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A New Approach for the Measurement of Criterion Weights in the Scope of Multi-Criteria Decision Making: Spearman Rank Correlation-based Expanded CRITIC Method (SRCBECM)

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Abstract: Advancing the field of multi-criteria decision making (MCDM), this study proposes the Spearman Rank Correlation-based Expanded CRITIC Method (SRCBECM) as a novel and objective method for computing criteria weight coefficients. Leveraging the intricate revised CRITIC method, SRCBECM aims to enrich and contribute the MCDM landscape. Drawing upon criterion values extracted from Freedom in the world (FIW) index assessments for 19 G20 member nations, the study showcases the sensitivity of SRCBECM in objectively deriving criteria weights for diverse contexts. Further bolstering its credibility and reliability, comparative analyses reveal MIEXCF's alignment with established methodologies such as ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC. Notably, the simulation analysis underscores SRCBECM's exceptional and stability in discerning criteria weights and its remarkable stability across diverse scenarios. In conclusion, SRCBECM emerges as a robust and objective criterion weighting technique, poised to make significant contributions to the burgeoning field of the broader MCDM corpus.
Keywords: MCDM, CRITIC, rho, SRCBECM

1. Introduction

Multi-criteria decision-making (MCDM) is a widely utilized methodology in intricate decision-making processes and mathematical modeling, often encompassing various factors. MCDM aims to assess and prioritize alternatives based on the preferences and priorities of decision-makers. To achieve this, it is crucial to establish the weights of the criteria, which reflect the decision-makers' preferences [1].

The field of MCDM provides a diverse range of techniques, including ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW, for the computation of criterion weights. These methods leverage two fundamental characteristics of objective criterion weights: 1) the extent of performance contrast among decision alternatives for each criterion, reflecting the range between maximum and minimum values, and the distinctiveness or conflict among criteria. By comprehending and utilizing these inherent data characteristics, decision-makers can obtain valuable insights to steer their decision-making process [2]. Consequently, in the literature on MCDM criterion weighting, the logic of criterion weighting may vary in methods that consider the relationships between criteria (CRITIC, DEMATEL, MEREC).

One of the most notable features of the CRITIC method is that it is fundamentally based on the Pearson correlation coefficient between criteria [2]. The Pearson correlation coefficient is a parametric method, and it can only measure the correlation value between variables that exhibit a normal distribution. Therefore, the correlation values between variables that do not exhibit a normal distribution may not yield accurate results with this method [3]. In contrast, the relationships between variables that do not exhibit a normal distribution can be measured using the non-parametric Spearman Rank Correlation (rho) coefficient [4]. Moreover, the rho coefficient can also be used to calculate relationships between

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variables that exhibit a normal distribution [5]. Hence, it can be considered that the rho correlation coefficient is more advantageous compared to the Pearson correlation coefficient. The primary motivation of this study is to propose the use of the rho correlation coefficient instead of the Pearson correlation coefficient for determining the relationships between criteria when calculating the weight values of criteria within the CRITIC method, regardless of whether the criteria values exhibit a normal distribution. This approach ensures a more accurate calculation of the relationships between criteria.

The second motivation of this study is to expand the criteria weighting calculation logic of the CRITIC method. The logic of CRITIC method relies on the differentiation or antagonism among criteria. This is because in the CRITIC method, the weight of a criterion increases with the growth of negative relationships among other criteria (along with a decrease in positive relationships) [2]. In contrast, the DEMATEL method considers not only the antagonism among criteria but also takes into account the similarity among them based on the logic of the method [6]. If a criterion influences other criteria both negatively and positively, and is influenced by other criteria, its weight increases in the DEMATEL method [7]. Therefore, in the DEMATEL method, the separation and similarity among criteria are considered on equal terms when calculating the weight of a criterion. Accordingly, the DEMATEL method possesses a more inclusive characteristic in terms of criterion weighting logic compared to the CRITIC method. Therefore, to make the CRITIC method more comprehensive (by considering both the contrasts and similarities between criteria), it is necessary to implement its calculation logic similar to the DEMATEL method. In this context, in the research, a method called Spearman Rank Correlation-based Expanded CRITIC Method (SRCBECM) is proposed, which forms equations that explain relationships among criteria more meaningfully, provide more separation and similarity among criteria, and thus, more effectively determine the characteristic features of criteria compared to the CRITIC method. The SRCBECM method aims to measure the weight coefficients of criteria objectively.

The data set of the study consists of the values of 12 criteria for the Freedom in the world (FIW) of 19 countries in the G20 group. In this sense, the methods of calculating criterion weights in the scope of MCDM, rho and CRITIC techniques are explained in the method section of the study. The implementation plan of the proposed method is shown in Figure 1.

