple criteria decision making (MCDM) is an approach used to solve decision-making problems involving multiple criteria, where each criterion has an important role in influencing the final decision[1,2]. In this process, decision-makers are faced with a situation where they have to evaluate several alternatives based on a number of relevant factors or criteria. The MCDM approach facilitates this process by providing a systematic framework for measuring and comparing various options, both qualitatively and quantitatively. This allows decision-makers to consider a variety of factors that may conflict with each other, such as cost, quality, and time, and ultimately choose the optimal solution. Due to the flexibility and ability of MCDM to handle complex decisions involving multiple criteria[3,4], MCDM has become an important tool in the decision-making process across various sectors. In the face of the challenge of determining the optimal solution, one of the main difficulties often faced is dealing with the weighting of different criteria. Each criterion in decision-making may have a different level of importance, and determining the appropriate weight for each criterion is critical for the resulting solution to truly reflect the desired priorities. An imbalance in the weighting can affect the final result and make the chosen solution less than optimal. Another challenge is the limitations of the MCDM method used[5]. Some methods may not be able to handle the complexity or characteristics of a particular problem. The development of new methods or modifications to existing methods can also be a solution to deal with these limitations, so that they are more adaptive to changes in conditions or complex dynamics in the decision-making process.

Complex proportional assessment (COPRAS) is a method in MCDM that is used to evaluate and rank alternatives based on several criteria[6,7]. This method takes into account the weight of each criterion and compares alternatives to each other by considering the positive and negative effects of the criteria considered. This method is designed to overcome limitations in traditional decision-making techniques that often do not take into account the aspect of proportional comparison between alternatives, especially related to positive and negative criteria. COPRAS was introduced as a method capable of effectively assessing alternatives by measuring the proportional contribution of each criterion to the final solution[8,9]. One of the key features of this method is its ability to take into account the benefit criteria (where a higher value is better) and the cost criteria (where a lower value is better) at the same time. One of the main advantages of the COPRAS method is its ability to handle decision-making problems that involve many criteria proportionally. COPRAS is able to consider the criteria of benefit and cost simultaneously, resulting in a more holistic and balanced solution[10]. This approach gives decision-makers a clearer picture of how an alternative can increase profits while minimizing losses. Although the COPRAS has many advantages, it also has some limitations that need to be noted. One of the main drawbacks is sensitivity to criteria weights. COPRAS relies heavily on accurate criteria weighting, as small changes in weights can significantly affect the final ranking results of the alternatives evaluated. This makes this method susceptible to subjective errors in weighting, which can reduce the validity of the decisions taken[11].

Improvement in the COPRAS method is essential so that it can be more adaptive and accurate in handling more complex applications. One of the main reasons is to address sensitivity to criteria weights. In many cases, the weighting of the criteria is done subjectively, and small changes in weighting can lead to very different alternative ranking results. By improvement the COPRAS method, such as through the use of data-based weighting methods (e.g., Entropy or CRITIC), the weighting process becomes more objective, reduces the risk of subjective and improves the accuracy of decision-making results[12]. Optimization is needed to increase the flexibility of the method in the face of dynamic conditions or uncertainties in the data. In many real applications, such as project management or supplier selection, decision-maker preferences can change over time, or there is uncertainty associated with certain criteria. Improvement COPRAS through an adaptive approach or in combination with other methods allows these methods to be more responsive to such changes. This makes COPRAS more effective in handling multi-criteria decisions in a dynamic environment, increasing its relevance and usability in complex decision-making scenarios[13].

1.1. Motivation for Conducting Research

The motivation in conducting research on improvement in the COPRAS is based on the need to improve the accuracy, efficiency, and relevance of methods in complex multicriteria decision-making. COPRAS has been proven to be one of the reliable methods in assessing and ranking alternatives based on the weight of the criteria given. However, in its application, this method still has some limitations, such as sensitivity to weight changes, difficulties in handling dynamic or uncertain data, and lack of flexibility in dealing with complex and diverse decision contexts. Therefore, this research is motivated to develop and improve the COPRAS method in order to be able to provide more objective, adaptive, and applicable results in various real-world situations. This development is expected to strengthen the ability of decision support systems to help decision-makers choose the best alternatives more rationally and efficiently, while opening up opportunities for the integration of COPRAS with modern approaches such as data-based weighting, uncertain information processing, or incorporation with artificial intelligence. By making improvements to the COPRAS method, it is hoped that a more comprehensive and responsive approach to the needs of end users can be created, especially in presenting more precise and credible decision results. This research is also intended to make a scientific contribution to the development of the MCDM method, as well as to be the basis for further research in creating a superior, flexible, and adaptive decision support system for future challenges.

