https://doi.org/10.31436/iiumej.v26i2.3494

MODIFICATION OF GREY RELATIONAL ANALYSIS FOR DYNAMIC CRITERIA WEIGHTING IN DECISION-MAKING SYSTEMS

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(Received: 2 November 2024; Accepted: 21 April 2025; Published online: 15 May 2025)

ABSTRACT: Grey relational analysis (GRA) is a grey system theory method used to solve multi-criteria decision problems with incomplete or uncertain data. The GRA analyzes the level of closeness or relationship between several alternatives based on a series of criteria. One of the limitations in using the GRA method is the weight of the criteria, which is often fixed or subjective. In many GRA applications, the criterion weights are set based on expert considerations or decision-maker preferences, which can be highly subjective and influenced by individual biases. Grey relational analysis change data driven (GRA-C) method emphasizes the increased effectiveness and flexibility of this method in performance appraisal for multi-criteria decision-making. GRA-C allows for more precise adjustments according to the importance of each criterion, leading to more accurate and relevant evaluation results. By modifying the weights, the GRA-C becomes more flexible and can be adapted to different contexts and specific decision-making needs, so that it can be applied in various industry sectors. These modifications help reduce bias due to improper weight allocation, resulting in more objective performance assessments. The results of the modified GRA-C can provide better insights for decision-makers, supporting a more effective and informed decision-making process. The comparison with the Spearman correlation shows that the GRA-C method has a very strong degree of conformity in producing alternative rankings, with a correlation value 1. This indicates that these methods provide similar results, making them reliable for consistent decision-making.

ABSTRAK: Analisis Perhubungan Kelabu (Grey Relational Analysis, GRA) merupakan satu kaedah dalam teori sistem kelabu yang digunakan untuk menyelesaikan masalah keputusan berbilang kriteria (multi-criteria decision-making) yang melibatkan data tidak lengkap atau tidak pasti. GRA menganalisis tahap keterkaitan atau hubungan antara beberapa alternatif berdasarkan satu siri kriteria. Salah satu kekangan dalam penggunaan kaedah GRA ialah pemberat kriteria yang sering kali bersifat tetap atau subjektif. Dalam banyak aplikasi GRA, pemberat kriteria ditentukan berdasarkan pertimbangan pakar atau keutamaan pembuat keputusan, yang boleh menjadi sangat subjektif dan dipengaruhi oleh bias individu. Kaedah Grey Relational Analysis Change Data Driven (GRA-C) menekankan keberkesanan dan fleksibiliti yang lebih tinggi dalam penilaian prestasi bagi sistem keputusan berbilang kriteria. GRA-C membolehkan pelarasan yang lebih tepat mengikut kepentingan setiap kriteria, yang membawa kepada keputusan penilaian yang lebih tepat dan relevan. Dengan pengubahsuaian pemberat, GRA-C menjadi lebih fleksibel dan boleh disesuaikan dengan pelbagai konteks serta keperluan khusus dalam membuat keputusan, membolehkannya diaplikasikan dalam pelbagai sektor industri. Pengubahsuaian ini membantu mengurangkan bias akibat pengagihan pemberat yang tidak sesuai, sekali gus menghasilkan penilaian prestasi yang lebih objektif. Hasil daripada GRA-C yang telah diubah suai dapat memberikan pandangan yang lebih baik kepada pembuat keputusan, seterusnya menyokong proses membuat keputusan yang lebih berkesan dan berasaskan maklumat. Perbandingan dengan korelasi Spearman menunjukkan bahawa kaedah GRA-C mempunyai tahap kesesuaian yang sangat tinggi dalam menghasilkan kedudukan alternatif, dengan nilai korelasi sebanyak 1. Ini menunjukkan bahawa kaedah-kaedah tersebut memberikan hasil yang serupa dan boleh dipercayai untuk proses membuat keputusan yang konsisten.

KEYWORDS: *Comparison, Decision, GRA-C, Modification.*

1. INTRODUCTION

Grey relational analysis (GRA) is a method in grey system theory that is used to solve multi-criteria decision problems with incomplete or uncertain data [1]. The GRA analyzes the level of closeness or relationship between several alternatives based on a series of criteria. In the GRA, the relationship between different data is calculated using the concept of gray relational grade, which represents the relative proximity of each alternative to the ideal condition [2]. The general application of GRA in multi-criteria systems is very broad and varied, due to its ability to handle problems with incomplete or uncertain data [3]. GRA is often used for performance evaluation in various fields, such as employee performance assessment, supplier selection, and product or service selection. In the manufacturing industry, GRA is applied to optimize production processes and evaluate product quality. In project management, GRA selects the best projects based on several criteria such as cost, time, and quality. In addition, GRA is also used in environmental research to analyze environmental performance and choose the best strategy in natural resource management [4]. The advantage of GRA in a multi-criteria system is its flexibility in assessing various alternatives based on several complex and diverse criteria [5]. One of the main advantages of GRAs is their ability to handle problems with incomplete or uncertain information, which often arises in multi-criteria decision-making. This method does not require complete or perfect data to perform the analysis, so it is suitable for applications when the available data is limited, inconsistent, or uncertain. GRA reduces complexity by focusing on patterns of relationships between data, rather than demanding absolute precision [6]. Despite the lack of information, GRA can use the gray relational grade to determine the degree of proximity between the evaluated alternatives to the ideal solution. This makes GRA a flexible and reliable tool in a variety of applications such as performance evaluation, risk analysis, and decision-making in environments full of uncertainty or incomplete information [7].