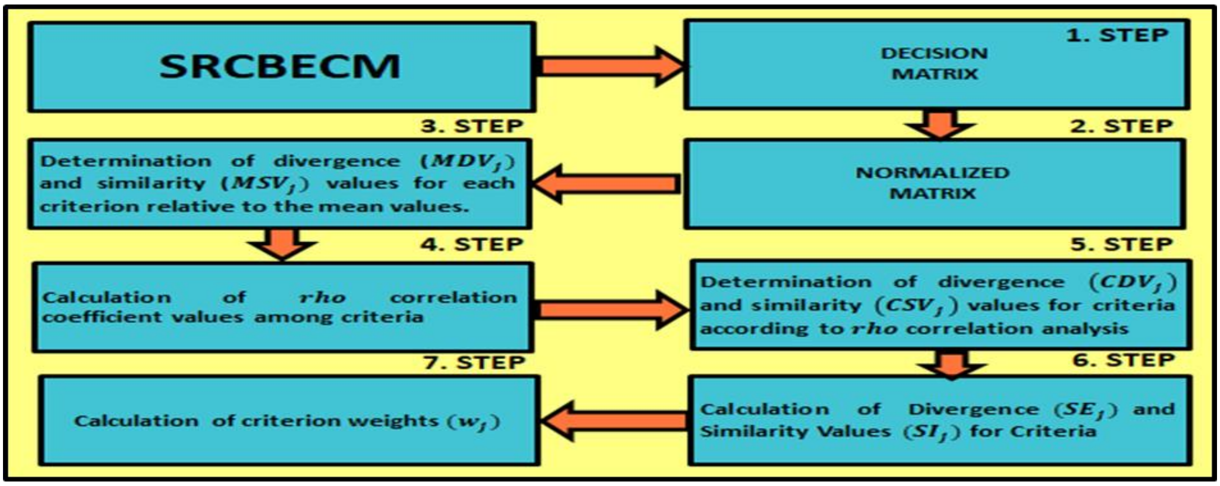

Figure 1. Implementation Plan of Proposed Method

2. Materials and Methods

2.1. Methods for calculating criterion weights in the scope of MCDM

Navigating the intricacies of decision-making often hinges on identifying the optimal choice amidst a tapestry of alternatives. However, each option may exhibit varying degrees of effectiveness across diverse criteria. This underscores the criticality of pinpointing the relative importance of these criteria to accurately compare the performance of potential solutions and ultimately arrive at the most suitable one [8]. Traditionally, this significance is quantified through the assignment of weight coefficients within the framework of MCDM problems [2].

The burgeoning field of Multi-Criteria Decision Making (MCDM) boasts a rich tapestry of objective weighting methods. These include CRITIC (Criteria Importance Through Inter-Criteria Correlation), ENTROPY, CILOS (Criterion Impact Loss Optimization System), IDOCRIW (Integrated Determination of Objective Criteria Weights), SVP (Statistical Variance Procedure), SD (Standard Deviation), MEREC (Method Based on Removal Effects of Criteria), LOPCOW (Logarithmic Percentage Change-driven Objective Weighting), and SECA (Simultaneous Evaluation of Criteria and Alternatives) [2].

The CRITIC method taps into the inherent information within a system by privileging criteria that exhibit greater disorder or distinctiveness compared to others, marking their heightened importance. This approach values the interconnectedness of criteria by meticulously examining their correlations to expose any inconsistencies. These contradictions, meticulously quantified using the standard deviation, inform the determination of criterion weight coefficients. The CRITIC method unfolds by first constructing a decision matrix and then normalizing its values. By analyzing the correlations between these normalized values, the method quantifies the relative weight of each criterion [9-12].

The ENTROPY method adds a valuable tool to the decision-making field. Building on the constructed decision matrix, this method leverages the standardized values and the calculated ENTROPY measure of each criterion to derive their corresponding ENTROPY-based weights [8-13].

The CILOS method prioritizes criteria based on their ability to influence the performance of other criteria relative to their ideal maximum and minimum values. In essence, criteria that cause the least deviation in others receive higher weight coefficients. This approach follows a structured process, beginning with the calculation of the decision matrix, normalization, and square matrix formation. Subsequently, a system of linear equations is solved to uncover the weight coefficients for each criterion [14-15].

The IDOCRIW method bridges the gap between the ENTROPY and CILOS approaches, forging a hybrid path to criterion weight determination. This innovative method delves into the relative impact of a missing index, initially leveraging the decision matrix and both ENTROPY and CILOS methodologies to calculate individual weight coefficients. Subsequently, it seamlessly integrates the ENTROPY and CILOS weights, culminating in the final IDOCRIW weights [14].