The main gap that COPRAS-R seeks to fill lies in the fundamental problems in the classical COPRAS method, namely the high dependence on the weighting of subjective criteria and the potential for instability in the ranking results due to small changes in weight. Although many COPRAS variants such as COPRAS-G and COPRAS have been developed based on fuzzy intuition to overcome data uncertainty, there is still a lack of research that specifically focuses on increasing objectivity in the weighting process itself. In addition, most studies tend to rely on integration with external weighting methods without making structural modifications to the internal processes of COPRAS. COPRAS-R is here to fill this gap by offering a new approach to data-driven criteria weighting through mathematical modification stages such as normalization and RMS calculations, resulting in more objective weights and more stable ranking results. Thus, COPRAS-R makes a significant contribution in strengthening the foundation of the reliability of the COPRAS method, especially in the context of multicriteria decision-making that demands accuracy, transparency, and replication.

1.2. Research Objectives

The purpose of improvement in the COPRAS in this study is to develop and improve the method to be more accurate and flexible in supporting the decision-making system[14–16]. The main focus of this study is to identify and address the limitations that exist in the traditional COPRAS method, thus allowing its application in more complex and dynamic contexts. One of the key objectives is to improve the process of determining the weighting of criteria, which is often subjective, by using a more objective data-driven approach it is hoped that the resulting weights can better reflect the priorities and needs of decision-makers[17,18].

Improvement in the COPRAS using root mean square (RMS) can be an effective approach to improve accuracy and precision in alternative assessments involving several criteria[19]. The use of RMS in this context focuses on determining the weight of criteria and normalizing alternative values, which can be helpful in dealing with data sensitivity and variability issues. By implementing COPRAS using RMS, this method not only becomes more adaptive to changes and uncertainties in data, but also improves the accuracy of alternative assessments in complex decision-making contexts. This approach provides a stronger foundation for better and more informed decision-making, and makes COPRAS a more effective tool in decision support systems[20–22]. The purpose of this improvement is to increase COPRAS flexibility in the face of uncertainty and changing preferences in decision-making. By developing mechanisms that can adapt to these changes, COPRAS is expected to be used in a variety of decision-making contexts, including in project management, supplier selection, and performance evaluation[23–25]. This research aims to create a more responsive and efficient decision-making system, which not only provides accurate solutions, but is also able to adapt to changing conditions.

Improvement in the COPRAS provides a number of significant benefits for Decision Support System (DSS) users, which can improve the quality of decision-making in various contexts. COPRAS optimization can improve accuracy in determining the weight of criteria and normalizing alternative values, users can obtain more valid and reliable results. This is especially important in situations where decisions must be based on complex and multi-dimensional data. More accurate decisions ensure that the alternatives chosen truly reflect the organization's priorities and goals, reducing the risk of errors in decision-making[26–28]. Improvement in the COPRAS also improves the efficiency of the decision-making process. By using a more adaptive and responsive method to changes in data and preferences, DSS users can save time and resources in the alternative evaluation process. COPRAS optimization ensures that decisions are made more in line with user needs. By considering more complex variables and interactions between criteria, this method can result in more relevant and appropriate solutions to the problem at hand. This helps DSS users in understanding the trade-offs that exist between the various alternatives and provides a clearer picture of the consequences of each decision.

2. Methodology

Purposed method is an approach or technique designed to solve a specific problem or achieve research objectives. This method aims to improve accuracy, efficiency, and objectivity in decision-making, as well as overcome the limitations of pre-existing methods. Purposed methods not only function as an analysis tool, but also as an innovative solution that improves the decision-making process in complex and dynamic contexts.