One limitation in using the GRA method is the weight of the criteria, which is often fixed or subjective [8]. In many GRA applications, the criterion weights are set based on expert considerations or decision-maker preferences, which can be highly subjective and influenced by individual biases. This weight determination is also less adaptive to changes in different contexts or decision scenarios, so it can reduce the accuracy of the analysis results if the weights do not reflect the actual conditions. In addition, unchanging weights often do not consider the dynamics in the relationship between criteria, for example, when criteria become more or less critical depending on the specific situation. These limitations can cause the results of decisions to be less than optimal or not follow real conditions, especially in complex and dynamic environments. The main limitation in using GRA is the often fixed or subjective weight of the criteria, resulting in a lack of flexibility in the analysis. The importance of adjusting the weight of the requirements is crucial so that the analysis can be more relevant to the desired goal [9].

https://doi.org/10.31436/iiumej.v26i2.3494

With weights that can be adjusted objectively or dynamically, GRA can capture changes in priorities between criteria, improve the accuracy of analysis results, and provide more effective solutions according to the contextual needs of the decisions at hand.

Problems that arise due to weights that are not adjusted to the reality of complex and varied decision-making can result in several negative impacts [10]. The resulting decision may not reflect actual conditions or needs, as the weight of the fixed criteria cannot capture the dynamics and complexity of the situation. Inaccuracies in weights can lead to dissatisfaction among stakeholders, as decisions taken may not be in line with their expectations or priorities [11]. This can reduce trust in the decision-making system used. The use of irrelevant weights can result in neglecting important criteria that should be considered in the decision-making process, potentially resulting in fatal errors in alternative selection. If the weight is not adjusted to the change, the decisions taken may become ineffective and unresponsive to the challenges that arise [12]. As such, it is important to develop methods that allow for objective and dynamic weight adjustments to make decision-making results more accurate and relevant. The main problem in this study is the lack of ability of conventional RA methods to accommodate the dynamics of criterion weights in decision-making. In many situations, the weight of the criteria is often considered fixed, although the relevance of each criterion may change based on context or changes in the data. For example, when selecting suppliers, criteria such as price may have a higher weight in times of economic crisis, but product quality can be a top priority in normal times. The GRA's inability to capture these changes can lead to less accurate analysis results, potentially resulting in suboptimal decisions. In addition, standard GRA methods tend to be sensitive to large-scale or multi-dimensional data, as they lack an adequate mechanism to balance the influence between criteria based on their relevance dynamically. This problem is exacerbated when data is complex, heterogeneous, or frequently updated. The reliance on fixed weights can also reduce the flexibility of these methods in responding to evolving decision needs, especially in highly competitive or rapidly changing environments, such as the business, technology, or crisis management sectors.

The development of a more flexible and adaptive GRA model for applications in multi-criteria performance assessment in this study uses change data-driven. The change-data-driven approach allows for real-time adjustment of criterion weights based on the analysis of the latest data [13], so that models can respond quickly to changing needs or evolving situations. Thus, decision-making becomes more precise and relevant, resulting in more accurate and effective performance evaluations. This approach also increases the flexibility of the model, allowing for better adaptation to frequent changes in operational and business contexts [14]. Increasing the accuracy and relevance of assessment results in the GRA can be achieved through a more dynamic adjustment of the criteria weight. By applying a responsive approach to change data, criterion weights can be adjusted in real-time based on recent data analysis on performance and environmental conditions. This means that when situations or priorities change, the weight of the criteria will reflect new needs and conditions, resulting in a more accurate and relevant analysis. This research contributes to enriching GRA-based decision-making methodologies by developing more effective and efficient models through dynamic and responsive adjustment of criterion weights. By integrating a change-driven data-driven approach, this study provides a framework that allows real-time adjustment of criterion weights based on changes in conditions and evaluation needs [15]. This not only improves the accuracy of the assessment results, but also ensures that the analysis remains relevant in an ever-changing context [16].

The main problem to be solved in this study is the limitation of the GRA method in handling the weight of criteria that change dynamically according to the conditions or context of the decision. In many cases, the weight of the criteria is often considered fixed, thus ignoring

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the dynamic nature of factors that affect the decision-making process, such as changing priorities, market situations, or environmental contexts. This can lead to less accurate and relevant analysis results. By modifying the GRA to integrate dynamic criteria weighting, this study aims to improve the flexibility and accuracy of the decision support system, so that it is more adaptive to changing conditions and produces more optimal decisions. The study aims to develop and improve the flexibility of the GRA method by modifying the weight parameters in performance assessment to provide a more accurate and relevant evaluation in the context of multi-criteria decision-making. This modification aims to overcome the limitations of traditional GRA methods that often use fixed weights by offering a more dynamic and responsive approach to the relative importance of each criterion. Thus, this research is expected to provide deeper insights for decision-makers in various industry sectors and improve the quality and effectiveness of the decision-making process.

2. RELATED WORKS

The GRA method has been widely used in various fields to solve multi-criteria decision problems. With its wide range of applications and innovations, GRA remains an interesting and relevant research topic in decision support systems. The following is related to research conducted using the GRA method.

Research from Andika (2024) shows that combining GRA and Rank Order Centroid (ROC) in determining supervisor promotions can provide a more objective and comprehensive approach. The GRA evaluates supervisors' performance based on several criteria that are not completely clear or cannot be measured with certainty. Meanwhile, ROC is used to determine the relative weight of each criterion by giving higher priority to the aspects that decision-makers consider most important. By combining these two methods, supervisor performance assessment can be carried out by considering the relationship between existing criteria, as well as giving more proportional weight to the most relevant criteria for promotion, so that the decisions taken are more transparent and fair [17].