The SVP method, a champion of objectivity in weighting criteria, stands tall amidst subjective biases. This method calculates criterion weights with an unwavering impartiality, eliminating the influence of expert opinions or subjective interpretations. SVP dives deep into the variance metrics associated with each criterion, treating them as the sole compass for determining their significance. Following the calculation of individual criterion variances, the method simply divides each value by the total variance across all criteria, yielding their respective weights. In essence, SVP empowers data-driven decision-making, transforming variance into a quantifiable measure of criterion importance [16-18].

The SD method shines a light on the inherent variability of criteria by leveraging their deviation from the average. This straightforward approach first normalizes the values within the decision matrix, ensuring a level playing field. Then, it delves into the standard deviations of each criterion, using these measures as a compass to navigate their relative importance. In essence, SD empowers data-driven decision-making by translating variability into quantifiable weights [19-20].

Like other weighting methods, MEREC lays the groundwork by constructing the decision matrix and its normalized counterpart. Then, it ventures into the realm of performance, calculating the overall effectiveness of each decision alternative through a natural logarithm-powered framework. Building on this foundation, MEREC re-evaluates the performance of each alternative, factoring in the influence of each remaining criterion. This iterative process, driven by natural logarithms, ultimately culminates in the calculation of criterion weight coefficients. These weights reflect the "removal effect" of each criterion, essentially the sum of their absolute influence on the performance of other alternatives. In essence, MEREC recognizes that as a criterion's impact on decision alternatives grows, so too does its weight coefficient [21-22].

The LOPCOW method harnesses the power of multidimensional data, weaving together information from various sources to craft a tapestry of optimal criterion weights. This approach seeks to level the playing field between the most and least influential criteria, while acknowledging the intricate web of connections that bind them. The journey begins with meticulously constructing the decision matrix, followed by a

rigorous normalization process that ensures all voices are heard equally. To overcome the disparities arising from data magnitudes, LOPCOW deploys a potent metric: the average square value expressed as a percentage of the criterion's standard deviation. This measure serves as a compass, guiding us towards the final weight coefficients and ultimately, a balanced and insightful weighting scheme [23].
The SECA method takes a holistic approach, simultaneously unveiling the true potential of decision alternatives and weighing the importance of criteria that shape their performance. This innovative method begins by leveling the playing field through decision matrix standardization. Then, it delves into the realm of disagreement, employing the standard deviation as its tool to quantify discrepancies. These insights, along with standardization values, form the bedrock for determining criterion weights. Finally, SECA leverages the power of multi-objective linear programming, optimizing a model to arrive at the optimal set of weights [24].
The decision matrix in the DEMATEL method is created by obtaining the opinions of experts, and thus, the method is recognized as one of the subjective criterion weighting methods. This is because it involves determining the impact values of variables on each other through the input of experts or their opinions [2]. The relationship structure of variables, including their contributions to the relational structure, influence, relational density, and relational quality (as influencers or influenced), can be determined through the DEMATEL MCDM method [25-26]. Therefore, in the DEMATEL method, variables that possess the quality of being an "influencer" within the relationship structure are considered as causes, while variables that have the quality of being "influenced" are considered as outcomes in said relational structure [23]. The DEMATEL method has demonstrated successful applications in various technical and social problems. In addition to identifying the relationship structure between variables, the DEMATEL method allows for the calculation of the significance values of variables [10]. In the DEMATEL method, for the preparation of the decision matrix, the impact values of variables on each other can be determined subjectively by obtaining the opinion of an expert or the opinions of multiple experts [2]. Apart from this, In the DEMATEL method, the weight of a criterion increases as its impact on other criteria, either positively or negatively, and its susceptibility to the influence of other criteria become more significant. Additionally, one of the most crucial features of the DEMATEL method is that in determining the weights of criteria, the interactive structure among criteria considers both positive and negative influences equally. This is because the weights of criteria can be calculated by taking the square root of the sum of the squares of the total of positive and negative impact values and the square of the difference between positive and negative impact values [27].

2.2. Spearman Rank Correlation Coefficient

The Spearman Rank Correlation Coefficient (rho) is a non-parametric correlation coefficient and is referred to as an alternative to the Pearson correlation coefficient. In this sense, the rho correlation coefficient is utilized to measure the linear relationship between two variables that do not exhibit a normal distribution feature [28-29]. Additionally, when variables possess the normal distribution feature, the relationship between the two variables can also be assessed using the rho coefficient. A coefficient value of -1 indicates a perfect negative relationship, whereas a value of +1 signifies a perfect positive relationship. If the coefficient value is 0, it implies no relationship between the two variables. The rho coefficient also possesses a symmetrical property; therefore, the relationship coefficient remains the same even if the roles of the variables change between dependent and independent variables. To measure the rho relationship coefficient between two variables, the following steps are followed [30-39].