2.1. Improvement COPRAS

The improvement of the COPRAS method aims to improve accuracy and efficiency in decision-making by perfecting various steps in it. COPRAS, which is widely used in multi-criteria decision-making, evaluates alternatives based on a variety of criteria, including benefit and cost criteria[29–31]. Improvement focuses on selecting the right weighting method, improving data quality through better pre-processing. Optimization of the COPRAS method using the (RMS named COPRAS-R) can increase accuracy in determining the weight of criteria and improve the data normalization process. RMS is used to calculate the average performance of alternatives on each criterion, which then helps in determining the weight of the criteria objectively. By using RMS, the variation in values in the data can be identified more clearly[32,33], so that the resulting weights better reflect the relative importance of each criterion. This process ensures that the differences between alternatives are more proportionally accounted for, avoiding the disproportionate influence of extreme values[34]. Improvement with RMS allows the COPRAS method to provide more precise and fair results in assessing alternatives, especially in datasets that have large variations among the criteria values. The stages of improvement of the COPRAS method are shown in Figure 1.

The process flow diagram in Figure 2 in the 2nd to 4th stages is part of the modifications made in the development of the COPRAS-R method. This modification starts from the normalization of criteria values stage, where the values of each criterion are normalized first to ensure a uniform scale between criteria. The next stage, calculate the RMS value, is used to calculate the mean value squared of each criterion, aiming to more accurately capture the rate of data spread. Then, in the fourth stage, the calculate the weight of the criteria process is carried out, which is an objective determination of the weight of the criteria based on the results of the RMS calculation. These three stages are not found in the classic COPRAS method and are a form of innovation to reduce subjectivity in weighting and increase the stability of ranking results. With this modification, COPRAS-R is able to produce more objective, adaptive decisions and in accordance with the characteristics of the analyzed data.

The completion stage using COPRAS-R is the first to form a decision matrix. The decision matrix is a representation of the data that contains the performance value of each alternative against a predetermined criteria. This matrix is arranged with alternatives (options to be evaluated) as rows and criteria (evaluation parameters) as columns. The decision matrix is made with the following equation.

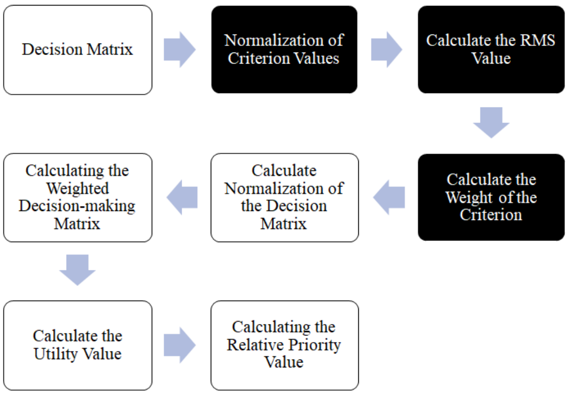

Fig. 1: Stages in the improvement of COPRAS

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

The second stage is to calculate the normalization of criteria values which is a development of the COPRAS stages carried out in this study, the normalization of criteria values aims to change the value of criteria that have different units or scales into a uniform scale, so that it can be compared fairly calculated using the following equations.

$$a_{ij} = \frac{x_{ij}}{max\, x_{rs}} \tag{2}$$

The third stage is to calculate the RMS value, which is a development of the COPRAS stage carried out in this study. RMS is a statistical measure used to determine the square root of the average square of a dataset, thereby providing an effective magnitude that represents the typical value of the data without regard to its positive or negative sign. The RMS value helps calculate the average performance value of alternatives against criteria calculated using the following equation.

$$m_j = \frac{1}{m} \sum_{i=1}^{m} a_{ij} \tag{3}$$

$$RMS_j = \sqrt{\sum_{i=1}^{m} \left(a_{ij} - m_j\right)^2} \tag{4}$$

The fourth stage is to calculate the weight of the criteria which is the development of the stages of COPRAS carried out in this study, the weight of the criteria is a value that represents how important the criteria in decision-making are calculated using the following equation.

$$w_j = \frac{RMS_j}{\sum_{k=1}^{m} RMS_k} \tag{5}$$

The fifth stage is to calculate the normalization of the decision matrix, the normalization of the decision matrix aims to change the values in the decision matrix so that everything is on a comparable scale. This is important because the criteria may have different units. Normalization is done by dividing the value on each matrix element by the total value in the same column using the following equation.