Research from Gao (2024) shows that combining GRA and Entropy in optimizing laser coating parameters for steel presents an effective approach in improving coating quality. GRA is used to evaluate the performance of various laser coating parameters such as laser power, scanning speed, and feed rate based on several quality criteria, such as coating thickness, hardness, and wear resistance. Meanwhile, the Entropy method helps to determine the objective weight for each criterion based on the variation of the data obtained from the experiment, so that the parameters significantly influencing the coating quality get a higher priority. By combining these two methods, the optimization process becomes more directional and data-driven, allowing for the selection of optimal coating parameters to achieve the best results in steel applications [18].

Research from Lu (2024) The combination of GRA and Criteria Importance Through Intercriteria Correlation (CRITIC) in selecting agricultural machinery provides a smarter, data-driven approach to support decision-making. GRA measures the performance of various alternative agricultural machinery based on several important criteria. On the other hand, it is used to objectively calculate the weight of the criteria by considering the variation and correlation between them, so that the more important and unrelated criteria get greater weight. By combining GRA and CRITIC, decision-making becomes more comprehensive, taking into account both the relative performance of each machine and the importance of each criterion objectively, which ultimately allows the selection of agricultural machinery that best suits the needs and operational conditions [19].

Research from Arshad (2024) suggests that combining GRA and the Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA) method in selecting warehouse heads offers an effective and structured approach. GRA is used to evaluate the performance of prospective warehouse heads based on several criteria. Meanwhile, the PIPRECIA method helps to determine the weight of the criteria subjectively by involving repeated assessments from experts who consider the relative importance of each criterion. Through this stage, the weight of the criteria can be obtained more accurately according to the specific priorities and needs of the organization. By combining GRA for performance analysis and PIPRECIA for criteria weighting, the warehouse head selection process becomes more transparent and accurate, ensuring that the best candidates are selected based on a thorough and relevant evaluation [20].

The results of comparing the combination of the GRA method with various weighting methods, such as ROC, Entropy, CRITIC, and PIPRECIA, show how different approaches can be used for optimization and decision selection based on relevant criteria.

3. MATERIALS AND METHODS

The GRA method has been widely used in various fields to solve multi-criteria decision problems. With its wide range of applications and innovations, GRA remains an interesting and relevant research topic in decision support systems.

3.1. Case Study and Dataset

In this study using a case study on the selection of the best division head, the analysis was carried out using a decision support system approach that involved several performance criteria, such as leadership (C-01) it is a person's ability to motivate, direct, and influence team or organization members to achieve a common goal, managerial ability (C-02) this ability includes skills in managing company resources, including human, financial, time, and material, to achieve organizational targets efficiently, task completion (C-03) this a person's ability to complete assigned tasks on time and according to the expected standards. This includes work discipline, punctuality, reliability in meeting deadlines, and the ability to overcome obstacles and challenges in the execution of tasks, innovation (C-04), the ability to think creatively and create new solutions to existing challenges. These criteria include the development of new ideas, the ability to improve existing processes or products, and the courage to take risks in exploring untested approaches, and collaboration between teams (C-05). The ability to work with other team members effectively within and between divisions. Individuals who are strong in collaboration can communicate, share information, and work with various parties to achieve common goals. Each candidate is assessed using historical data on their performance and the results of interviews and assessments from colleagues and direct supervisors. By applying this approach, companies not only rely on intuition or experience alone but also obtain results based on comprehensive quantitative and qualitative analysis. Thus, selecting the best division head can be done objectively, reducing bias, increasing credibility and fairness in decision-making, and ensuring that the chosen candidates have optimal potential to lead the division towards better performance.

The dataset used contains performance appraisal data from some division head candidates, where each candidate is evaluated by the company's internal appraisal panel, which includes senior managers and related team members. The assessment is based on a predetermined value scale for each criterion, and the weight of the criteria is set to reflect the company's strategic priorities. This dataset allows testing various multi-criteria decision-making methods to determine the most qualified candidates based on the overall rating obtained. Table 1 is the dataset used in this study.

Table 1. Dataset assessment

Division Name	C1	C2	C3	C4	C5
Production Division	8	9	9	6	8
R&D Division	7	7	8	10	7
Quality Division	6	8	9	5	7
Logistics and Supply Chain Division	7	9	8	7	9
Maintenance Division	6	7	9	6	6
Finance Division	8	9	8	5	7
Human Resources Division	9	8	7	6	9
Purchasing Division	7	8	8	6	7
IT Division	6	7	8	8	8

Assessment data for each division is based on five criteria: leadership, managerial ability, task completion, innovation, and team collaboration. Scores are given on a scale of 1-10, where 1 is the lowest and 10 is the highest.

3.2. Modification of Grey Relational Analysis

The modification of the GRA aims to improve the accuracy and flexibility of the GRA method in the multi-criteria decision-making process. One of the most common modifications is to integrate advanced weighting techniques that are objective-based to better reflect the importance of each criterion. Other modifications focus on adjusting the gray relational coefficient to handle high-dimensional data more effectively or applying normalization techniques to minimize outlier influence and ensure consistency of results. These improvements aim to make GRA more reliable and versatile, enabling it to tackle more complex decision-making scenarios with higher precision.