Step 1: Calculation of the total values of row entries in the contingency table (t')

Let t represent the sum of each row. Therefore, the sum of the row values in the contingency table is shown in Equation 1.

$$t' = \frac{(\sum t^3 - \sum t)}{12} \tag{1}$$

Step 2: Calculate the sum of the column values in the contingency table (u')

Let u represent the sum of each column. Therefore, the sum of the column values in the contingency table is shown in Equation 2.

$$u' = \frac{(\sum u^3 - \sum u)}{12} \quad (2)$$

Step 3: Calculation of the rho (r_{rho})

$$r_{rho} = \frac{n^3 - n - 6\sum d^2 - 6(t' + u')}{\sqrt{n^3 - n - 12t'}\sqrt{\sqrt{n^3 - n - 12u'}}} \quad (3)$$

When the correlation coefficient literature is examined, it is possible to come across many studies that measure the relationships between two variables with the rho coefficient. Studies related to the current rho correlation coefficient are shown in Table 1.

Table 1. rho literature

Author(s)	Method(s)	Theme
[40]	rho	Relationship between atmospheric stability and cloud tops temperature of Himawari-8 IR satellite images
[41]	rho	Relationship between communication skills and emotional intelligence among nurses
[42]	rho	Relationships between various cyber threats and their patterns with respect to duration, IP address, target systems/ports
[43]	rho	Relationship between hemoglobin and lactate dehydrogenase
[44]	rho	Relationship between Dysphonia and voice fatigue
[45]	rho	Relationship between aortopulmonary collaterals and common non-invasive clinical variables
[46]	rho	Relationship between bilateral dFIWcit and maximal sprint speed judo test, maximal aerobic speed Judo test and special judo fitness test
[47]	rho	Relationship between performance of magnetic resonance imaging and histopathology
[48]	rho	Relationship between abundance of short-chain fatty acids (SCFAs) and lipopolysaccharide
[49]	rho	Relationship between neutrophil-to-lymphocyte ratio and alzheimer-related biomarkers in cerebrospinal fluid

2.3. CRITIC method

The CRITIC (Criteria importance through inter criteria correlation) method is a technique that objectively measures the weight coefficients or importance levels of criteria based on the data of decision alternatives regarding the criteria [19]. The foundation of the method is based on the intensity of the dichotomy within the structure of the decision-making problem [2]. Furthermore, this method provides an analytical approach to revealing all the information inherent within the criteria [50]. The most significant feature that sets the CRITIC method apart from other weight coefficient calculation techniques is that it calculates the weight coefficients of criteria not based on subjective results provided by expert opinions, but by taking into account standard deviation and correlation analysis of the criteria [2]. In this context, the application steps of the method are explained below [50].

A_i: Decision alternative i

C_j: $J-th$ evaluation criterion

x_{ij}: The value of alternative i according to evaluation criterion j.

x_j^{mak}: The maximum value of decision alternatives according to criterion j.

x_j^{min}: The minimum value of decision alternatives according to criterion j.

r_{ij}: The value received by alternative i according to evaluation criterion j.

p_{jk}: Relationship coefficients between any j criterion and k criterion

σ_J: Standard deviation value of criterion j $(j = 1,2,\dots,n)$

w_J: Weight of evaluation criterion $(j = 1,2,\dots,n)$.

Step 1: Acquisition of the Decision Matrix (X)

$$X = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix} \quad (4)$$

2. Step: Normalization Process of the Decision Matrix.

For Benefit-Oriented Criteria

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{maks} - x_j^{min}} \ldots\ldots\ldots.. j = 1,2,\ldots.,n \quad (5)$$

For Cost-Oriented Criteria

$$r_{ij} = \frac{x_j^{maks} - x_{ij}}{x_j^{maks} - x_j^{min}} \ldots\ldots\ldots.. j = 1,2,\ldots.,n \quad (6)$$

3. Step: Creation of the Relationship Coefficient Matrix (p_{jk})

$$p_{jk} = \frac{\sum_{i=1}^{m}(r_{ij} - \overline{r_j}).(r_{ik} - \overline{r_k})}{\sqrt{\sum_{i=1}^{m}(r_{ij} - \overline{r_j})^2.(r_{ik} - \overline{r_k})^2}} \quad j,k = 1,2,\ldots,n \quad (7)$$

4. Step: Measurement of C_j Values

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(r_{ij} - \overline{r_j})^2}{m-1}} \quad (8)$$

$$C_j = \sigma_j.\sum_{k=1}^{n}(1 - p_j), \quad j = 1,2,\ldots,n \quad (9)$$

5. Step: Measurement of Criterion Weights (Importance Degrees) (w_j)

$$w_j = \frac{C_j}{\sum_{k=1}^{n} C_j} \quad (10)$$

When the MCDM literature is examined, it is observed that many researchers have benefited from the CRITIC method in calculating the weights of criteria according to decision alternatives. The current research related to the CRITIC method is explained Table 2.