$$r_{ij} = \frac{x_{ij}}{\sum_{r=1}^{n} x_{rj}} \tag{6}$$

The sixth stage, namely calculating the weighted decision-making matrix, is the matrix of the results of the multi-criteria evaluation process that has gone through the stages of normalization and weighting. In this process, the alternative values of each criterion are first normalized so that they can be proportionally compared, then multiplied by weights that reflect the importance of each criterion using the following equation.

$$y_{ij} = r_{ij} * w_j \tag{7}$$

The seventh stage is to calculate the utility value (positive and negative), the utility value is a representation of alternative performance on certain criteria. The positive utility value is calculated using the following equation.

$$S_i^+ = \sum_{j=1}^{n} y_{ij}\, ;\, benefit\ criteria \tag{8}$$

y_+ is a positive utility value obtained from the criteria of benefit, the negative utility value is calculated using the following equation.

$$S_i^- = \sum_{j=k+1}^{n} y_{ij}\, ;\, cost\ criteria \tag{9}$$

y_- is a negative utility value obtained from the criteria of cost.

The eighth stage, which is calculating the relative priority value, is a measure used in the multi-criteria decision-making method to show the relative level of importance or contribution of each alternative or criteria compared to the others. This value is usually calculated based on the weights assigned to the criteria or alternatives in an evaluation process using the following equation.

$$Q_i = s_i^+ + \frac{\sum_{k=1}^{m} S_k^-}{S_i^- \cdot \sum_{k=1}^{m} \left(\frac{1}{S_k^-}\right)} \tag{10}$$

The last stage is to calculate the quantitative utility value, the quantitative utility value is a numerical measure used to evaluate the level of satisfaction or preference of a decision-maker towards various alternatives in a multi-criteria decision-making process. This utility value indicates the extent to which an alternative meets certain criteria, taking into account the relative weight or importance of each criterion calculated using the following equation.

$$U_i = \left(\frac{Q_i}{max\, Q_k}\right) * 100\% \tag{11}$$

Optimization with RMS allows the COPRAS method to provide more precise and fair results in assessing alternatives, especially in datasets that have large variations among the criteria values.

3. Results and Discussion

Optimize the proposed complex proportional assessment approach by integrating RMS into the COPRAS method. The use of RMS in performance evaluation aims to measure the mean square deviation from the criteria value to the ideal solution, resulting in a more objective weighting and reducing errors in decision-making. This methodology corrects the shortcomings of traditional COPRAS which often ignores variations in data. This approach provides an advantage in dealing with data that has large fluctuations or imbalances between criteria, where RMS is able to absorb these differences more accurately than the standard CORRAS method. The application of RMS ensures that proportional assessment in a multi-criteria system can consider extreme differences more systematically. The merger of COPRAS and RMS improves the quality of the final result, making this approach more reliable in supporting complex and dynamic decision-making.

3.1. Case Study of Contract Employee Acceptance

In a case study, contract employee recruitment using a COPRAS approach optimized with RMS can be used to evaluate prospective employees based on various criteria. Each candidate is scored on each criterion and using COPRAS optimized with RMS, extreme differences in assessment can be better accommodated. Contract employee assessment data is shown in Table 1.
The source of assessment data for the case study of contract employee acceptance Table 1 was obtained through a questionnaire to the HR Panel or the recruitment team in assessing candidates based on the criteria that have been set. Each panel member provides a rating for each criterion and those values are used as preliminary data. The criteria used in accepting contract employees are work experience (C1) is the benefit criteria, salary (C2) is the cost criteria, skills (C3) are the benefit criteria, communication skills (C4) are the benefit criteria, and teamwork (C5) is the benefit criteria.