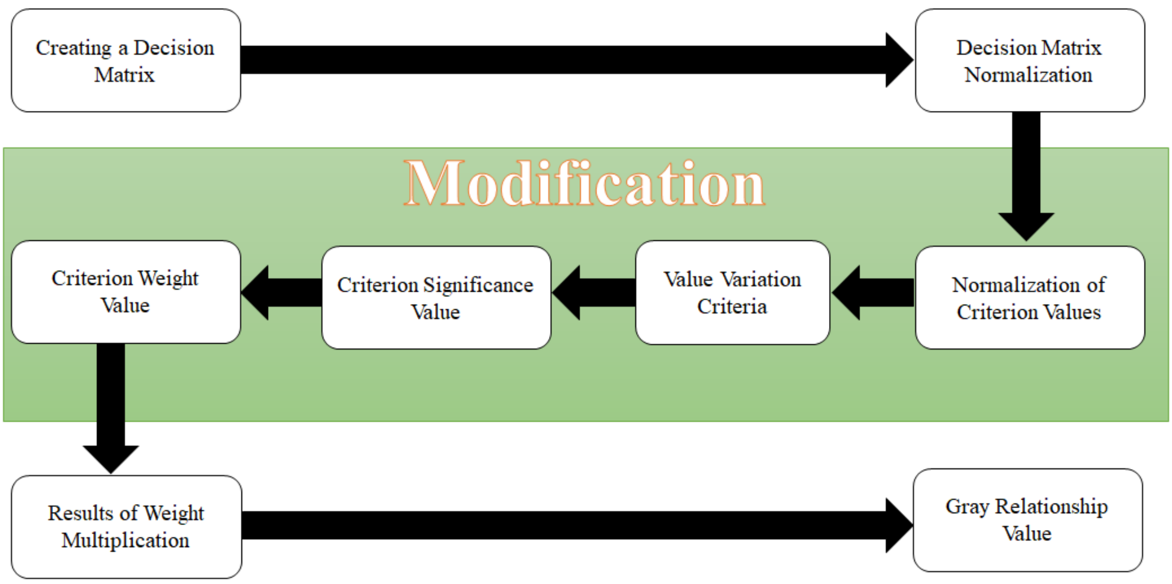

Figure 1. Framework GRA-C

The modification of GRA with a change data-driven approach called grey relational analysis change data-driven (GRA-C) focuses on adjusting the GRA method to be more responsive to dynamic data changes in the decision-making process. In this approach, the GRA algorithm is modified to accommodate real-time or periodic data updates, so the analysis results can continue to reflect current conditions. The weighting of the criteria and the relational coefficient are changed based on significant changes in data patterns, which allows for more adaptive analysis. As such, these modified GRA-C can handle scenarios with ever-evolving data, such as market changes or technological developments, providing more relevant and accurate results in real-time. Figure 1 is the GRA-C framework conducted in this study.

The GRA-C framework is designed to improve the effectiveness of grey relational analysis by handling dynamic data in multi-criteria decision-making. Within this framework, there are five main modification processes. First is the normalization of criterion values, which are changed to the same scale to ensure equivalence in the analysis. Second, the criterion average score is used to calculate the middle score of each criterion, providing an overview of the candidate's performance. Third, the criterion variation value measures how far the criterion value spreads, aiding in identifying performance stability. Fourth, the significance value of the criteria assesses the relative contribution of each criterion to the final decision, so that the more critical criteria can be recognized. Fifth, the criterion weighting value determines the priority of the criteria based on the calculated significance value, providing a solid basis for the final calculation in the GRA. By integrating these five processes, GRA-C can provide more accurate and relevant analysis results in an ever-changing situation.

Creating a Decision Matrix: This stage involves collecting data from alternatives that will be evaluated based on predetermined criteria. The data is organized in the form of a decision matrix, where rows represent alternatives [21], and columns represent evaluation criteria. Each cell in the matrix contains a value that indicates how well each alternative meets those criteria. Eq. (1) creates a decision matrix.

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

Decision matrix normalization: At this stage, the values in the decision matrix are normalized to convert them into the same scale [22]. Normalization aims to eliminate differences in units and scales between criteria, so that all criteria can be directly compared. Decision matrix normalization uses Eq. (2).

$$X_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \tag{2}$$

Normalization of criterion values: After the decision matrix is normalized, the criterion values for each alternative are further processed to ensure that the values obtained reflect consistent performance [23]. Normalization of these criteria is important to provide a more accurate picture of how each alternative performs in the same context. Normalization of criterion values uses Eq. (3).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}} \tag{3}$$

The average value of the criteria results from a calculation that describes the level of performance or the general score of a group based on certain criteria. This modification stage is carried out in this study. The average value of the criteria is important because it provides an overview of how the group as a whole performs against those criteria[24], which can help in more objective and balanced decision-making. The average value of the criteria in Eq. (4).

$$N_i = \frac{1}{m}\sum_{i=1}^{m} r_{ij} \tag{4}$$

Value variation criteria: At this stage, the variation value is calculated for each criterion to measure how much the spread of the existing value is at a modification stage carried out in this study. The value of variation provides insight into the consistency of alternative performance under certain criteria [25], aiding in identifying highly variable criteria that can influence decisions. For the value variation criteria, use Eq. (5).

$$\emptyset_j = \sum_{i=1}^{m} (r_{ij} - N_i)^2 \tag{5}$$

Criterion significance value: This stage measures the relative significance of each criterion in the overall context of this analysis, which is the modification stage carried out in this study. The significance value is calculated by taking into account the average value and variation [26] to determine which criteria have a greater impact on the final decision. The criterion significance value uses Eq. (6).

$$\varphi_j = 1 - \emptyset_j \tag{6}$$

Criterion weight value: Once the significance value is determined, this step involves determining the weight for each of these criteria, and a modification stage is carried out in this study. The criterion weights reflect the relative priority of each criterion based on its significance and are used to make the appropriate contribution in the final calculation [27]. The criterion weight value uses Eq. (7).

$$w_j = \frac{\varphi_j}{\sum_{j=1}^{n} \varphi_j} \tag{7}$$

Results of weight multiplication: At this stage, the normalized criterion value is multiplied by the predetermined weight. The result of this multiplication contributes from each criterion to the overall value of each alternative, thus allowing for a more precise comparison between the alternatives being evaluated [28]. The results of weight multiplication use Eq. (8).