Table 2. CRITIC literature

Author(s)	Method(s)	Theme
[51]	CRITIC based MARCOS	Evalation of zero-carbon measures for sustainable transportation in smart cities
[52]	CRITIC based TOPSIS	Optimum Site Selection for Solar PV Farm
[53]	CRITIC based TOPSIS	Analytically Identify the Air Pollutant's
[54]	CRITIC based GRA	investment portfolio selection
[55]	CRITIC based TOPSIS	Solving the material handling equipment selection problem
[56]	Fuzzy CRITIC based TOPSIS	Smartphone addiction assessment
[57]	CRITIC based EDAS	Geometric aggregation operator
[58]	CRITIC based TOPSIS	Stakeholder assessment in construction projects
[59]	CRITIC based MultiMOORA	Warehouse manager selection
[60]	CRITIC-SD based GRA and TOPSIS	Assessing the energy security of European Union countries

2.4. Proposed method: Spearman Rank Correlation Coefficient-based expanded CRITIC method (SRCBECM)

The Pearson correlation coefficient is a parametric measure, so it can be used to measure the relationships between criteria under the assumption of normal distribution of the data. However, when the relationship between criteria in a dataset that does not follow the normal distribution is measured with the Pearson correlation coefficient, the relationship between the criteria may not reflect reality [4]. In contrast, the rho coefficient is a non-parametric measure, so the normal distribution assumption is not required for measuring the relationship between criteria [35]. In addition, the rho coefficient can be used to obtain real results in detecting nonlinear relationships between variables [61]. In this context, the rho coefficient is considered to be more advantageous than the Pearson correlation coefficient for calculating the weights of criteria due to its aforementioned properties [62]. Therefore, the relationships between criteria can be calculated with the rho coefficient in the CRITIC method.

In the ENTROPY method, as the uncertainty level of a criterion increases relative to other criteria, the weight coefficient of the criterion decreases. Consequently, the criterion with the highest degree of uncertainty attains a more pronounced significance compared to other criteria [2]. In the MEREC method, the weight of a specific criterion increases when the absolute difference between the averages of criteria concerning decision alternatives, either by excluding or considering the criterion, becomes smaller [21]. As a result, the criterion with the highest weight exerts the greatest influence on decision alternatives. In the SD method, the weight of a criterion is maximized when its standard deviation is the highest [19]. Similarly, in the SVP method, the weight of a criterion is maximized when its variance is the highest [20]. In the LOPCOW method, the mean square value of each criterion is calculated as a percentage of the standard deviations, effectively addressing the discrepancy (gap) arising from the dimensionality of the data. Consequently, a decrease in the standard deviation of a criterion diminishes the gap attributed to the data size for that criterion, resulting in an increase in the weight assigned to the criterion [23]. Therefore, in these methods, the weight calculation logic is based on the degree of separation (contrast) of the criteria from each other; the more a criterion is separated or contrasted, the higher its weight value.

As is well known, the increase in the weight coefficient of a criterion in the CRITIC method depends on the intensity of its contrast with other criteria. Therefore, if the contrast intensity of a criterion with other criteria increases, the weight value of the criterion also increases [2]. This is because, according to Equation 9 in the CRITIC method, the importance and weight of a criterion is highest if its negative relationship with other criteria is the greatest and its positive relationship is the least [19]. Therefore, if a criterion is the most distinct from other criteria, the weight of that criterion is greater. In conclusion, the method's logic takes into account the degree of separation of the criteria from each other.

In addition to Equation 9, the CRITIC method also takes into account the standard deviation values of the criteria. In the CRITIC method, the standard deviation only provides information on how far the average value of any criterion's data set is from the mean or how different the criterion's data are from each other. Therefore, when the standard deviation values of any criterion are calculated, the standard deviation values of other criteria are not taken into account. Thus, the standard deviation value in Equation 8 does not support the separation (contrast) logic of the CRITIC method. This is because the standard deviation value shown in Equation 8 shows how far each criterion deviates from the mean based on its own data. In this case, the separation (contrast) between criteria that constitute the logic of the CRITIC method is supported excluded standard deviation only by the process in Equation 9 ($\sum_{k=1}^{n}(1-p_j)$).

To increase the contrast of a criterion with another criterion in the CRITIC method, the standard deviation shown in Equation 9 ($\sigma_j.\sum_{k=1}^{n}(1-p_j)$) can be replaced with the absolute difference between the arithmetic mean of the normalization values of any criterion and the arithmetic mean value of all criteria (MDV), which shows how much the mean value of the criterion deviates from the arithmetic mean values of all criteria. This will strengthen the degree of separation (contrast) between criteria by multiplying the calculated deviation value (MDV) with the Equation 9 ($MDV_j.\sum_{k=1}^{n}(1-p_j)$).