Table 1: Contract employee assessment data

Name	Criteria				
	C1	**C2**	**C3**	**C4**	**C5**
Daniel	4	2800000	5	4	4
Samuel	5	3500000	4	5	4
Junaidi	3	2200000	3	3	3
Alvian	5	3800000	5	4	5
Rivaldo	4	3200000	4	4	4
Arifin	2	2600000	3	2	2
Bambang	5	3600000	5	5	5
Rian	3	2900000	3	4	3
Tio	4	3400000	4	5	4
Alvin	5	4000000	5	5	5
Sandi	4	2700000	3	3	3
Toni	5	3300000	4	4	4

3.2. Implementation of the COPRAS-R Method

The implementation of the COPRAS-R method in the multi-criteria decision-making process involves several systematic steps. The first step is to create a mortality matrix based on the assessment data in Table 1 using Equation (1).

$$X = \begin{bmatrix} 4 & 2800000 & 5 & 4 & 4 \\ 5 & 3500000 & 4 & 5 & 4 \\ 3 & 2200000 & 3 & 3 & 3 \\ 5 & 3800000 & 5 & 4 & 5 \\ 4 & 3200000 & 4 & 4 & 4 \\ 2 & 2600000 & 3 & 2 & 2 \\ 5 & 3600000 & 5 & 5 & 5 \\ 3 & 2900000 & 3 & 4 & 3 \\ 4 & 3400000 & 4 & 5 & 4 \\ 5 & 4000000 & 5 & 5 & 5 \\ 4 & 2700000 & 3 & 3 & 3 \\ 5 & 3300000 & 4 & 4 & 4 \end{bmatrix} \tag{12}$$

The next step is to calculate the normalizing the criteria value, using equation (2).

$$a_{11} = \frac{x_{11}}{max\, x_{r1}} = \frac{4}{5} = 0.8 \tag{13}$$

The overall value of the matrix normalization is displayed in Table 2.
The third step is to calculate the RMS value, which is used to measure the root mean square value of each criterion using equation (3) and (4).

$$m_1 = \frac{1}{12}\sum_{i=1}^{12} a_{i1} = \frac{1}{12} * 9.8 = 0.817 \tag{14}$$

The overall value of the mean value is displayed in Table 3.

$$RMS_1 = \sqrt{\sum_{i=1}^{12}(a_{i1} - m_1)^2} \tag{15}$$

$$RMS_1 = \sqrt{0.436666667} = 0.661 \tag{16}$$

The overall value of the RMS value is displayed in Table 4.
The third step is to calculate the weight of the criteria using equation (5).

Table 2: The overall value of normalization criteria

Name	Criteria				
	C1	C2	C3	C4	C5
Daniel	0.8	0.7	1	0.8	0.8
Samuel	1	0.875	0.8	1	0.8
Junaidi	0.6	0.55	0.6	0.6	0.6
Alvian	1	0.95	1	0.8	1
Rivaldo	0.8	0.8	0.8	0.8	0.8
Arifin	0.4	0.65	0.6	0.4	0.4
Bambang	1	0.9	1	1	1
Rian	0.6	0.725	0.6	0.8	0.6
Tio	0.8	0.85	0.8	1	0.8
Alvin	1	1	1	1	1
Sandi	0.8	0.675	0.6	0.6	0.6
Toni	0.102	0.087	0.083	0.083	0.087

Table 3: The Overall criterion mean value

Criteria				
C1	C2	C3	C4	C5
0.817	0.792	0.800	0.800	0.767

Table 4: The Overall RMS values

Criteria				
C1	C2	C3	C4	C5
0.661	0.443	0.566	0.632	0.622

$$w_1 = \frac{RMS_1}{\sum_{k=1}^{5} RMS_k}$$

$$w_1 = \frac{0.839}{2.924} = 0.226$$

$$w_2 = \frac{RMS_2}{\sum_{k=1}^{5} RMS_k}$$

$$w_2 = \frac{0.443}{2.924} = 0.152$$

$$w_3 = \frac{RMS_3}{\sum_{k=1}^{5} RMS_k}$$

$$w_3 = \frac{0.566}{2.924} = 0.193$$

$$w_4 = \frac{RMS_4}{\sum_{k=1}^{5} RMS_k}$$

$$w_4 = \frac{0.632}{2.924} = 0.216$$

$$w_5 = \frac{RMS_5}{\sum_{k=1}^{5} RMS_k}$$

$$w_5 = \frac{0.622}{2.924} = 0.213$$

The third step is to calculate the normalization value of the decision matrix using equation (6).

$$r_{11} = \frac{x_{11}}{\sum_{r=1}^{n} x_{r1}} = \frac{4}{49} = 0.082$$

The overall value of the matrix normalization is displayed in Table 5.