$$V_{ij} = w_j \times x_{ij} \tag{8}$$

Gray relationship value: Finally, the gray relationship value is calculated by integrating the results of multiplying the weights and the criterion value. This value reflects the relationship between the alternatives and the criteria, indicating how well each alternative meets all the criteria that have been set [29]. These end results are used to rank alternatives based on their overall performance. Grey relationship value uses Eq. (9).

$$GRG_i = \frac{1}{n}\sum_{j=1}^{n} V_{ij} \tag{9}$$

4. RESULT AND DISCUSSION

Modifying the weight parameters in the GRA for performance assessment in multi-criteria decision-making provides greater flexibility than traditional methods. By changing the weight of the criteria, the GRA can better adjust to specific preferences or different priorities in the evaluation, so that the results are more accurate and relevant to the specific context. This increased flexibility allows decision-makers to consider the importance of each criterion more dynamically, providing more precise solutions in complex and diverse situations. It also expands the application of GRA in various fields, from performance appraisal to selection of the best alternatives.

https://doi.org/10.31436/iiumej.v26i2.3494

GRA-C modification is a development of the GRA method that focuses on dynamic changes in data in multi-criteria decision-making. This approach takes advantage of constantly changing or updated data, so that it can adjust analysis and decision results more responsively to changes in information or conditions. GRA-C allows for more accurate performance evaluations or decision alternatives because it considers trends and changes in the data. GRA-C becomes more adaptive and relevant in contexts requiring rapid response to changes, such as fast-moving business environments or technologies, using this dynamic, data-driven approach.

4.1. Implementation of GRA-C in Case Studies

The implementation of GRA-C in the case study of the performance assessment of division heads can be applied to evaluate the performance of each division based on various criteria that are important in achieving organizational goals. Using GRA-C, the analysis is carried out by taking into account dynamic changes in the performance data of division heads from time to time. GRA-C will calculate the level of gray relationship (gray relational grade) between the performance of the division head and the desired ideal target. Changes in the weight of criteria and up-to-date performance data allow for a more adaptive and accurate assessment of the performance of division heads, which may be subject to change due to internal or external conditions.

The decision matrix is the first stage in GRA-C, a representation of data in tables used to assist decision-making. Normalization of the decision matrix uses Eq. (10).

$$X=\begin{bmatrix} x_{11} & x_{21} & x_{31} & x_{41} & x_{51} \\ x_{12} & x_{22} & x_{32} & x_{42} & x_{52} \\ x_{13} & x_{23} & x_{33} & x_{43} & x_{53} \\ x_{14} & x_{24} & x_{34} & x_{44} & x_{54} \\ x_{15} & x_{25} & x_{35} & x_{45} & x_{55} \\ x_{16} & x_{26} & x_{36} & x_{46} & x_{56} \\ x_{17} & x_{27} & x_{37} & x_{47} & x_{57} \\ x_{18} & x_{28} & x_{38} & x_{48} & x_{58} \\ x_{19} & x_{29} & x_{39} & x_{49} & x_{59} \end{bmatrix}=\begin{bmatrix} 8 & 9 & 9 & 6 & 8 \\ 7 & 7 & 8 & 10 & 7 \\ 6 & 8 & 9 & 5 & 7 \\ 7 & 9 & 8 & 7 & 9 \\ 6 & 7 & 9 & 6 & 6 \\ 8 & 9 & 8 & 5 & 7 \\ 9 & 8 & 7 & 6 & 9 \\ 7 & 8 & 8 & 6 & 7 \\ 6 & 7 & 8 & 8 & 8 \end{bmatrix} \tag{10}$$

The normalization of the decision matrix is the second stage in the GRA-C to convert it to the same scale calculated using Eq. (11).

$$X_{11}=\frac{x_{11}-x_{11,19}}{x_{11,19}-x_{11,19}}=\frac{8-6}{9-6}=\frac{2}{3}=0.667 \tag{11}$$

Table 2 is the calculation result of the matrix normalization assessment of each alternative for each criterion.

Table 2. Normalization matrix

Division Name	C1	C2	C3	C4	C5
Production Division	0.667	1	1	0.2	0.667
R&D Division	0.333	0	0.5	1	0.333
Quality Division	0	0.5	1	0	0.333
Logistics and Supply Chain Division	0.333	1	0.5	0.4	1
Maintenance Division	0	0	1	0.2	0
Finance Division	0.667	1	0.5	0	0.333
Human Resources Division	1	0.5	0	0.2	1
Purchasing Division	0.333	0.5	0.5	0.2	0.333
IT Division	0	0	0.5	0.6	0.667

The criterion of value variation is the third stage in the GRA-C to measure how much the spread of existing values is calculated using Eq. (12).

$$r_{11} = \frac{x_{11}}{\sqrt{\sum_{i=1}^{m} x_{11,19}}} = \frac{8}{\sqrt{8^2+7^2+6^2+7^2+6^2+8^2+9^2+7^2+6^2}} = \frac{8}{\sqrt{464}} = 0.371 \tag{12}$$

Table 3 is the result of the calculation of the normalization of the criteria of each alternative for each criterion.

Table 3. Normalization of the criteria

Division Name	C1	C2	C3	C4	C5
Production Division	0.371	0.373	0.364	0.297	0.350
R&D Division	0.325	0.290	0.323	0.496	0.306
Quality Division	0.279	0.332	0.364	0.248	0.306
Logistics and Supply Chain Division	0.325	0.373	0.323	0.347	0.394
Maintenance Division	0.279	0.290	0.364	0.297	0.263
Finance Division	0.371	0.373	0.323	0.248	0.306
Human Resources Division	0.418	0.332	0.283	0.297	0.394
Purchasing Division	0.325	0.332	0.323	0.297	0.306
IT Division	0.279	0.290	0.323	0.397	0.350

The average value of the criteria is the fourth stage in the GRA-C, which helps provide an overview of how the group as a whole performs against certain criteria calculated using Eq. (13).

$$N_1 = \frac{1}{9}\sum_{i=1}^{m} r_{11,19} = 0.111 * 2.971 = 0.3301 \tag{13}$$

Table 4 is the result of calculating the average value for each criterion.