In the DEMATEL method, the criterion weighting logic is more comprehensive than in the CRITIC method. This is because in the DEMATEL method, the weight coefficient of a criterion increases as it affects other criteria both positively and negatively, and is affected by other criteria. Accordingly, in the DEMATEL method, the weight coefficient of a criterion is reflected by the square root of the sum of the squares of the values of the criterion affecting and being affected by other criteria, and the sum of the squares of the difference between the values of the criterion affecting and being affected by other criteria [25]. This situation is illustrated in Equation 11, which shows the criterion weights in the final step of the DEMATEL method [23-24].

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squares of the difference between the values of the criterion affecting and being affected by other criteria [25]. This situation is illustrated in Equation 11, which shows the criterion weights in the final step of the DEMATEL method [25-26].

$w =$ Weight of criteria.

$d =$ Total influence value of a criterion on other criteria.

$r =$ Total influenced value of a criterion by other criteria.

$$w = \sqrt{(d+r)^2 + (d-r)^2} \quad (11)$$

The similarities and contrasts between criteria shown in Equation 11 are explained in Table 3.

Table 3. The similarities and contrasts of a criterion with other criteria according to the DEMATEL method

$\boldsymbol{d}$	$\boldsymbol{r}$	**Conditions**	$\boldsymbol{d+r}$	$\boldsymbol{d-r}$
$d > 0$	$r > 0$	$d > r$	Similarity	Similarity
$d > 0$	$r > 0$	$d < r$	Similarity	Similarity
$d < 0$	$r < 0$	$\lvert d\rvert > \lvert r\rvert$	Contrast	Contrast
$d < 0$	$r < 0$	$\lvert d\rvert < \lvert r\rvert$	Contrast	Contrast
$d > 0$	$r < 0$	$d > \lvert r\rvert$	Similarity	Similarity
$d > 0$	$r < 0$	$d < \lvert r\rvert$	Contrast	Contrast
$d < 0$	$r > 0$	$\lvert d\rvert < r$	Similarity	Similarity
$d < 0$	$r > 0$	$\lvert d\rvert > r$	Contrast	Contrast

According to the eight scenarios explained in Table 13, the similarities and contrasts of a criterion with other criteria in terms of influencing and being influenced by them within the DEMATEL method are demonstrated. When Table 3 is examined, it is evident that the positive or negative nature of a criterion's relationships (influence and being influenced) with other criteria reflects the criterion's similarity or contrast with those criteria. Therefore, in the DEMATEL method, the importance of criterion weight is evaluated not only by the criterion's separation from other criteria (the negative impact of criteria on each other and negative being affected by each other), but also by its similarity (the positive impact of criteria on each other and positive being affected by each other). As a result, in the DEMATEL method, the weight of a criterion is considered equally in terms of the criterion's negative impact on other criteria and being affected by other criteria, as well as the criterion's positive impact on other criteria and being affected by other criteria. Therefore, the DEMATEL method is based on a more comprehensive criterion weighting logic than the CRITIC method. In light of all this information, the CRITIC method can be improved by taking into account the advantages of the rho correlation coefficient over the Pearson correlation coefficient (rho is non-parametric and gives better results than Pearson correlation for non-linear relationships) and the advantageous comprehensiveness feature of the DEMATEL method over the CRITIC method.

Taking into consideration the aforementioned points, in the context of the proposed method (SRCBECM), the application steps are outlined as follows: in the first step, decision is formulated using Equation 4, and in the second step, normalized decision matrix is constructed with Equation 5. The third step of the method involves calculating the divergence (MDV_j) through Equation 14, based on Equations 12 and 13 and similarity (MSV_j) values for each criterion through Equation 14.

Third Step: Determination of divergence (MDV_j) and similarity (MSV_j) values for each criterion relative to the mean values.