Table 5: The overall value of the matrix normalization

Name	Criteria				
	C1	C2	C3	C4	C5
Daniel	0.082	0.074	0.104	0.083	0.087
Samuel	0.102	0.092	0.083	0.104	0.087
Junaidi	0.061	0.058	0.063	0.063	0.065
Alvian	0.102	0.100	0.104	0.083	0.109
Rivaldo	0.082	0.084	0.083	0.083	0.087
Arifin	0.041	0.068	0.063	0.042	0.043
Bambang	0.102	0.095	0.104	0.104	0.109
Rian	0.061	0.076	0.063	0.083	0.065
Tio	0.082	0.089	0.083	0.104	0.087
Alvin	0.102	0.105	0.104	0.104	0.109
Sandi	0.082	0.071	0.063	0.063	0.065
Toni	0.102	0.087	0.083	0.083	0.087

The sixth step is to calculate the value of multiplying the weight by the result of the normalization of the matrix using equation (7).

$y_{11} = r_{11} * w_1 = 0.082 * 0.226 = 0.018$

The overall value of the weight multiplication value is displayed in Table 6.

Table 6: The overall value of the weight multiplication

Name	Criteria				
	C1	C2	C3	C4	C5
Daniel	0.018	0.011	0.020	0.018	0.018
Samuel	0.023	0.014	0.016	0.023	0.018
Junaidi	0.014	0.009	0.012	0.014	0.014
Alvian	0.023	0.015	0.020	0.018	0.023
Rivaldo	0.018	0.013	0.016	0.018	0.018
Arifin	0.009	0.010	0.012	0.009	0.009
Bambang	0.023	0.014	0.020	0.023	0.023
Rian	0.014	0.012	0.012	0.018	0.014
Tio	0.018	0.014	0.016	0.023	0.018
Alvin	0.023	0.016	0.020	0.023	0.023
Sandi	0.018	0.011	0.012	0.014	0.014
Toni	0.023	0.013	0.016	0.018	0.018

The seventh step is to calculate the positive utility value using equation (8).

$$S_1^+ = \sum_{i=1}^{5} y_{1j} = 0.0751$$

Calculate the negative utility value using equation (9).

$$S_1^- = y_{21} = 0.0112$$

The overall positive and negative utility values are shown in Table 7.
The eighth step is to calculate the relative priority value using equation (10), the overall result of the positive and negative utility values is displayed in Table 8.
The last step is to calculate the quantitative utility value using equation (10).

$$U_1 = \left[\frac{Q_1}{max\ Q_t}\right] * 100\% = \left[\frac{0.0751}{0.0889}\right] * 100\% = 84.54\%$$

Table 7: The overall positive and negative utility values

Name	S_i^+	S_i^-
Daniel	0.0751	0.0112
Samuel	0.0802	0.0140
Junaidi	0.0533	0.0088
Alvian	0.0843	0.0152
Rivaldo	0.0711	0.0128
Arifin	0.0396	0.0104
Bambang	0.0889	0.0144
Rian	0.0578	0.0116
Tio	0.0756	0.0136
Alvin	0.0889	0.0160
Sandi	0.0579	0.0108
Toni	0.0757	0.0132

Table 8: The overall relative priority values

Name	$1/S_1^-$	$S_1^- \sum 1/S_1^-$	Q_i
Daniel	89.490	87402.81	0.0751
Samuel	71.592	69922.25	0.0802
Junaidi	113.896	111239.94	0.0533
Alvian	65.940	64402.07	0.0843
Rivaldo	78.304	76477.46	0.0711
Arifin	96.374	94126.11	0.0396
Bambang	69.603	67979.97	0.0889
Rian	86.404	84388.92	0.0578
Tio	73.698	71978.79	0.0756
Alvin	62.643	61181.97	0.0889
Sandi	92.804	90639.95	0.0579
Toni	75.931	74159.96	0.0757

Table 9: The overall relative priority values

Name	U_i
Daniel	84.54%
Samuel	90.26%
Junaidi	60%
Alvian	94.93%
Rivaldo	80%
Arifin	44.54%
Bambang	100%
Rian	65.07%
Tio	85.07%
Alvin	100%
Sandi	65.19%
Toni	85.19%