Table 4. Average value of the criteria

Criteria	C1	C2	C3	C4	C5
Average value	0.3301	0.3316	0.3324	0.3249	0.3307

The value of the variation criterion is the fifth stage in the GRA-C, helping with criteria with high variability and influencing the decision calculated using Eq. (14).

$$\emptyset_1 = \sum_{i=1}^{m} (r_{11,19} - N_1)^2 = 0.019157 \tag{14}$$

Table 5 is the result of calculating the variation value for each criterion.

Table 5. Variation value of the criteria

Criteria	C1	C2	C3	C4	C5
Variation value	0.019157	0.010309	0.005810	0.049686	0.015751

The significance value of the criterion is the sixth stage in the GRA-C to help determine which criterion has the greatest impact on the final decision, calculated using Eq. (6), i.e., $\varphi_1 = 1 - \emptyset_1 = 1 - 0.019157 = 0.980843$. Table 6 is the result of the calculation of the significance value of the criterion.

Table 6. Significance value of the criteria

Criteria	C1	C2	C3	C4	C5
Significance value	0.980843	0.989691	0.994190	0.950314	0.984249

The criterion weight value is the seventh stage in the GRA-C to reflect the relative priority of each criterion based on its significance, calculated using Eq. (7), i.e., $w_1 = \frac{\varphi_1}{\sum_{j=1}^{n} \varphi_1} = \frac{0.980843}{4.899286} = 0.2002$. Table 7 is the result of the calculation of the weight value of the criterion.

Table 7. Weight value of the criteria

Criteria	C1	C2	C3	C4	C5
Weight value	0.2002	0.202	0.2029	0.194	0.2009

The result of weight multiplication is the eighth stage in the GRA-C to contribute from each criterion to the overall value of each alternative calculated using Eq. (8), i.e., $V_{11} = w_1 * x_{11} = 0.2002 * 0.667 = 0.13347$. Table 8 is the result of calculating the value of weight multiplication for each alternative of the existing criteria.

Table 8. Calculating the value of weight multiplication

Division Name	C1	C2	C3	C4	C5
Production Division	0.13347	0.20201	0.20293	0.03879	0.13393
R&D Division	0.06673	0	0.10146	0.19397	0.06697
Quality Division	0	0.10100	0.20293	0	0.06697
Logistics and Supply Chain Division	0.06673	0.20201	0.10146	0.07759	0.20090
Maintenance Division	0	0	0.20293	0.03879	0
Finance Division	0.13347	0.20201	0.10146	0	0.06697
Human Resources Division	0.20020	0.10100	0	0.03879	0.20090
Purchasing Division	0.06673	0.10100	0.10146	0.03879	0.06697
IT Division	0	0	0.10146	0.11638	0.13393

The gray relationship value is the eighth, ninth, or last stage in the GRA-C. This value reflects the relationship between the alternative and the criterion, which indicates how well each alternative meets all the predetermined criteria calculated using Eq. (9), i.e., $GRG_1 = \frac{1}{5}\sum_{j=1}^{n} V_{11,51} = 0.13347 + 0.20201 + 0.20293 + 0.03879 + 0.13393 = 0.71112$. Table 9 is the result of calculating the grey relationship value for each existing alternative.

The ranking of division heads' performance assessments involves sorting or arranging objects, individuals, or alternatives based on certain criteria to determine the best priority or performance. The ranking results provide an overview of the best to worst alternatives, which helps decision-makers choose the option that best suits the division head's performance assessment. The ranking results are shown in Figure 2.

Table 9. Calculation of the grey relationship value

Division Name	Grey Value
Production Division	0.71112
R&D Division	0.42913
Quality Division	0.37089
Logistics and Supply Chain Division	0.64869
Maintenance Division	0.24172
Finance Division	0.50390
Human Resources Division	0.54090
Purchasing Division	0.37496
IT Division	0.35178