Case 1: Calculation of the mean value for each normalized criterion(V_j)

$$V_j = \frac{\sum_{i=1}^{m} r_i}{m} \quad (12)$$

Case 2: Calculation of the mean value of the normalized criteria relative to the overall mean value (VV)

$$VV = \frac{\sum_{j=1}^{n} V_j}{n} \quad (13)$$

Case 3: Measure the deviation value of each criterion from the mean value (MDV_j)

For each criterion, the divergence value:

$$MDV_j = \left|V_j - VV\right| \quad (14)$$

Case 4: Measure the inverse of the deviation value of each criterion from the mean value (MSV_j)
For each criterion, the similarity value:
Similarly, within the context of the expansion of the logical foundation of the CRITIC method, the situation of similarity among criteria can be determined by comparing the value of 1 with the MDV_j value. This is because as the MDV_j value decreases (increases), the similarity among criteria will increase (decrease).

$$MSV_j = \frac{1}{MDV_j} \tag{15}$$

Fourth Step: Calculation of rho correlation coefficient values among criteria
In the fourth step of the method, the rho relationship matrix among criteria is constructed using Equations 1, 2, and 3. Statistical programs such as SPSS can be utilized for the calculation of these correlation coefficient values.
Fifth Step: Determination of divergence (CDV_j) and similarity (CSV_j) values for criteria according to rho correlation analysis.
Case 1: Divergence of criteria according to rho correlation analysis (CDV_j)
In the 4th step of the CRITIC method, the increase in the difference between the Pearson correlation values of criteria, excluding the 1 value in Equation 9, results in an increase in the weight coefficients of criteria for negative relationships (divergence). Therefore, the divergence degree of criteria according to rho correlation analysis can be calculated using Equation 16 in the 4th step of the CRITIC method, utilizing Equation 9 excluding standard deviation.

$$CDV_j = \sum_{i=1}^{m}(1 - rho_i), \qquad i = 1,2, \dots m, j = 1,2, \dots, n \tag{16}$$

Case 2: Identification of the inverse of the divergence value according to rho correlation analysis (similarity) (CSV_j)
Taking into account Equation 16, the degree of similarity among criteria can be calculated as shown in Equation 16, which involves summing the rho coefficients between criteria with a value of 1.

$$CSV_j = \sum_{i=1}^{m}(1 + rho_i), \qquad i = 1,2, \dots m, j = 1,2, \dots, n \tag{17}$$

Sixth Step: Calculation of Divergence (SE_j) and Similarity Values (SI_j) for Criteria
Case 1: Calculation of divergence values for criteria (SE_j)
The value (SE_j) for each criterion is calculated by dividing the product of the deviation from the mean value for criteria MDV_j and the divergence value according to rho correlation analysis CDV_j by the total divergence values of criteria.

$$SE_j = \frac{MDV_j . CDV_j}{\sum_{j=1}^{n} MDV_j . CDV_j} \tag{18}$$

Case 2: Calculation of similarity values for criteria (SI_j)
The similarity values for each criterion are explained by the summation of the product of the inverse of the deviation from the mean value for each criterion (MSV_j) and the similarity according to rho correlation analysis (CSV_j) as described in Equation 19, which represents the total similarity values for criteria.

$$SI_j = \frac{MSV_j . CSV_j}{\sum_{j=1}^{n} MSV_j . CSV_j} \tag{19}$$

Seventh Step: Calculation of criterion weights (w_j)
Case 1: Taking into account the equal-weight divergence and similarity situations of criteria (EW_j)
Considering the divergence and similarity situations of criteria with equal weight, the values of criteria (EW_j) are determined, as explained in Equation 20.

$$EW_j = \frac{SE_j + SI_j}{2} \tag{20}$$

Case 2: Calculation of criterion weights

$$w_j = \frac{EW_j}{\sum_{j=1}^{n} EW_j} \tag{21}$$

In light of the above, the SRCBECM method has some advantages compared to other methods. Firstly, one of the advantages of the SRCBECM method is its insensitivity to 0 and negative values. In contrast, in the ENTROPY and MEREC methods, when there are 0 or negative values in the decision matrix, calculations can become undefined as these methods allow for logarithmic transformation. Consequently, negative values in the decision matrix can be transformed using Z-score. However, the presence of a 0 value in the decision matrix poses a challenge to the calculation of criterion weights in these methods. Secondly, the foundation of the method is based on the rho correlation coefficient among criteria. Especially in the CRITIC method, the relationships between criteria are measured with the Pearson correlation coefficient, which has a parametric structure. Therefore, the Pearson correlation coefficient may not yield accurate results, especially among criterion data that do not exhibit a normal distribution. In contrast, in the SRCBECM method, the relationships among criteria, without the assumption of a normal distribution, are measured using the non-parametric rho correlation coefficient. Thirdly, another advantage is that the SRCBECM method considers both divergence (opposition) and similarity conditions among criteria on equal terms, similar to the DEMATEL method. In contrast, in methods such as ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW, the logic of the weights of criteria focuses solely on the divergence (opposition) of criteria from each other. Therefore, the weighting logic of the SRCBECM method is more comprehensive than other methods. Finally, due to the broad focus of the SRCBECM method, the weights of criteria in SRCBECM have more characteristic features compared to other methods. Thus, the characteristic features of criteria with prominent characteristics result in more differences in the weight coefficients of criteria between them and other criteria compared to other methods.