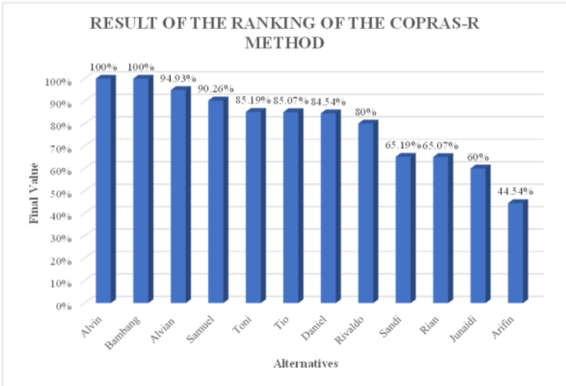

Fig. 2: The ranking results using the COPRAS-R

The overall results of the quantitative utility value are displayed in Table 9.
Ranking results play an important role in the multi-criteria-based decision-making process, especially in the context of performance evaluation, selection of the best alternative, or prioritization of actions. Ranking results allow decision-makers to evaluate alternative performance or quality in a more measurable and reliable manner, reducing subjective preference, and improving decision accuracy. The ranking results using the COPRAS-R method are shown in Figure 1.
The ranking results using the COPRAS-R method show that Alvin and Bambang occupy the highest positions with performance scores of 100% each, indicating optimal performance among all the evaluated alternatives. The next rank is held by Alvian with a score of 94.93%, followed by Samuel (90.26%), Toni (85.19%), Tio (85.07%), and Daniel (84.54%), who are still in the high-performance category but with gradually decreasing scores. Subsequently, Rivaldo scores 80%, followed by Sandi (65.19%), Rian (65.07%), Junaidi (60%), and Arifin as the alternative with the lowest score of 44.54%. These results show a varied distribution of performance among individuals evaluated using the COPRAS-R method.

3.3. Method Comparison

The COPRAS-R method is a modification of the classic COPRAS method that aims to improve the accuracy of assessment in multi-criteria decision-making. The use of the RMS concept in this method serves to overcome large variations in data that may occur between criteria, so that it can produce more stable and consistent calculations. RMS takes into account the square value of each criterion before calculating the average result, which allows the COPRAS-R method to give more proportional weight to criteria with a wider range of values. This distinguishes it from the traditional COPRAS method, which is more sensitive to fluctuations in values between criteria, so COPRAS-R provides a more optimal and robust solution in decision-making. The results of the comparison of the ranking of the COPRAS-S method with several COPRAS combination methods with the criteria weighting method are shown in Table 10.

The ranking comparison of the COPRAS-ROC, COPRAS-Rank Sum, COPRAS-Entropy, and COPRAS-S methods are all variations of the COPRAS method used in multi-criteria decision-making. COPRAS-ROC (Rank Order Centroid) combines the ROC approach to determine the weighting of criteria based on the order of importance, where the weights are calculated based on rank. COPRAS-Rank Sum also uses a weighting based on order, but uses the rank sum method to calculate the weight. COPRAS-Entropy uses the entropy method to calculate the weight of the criteria, by measuring the level of uncertainty or information associated with each criterion, thus placing greater emphasis on the more diverse criteria of the information. Meanwhile, COPRAS-S adds a subjective aspect in the weighting process, usually through input from decision-makers, and is more flexible in handling individual or group preferences. These four methods focus on the proportional assessment of alternatives based on the weights determined with different approaches.

Table 11: The results of the ranking correlation

Method	Correlation Value
COPRAS-ROC	0.97
COPRAS-Rank Sum	0.97
COPRAS-Entropy	0.97
COPRAS-R	1

Kendall's Tau is a statistical method used to measure the level of correlation between two sets of rankings or rankings. When the ranking results of several methods such as COPRAS-ROC, COPRAS-Rank Sum, COPRAS-Entropy[35], and COPRAS-S want to be compared, Kendall's Tau can be used to see how consistent or close the ranking results are. The results of the ranking correlation using Kendall's Tau are shown in Table 11.