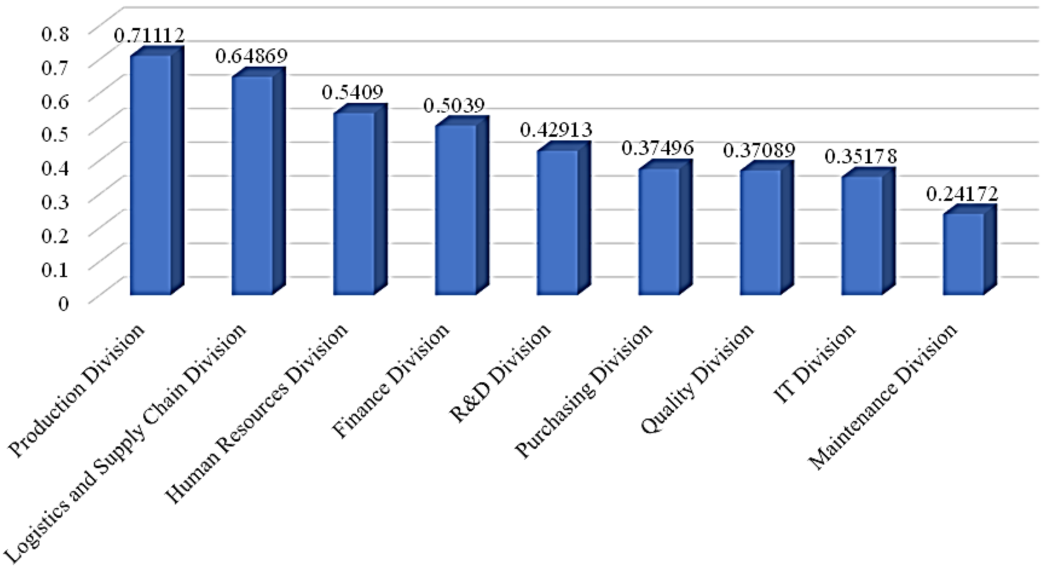

Figure 2. Results of the ranking of the performance assessment of division heads

The results of the division head's performance assessment ranking, Production Division, ranked highest with a score of 0.71112, indicating that this division head performs superior to other divisions. Followed by the Logistics and Supply Chain Division with a score of 0.64869 and the Human Resources Division in third place with a score of 0.5409. The Finance Division is ranked fourth with a score of 0.5039, slightly higher than the R&D Division with a score of 0.42913. The Purchasing Division, Quality Division, and IT Division recorded scores of 0.37496, 0.37089, and 0.35178, respectively. The Maintenance Division was in last position with a score of 0.24172, indicating the lowest performance among all the divisions assessed.

4.2. Discussion

In the context of multi-criteria decision-making, the GRA method has been widely used because of its ability to analyze the relationship between various alternatives based on established criteria. However, one of the main challenges in implementing GRA is its limited flexibility, especially when setting parameter weights that can affect the final result. Therefore, modifications to the weighting parameters can increase the flexibility of the GRA, allowing this method to be more adaptive in handling the complexity of performance assessment problems. Modifying weights in GRA enables this method to be more responsive to differences in significance between criteria used in performance assessment. In the case of decision-making involving many criteria, not all criteria have the same weight or level of importance.

Therefore, by introducing customized weighting parameters, GRA can prioritize more relevant criteria more precisely, increasing accuracy in ranking results. This increased flexibility also allows decision-makers to tailor the analysis to specific needs, including considering various scenarios and dynamic business or operational environment changes.

Grey Relational Analysis Change Data Driven (GRA-C) is a modified GRA method designed to handle dynamic changes in assessment data. This method introduces a data-driven approach, where changes in the dataset directly affect the weighting process and the relationships between alternatives. By accounting for real-time data changes, GRA-C enables more responsive analysis of fluctuations in criteria or dynamic environmental conditions, such as changes in customer preferences, performance, or market conditions. The GRA-C method leverages a data-change-based algorithm to adapt weighting and increase flexibility in multi-criteria evaluations. For example, suppose there is a significant change in relevant criteria, such as a decrease in the performance of a division or an improvement in the performance of an alternative. In that case, the GRA-C automatically adjusts the relationship between the alternatives based on the new data. This method is particularly effective in applications requiring continuous adjustment and real-time assessment, such as project management, performance appraisal, or supplier selection in highly competitive environments. GRA-C offers a more dynamic solution than conventional GRA methods, as it can model changes directly in a multi-criteria decision-making system, resulting in more relevant and accurate decisions as data continues to change.

The comparison between GRA-C and GRA combined with the criterion weighting method offers an interesting perspective on flexibility and adaptability in multi-criteria decision-making. GRA-C has the advantage of responsiveness to real-time data changes, where criteria weighting and relationships between alternatives can be adjusted automatically based on data dynamics. On the other hand, GRA combined with criterion weighting methods, such as ROC [17], Entropy [18], CRITIC [19], and PIPRECIA [20], prioritizes a more objective or user-preference-based initial weighting before the analysis. However, these methods tend to be static, so they cannot easily adjust weights when there are changes in the data or environment. Table 10 compares the GRA-C and the GRA methods combined with the criterion weighting methods.

Table 10. The result of a comparison of the GRA-C method and the GRA method

Division Name	Original Rank	ROC Rank	Entropy Rank	CRITIC Rank	PIPRECIA Rank	GRA-C Rank
Production Division	1	1	4	1	1	1
Logistics and Supply Chain Division	2	4	2	2	4	2
Human Resources Division	3	3	3	4	2	3
Finance Division	4	2	6	3	3	4
R&D Division	5	6	1	5	5	5
Purchasing Division	6	5	7	7	6	6
Quality Division	7	7	8	6	7	7
IT Division	8	9	5	8	8	8
Maintenance Division	9	8	9	9	9	9

The results of the comparison of Original, ROC, Entropy, CRITIC, PIPRECIA, and GRA-C methods show a variety of approaches in weighting criteria and performance evaluation. The

Original Method is the result of the ranking obtained from the company. ROC gives weight based on a simple order of priority, but does not consider the relationship between criteria. Entropy offers a more objective weighting by considering the variation of data between criteria, which is suitable for situations where quantitative data is the basis for assessment. CRITIC combines objectivity by looking at correlations between criteria, resulting in a more balanced weight, and considering the influence of factors. PIPRECIA provides an approach based on repeated assessments from experts, suitable for decisions that require a subjective but more systematic professional assessment. Finally, GRA-C integrates performance between alternatives with criterion weighting, resulting in a comprehensive approach to decision-making involving various factors.

The comparison results using Spearman's correlation between the Original, ROC, Entropy, CRITIC, PIPRECIA, and GRA-C methods provide an overview of the extent to which the alternative rankings of each method correlate with each other. Spearman correlation measures the strength of the monotonic relationship between two ranks, so the higher the correlation value, the more similar the ratings produced by the two methods. Figure 3 is the result of Spearman's correlation of the existing ranking.

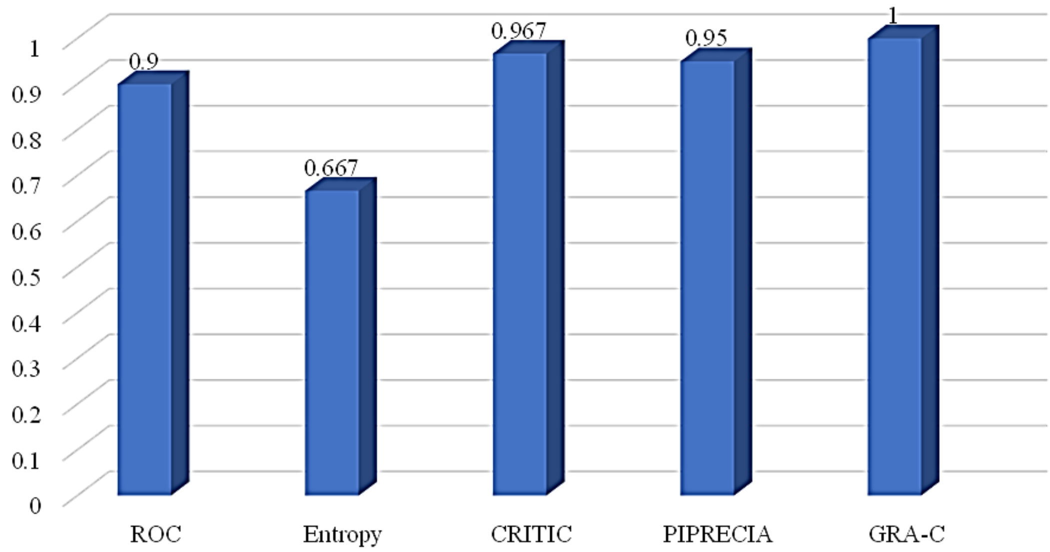

Figure 3. The results of the comparison used Spearman's correlation.

The comparison results displayed in the graph using Spearman correlation show the degree of alignment between the different methods compared. The Spearman correlation value varied from 0.667 to 1, indicating the degree of correlation between these methods in generating alternative rankings. ROC has a correlation value of 0.9, indicating a relatively strong alignment with the ranking of the calculation results. Entropy showed the lowest correlation, 0.667, indicating that this method had a more significant difference in alternative rankings than other methods. CRITIC has a high correlation of 0.967, indicating an almost perfect fit with ratings from different methods, especially those based on objective data. PIPRECIA also showed a strong correlation of 0.95, indicating that this method provides a fairly consistent rating with other methods used. GRA-C achieves the highest correlation value, 1, indicating that the rating generated by GRA-C is entirely consistent with the reference rating or other methods.

The conclusion of the comparison with the Spearman correlation shows that the GRA-C method has an extreme degree of conformity in producing alternative rankings, with a correlation value of 1 each. This indicates that these methods provide similar results, making them reliable for consistent decision-making.

The limitations of the proposed research related to the GRA method need to be considered to provide a clear context regarding the limitations of this methodology. One of the main limitations is the reliance of GRA on fixed criterion weights, which do not consider the dynamics or changes in the relevance of the criteria based on a particular context or situation. This makes this method less flexible when changing data or in rapid decision-making environments. In addition, GRAs tend to be sensitive to the scale of the data and the normalizations used. Extreme scale differences between criteria can influence specific criteria to become too dominant, thus affecting the analysis results. Improper normalization can also result in gray relationships that do not reflect the proper relationship between alternatives and criteria. The GRA method also has limitations in handling large and complex datasets, especially those that involve many criteria or alternatives. This can increase computing time and decrease the efficiency of the analysis. In addition, GRA is less efficient in handling subjective or qualitative data, as the measurement and quantification process for these kinds of criteria can be complex and prone to bias. Interpreting results from GRA often requires a deep understanding of these methods, which can be challenging for non-technical users or stakeholders who do not have a technical background. Discussing these limitations is essential to provide insight into the scope and application limits of the GRA method and guide further development to address existing shortcomings.

5. CONCLUSION

The GRA-C method emphasizes the increased effectiveness and flexibility of this method in performance appraisal for multi-criteria decision-making. GRA-C allows for more precise adjustments according to the importance of each criterion, leading to more accurate and relevant evaluation results. By modifying the weights, the GRA-C becomes more flexible and can be adapted to different contexts and specific decision-making needs, so that it can be applied in various industry sectors. These modifications help reduce bias due to improper weight allocation, resulting in more objective performance assessments. The results of the modified GRA-C can provide better insights for decision-makers, supporting a more effective and informed decision-making process. The comparison with the Spearman correlation shows that the GRA-C method has extreme conformity in producing alternative rankings, with a correlation value of 1 each. This indicates that these methods provide similar results, making them reliable for consistent decision-making. The comparison results using Spearman's correlation show the degree of alignment between the different methods being compared. The Spearman correlation value varies between 0.667 and 1, showing the degree of correlation between the methods producing alternative rankings. ROC has a correlation value of 0.9, which shows a fairly strong alignment with the ranking of the calculation results. Entropy shows the lowest correlation of 0.667, which shows that this method has a more significant difference in alternative rankings than other methods. CRITIC has a high correlation of 0.967, which indicates almost perfect agreement with the rankings of different methods, especially those based on objective data. PIPRECIA also shows a strong correlation of 0.95, which shows that this method provides a ranking consistent with other methods. GRA-C obtains the highest correlation value of 1, which shows that the ranking produced by GRA-C is entirely consistent with the reference ranking or other methods. Future work in this study can be focused on developing and testing a more flexible GRA-C analysis model with modification of weight parameters for performance assessment in multi-criteria decision-making. Furthermore, research can investigate integrating these methods with other analytical techniques, such as boundary-based decision analysis or multi-objective programming methods, to provide a more comprehensive view of performance appraisal.

ACKNOWLEDGEMENT

This research was funded by Universitas Teknokrat Indonesia, Hibah Publikasi Terindeks Scopus (HiPuTS) grant number 022/UTI/LPPMI/E.1.1/VIII/2023.

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