The results of the correlation of the COPRAS-ROC, COPRAS-Rank Sum, and COPRAS-Entropy methods each produced a correlation value of 0.97 against the original ranking. This shows that all three methods provide results that are almost identical to the original rankings, with a very high degree of consistency. Meanwhile, the COPRAS-R method gives a perfect correlation value of 1, which means that the ranking results of this method are completely the same as the original ranking. Overall, all four methods have very strong similarities to the original ratings, with COPRAS-R showing full suitability.

3.4. Discussion

The COPRAS-R method offers a promising new approach in increasing objectivity and stability in multicriteria decision-making, this method is inseparable from a number of limitations that need to be observed. One of the main limitations is the complexity of the calculation,

Table 10: The results of the comparison of the ranking

Name	Original	COPRAS			COPRAS-R
		ROC	Rank Sum	Entropy	
Alvin	1	1	1	1	1
Bambang	2	2	2	2	2
Alvian	3	3	3	3	3
Samuel	4	4	4	4	4
Toni	5	5	5	5	5
Tio	6	7	7	7	6
Daniel	7	6	6	6	7
Rivaldo	8	8	8	8	8
Sandi	9	9	9	9	9
Rian	10	10	10	10	10
Junaidi	11	11	11	11	11
Arifin	12	12	12	12	12

mainly due to the presence of additional stages such as the modification of the normalization of the criteria and the calculation of the RMS for the weight of the criteria. This process can be more complicated and time-consuming when applied to large-scale datasets or involves many alternatives and criteria.

Although the COPRAS-R method was developed to remedy the weaknesses of traditional COPRAS—particularly in terms of the objectivity of weighting and the stability of the rating results, it also presents new challenges. One such challenge is the complexity in the calculation process, which increases as COPRAS-R introduces several additional stages in its analysis procedure. calculations in the normalization stage of the COPRAS-R criteria do not only perform normal normalization, but use a modification approach that aims to ensure that the scale between criteria becomes objectively proportional. In addition, this method also involves the calculation of RMS in determining the weight of the criteria, which is a statistical-based method that calculates the relative strength of each criterion based on the spread of its values. These stages do improve the accuracy and reliability of the final result, but they also require a longer and more detailed calculation process. When this method is applied to a large dataset, with many alternatives (options to be assessed) and many criteria (aspects used to assess), the computational burden becomes much greater. This can require a long computational time as well as more powerful software or systems to process that data. In a real-world context that often requires quick decisions, this can be a practical limitation, especially if it is not supported by efficient calculation tools.

4. Conclusions

The improvement of the COPRAS method to COPRAS-S is a significant advance in the field of decision support systems. The application of more objective weighting techniques using RMS, increases accuracy and fairness in decision-making by minimizing subjective judgment. The COPRAS-S method is able to overcome the main challenges in MCDA, including the problem of changing the rating and handling the benefit and cost criteria more efficiently. The integration of sensitivity analysis also adds to the resilience of this methodology, allowing decision-makers to evaluate how weight adjustments affect results. The results of the ranking of the COPRAS-R method in the case study used, namely Contract Employee Acceptance, resulted in Alvin ranking first with the highest score of 100.00%, followed by Bambang in second position with a score of 95.99%, and Arlian in third position with a score of 90.43%.

The correlation results using the Kendall technique from the COPRAS-ROC, COPRAS-Rank Sum, and COPRAS-Entropy methods each resulted in a correlation value of 0.97 to the original ranking. This shows that all three methods provide results that are almost identical to the original rankings, with a very high degree of consistency. Meanwhile, the COPRAS-R method gives a perfect correlation value of 1, which means that the ranking results of this method are completely the same as the original ranking. Overall, all four methods have very strong similarities to the original ratings, with COPRAS-R showing full suitability. The COPRAS-S method offers a more dynamic and flexible approach that can be applied in a variety of decision-making environments. COPRAS-S contributes to more informed, objective, and data-driven decision-making, making it a valuable tool for facing complex real-world decision-making challenges. Future research may focus on dealing with data uncertainty or a probabilistic approach to dealing with situations where the criteria information is not entirely clear or definitive. This research provides an important contribution to the development of decision-making methods by introducing modifications to the COPRAS Method that can improve the accuracy, flexibility, and reliability of the results. This new approach is expected to serve as a reference for future research and to be widely applied in various fields that require more objective and targeted multi-criteria analysis.

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