The SRCBECM method offers a more balanced weighting by considering both similarities and differences among criteria, providing a more comprehensive analysis compared to methods that typically focus solely on differences. Its insensitivity to zero and negative values, along with its lack of a normal distribution assumption, makes the method applicable to a wide range of datasets. Consequently, SRCBECM yields reliable results, particularly in scenarios involving heterogeneous and complex datasets. Furthermore, by considering both similarities and differences among criteria, SRCBECM provides decision-makers with more balanced and accurate weights. This contributes to more accurate outcomes in decision-making processes and makes the method applicable across various sectors, including financial decisions, project management, resource allocation, product design, project selection, environmental impact assessment, and sustainable project selection. In practice, the method aids in making more meaningful and consistent decisions, especially in cases involving complex inter-criteria relationships, particularly in big data analysis. It can be particularly beneficial in decision-making processes such as corporate strategy formulation, investment evaluations, and public policy development. Moreover, SRCBECM can simplify complex decision-making processes for individuals or organizations. For instance, when making a multi-criteria investment decision, the method's criterion weighting approach helps achieve clearer and more reliable results. In daily life, SRCBECM enables individuals or organizations working with data to conduct more sound and comprehensive analyses. This facilitates more effective decision-making in workplace performance evaluations, risk analyses, and multi-criteria choices encountered in everyday life. Thanks to its flexible structure that can adapt to different data types and criterion structures, SRCBECM can be applied to various decision-making mechanisms in daily life. This flexibility makes the method more practical and user-friendly.

2.5. Data set and analysis of the study

The research dataset consists of the criteria from the Freedom in the world (FIW) by Freedom House for the year 2022, focusing on 19 countries within the G20 group. The reason for selecting this dataset is to evaluate the discriminatory effectiveness of the model criteria proposed among countries, considering the significant variations in values within this specific dataset. To enhance clarity in the research, Table 4 provides explanations for the abbreviations associated with this dataset.

Table 4. Data Set

FIW Criteria	Criteria Abbreviations
Electoral Process	FIW1
Political Pluralism and Participation	FIW2
Functioning of Government	FIW3
Freedom of Expression and Belief	FIW4
Associational and Organizational Rights	FIW5
Rule of Law	FIW6
Personal Autonomy and Individual Rights	FIW7

3. Results (The case study)

3.1. Computational analyses

In the research, the first step of the SRCBECM method involves creating the decision matrix using Equation 4. In the second step of the method, since all criteria are benefit-oriented, the decision matrix values were normalized using Equation 5. In this regard, the decision matrix and the normalized decision matrix values are presented in Table 5.

Table 5. Decision and normalized matrix

Decision Matrix							
Country	**FIW1**	**FIW2**	**FIW3**	**FIW4**	**FIW5**	**FIW6**	**FIW7**
Argentina	11	16	8	15	11	10	14
Australia	12	15	11	15	12	15	15
Brazil	10	13	7	13	9	8	12
Canada	12	16	12	15	12	15	16
China	0	0	1	1	2	2	6
France	12	15	11	14	10	13	14
Germany	12	15	12	14	12	14	15
India	12	12	9	9	7	8	9
Indonesia	11	13	6	9	6	5	8
Italy	12	14	10	15	12	13	14
Japan	12	16	12	15	12	15	14
Mexico	9	13	5	12	7	5	9
Saudi Arabia	11	13	9	14	11	12	13
Russia	0	3	2	2	2	2	5
South Africa	12	13	8	15	12	9	10
South Korea	11	13	9	14	11	12	13
Turkey	5	8	3	5	3	3	5
United Kingdom	12	16	11	14	12	13	15
United States	10	14	9	14	11	11	14
Min.	0	0	1	1	2	2	5
Max.	12	16	12	15	12	15	16
Normalized Decision Matrix							
Country	**FIW1**	**FIW2**	**FIW3**	**FIW4**	**FIW5**	**FIW6**	**FIW7**
Argentina	0,917	1,000	0,636	1,000	0,900	0,615	0,818
Australia	1,000	0,938	0,909	1,000	1,000	1,000	0,909
Brazil	0,833	0,813	0,545	0,857	0,700	0,462	0,636
Canada	1,000	1,000	1,000	1,000	1,000	1,000	1,000
China	0,000	0,000	0,000	0,000	0,000	0,000	0,091
France	1,000	0,938	0,909	0,929	0,800	0,846	0,818
Germany	1,000	0,938	1,000	0,929	1,000	0,923	0,909
India	1,000	0,750	0,727	0,571	0,500	0,462	0,364
Indonesia	0,917	0,813	0,455	0,571	0,400	0,231	0,273
Italy	1,000	0,875	0,818	1,000	1,000	0,846	0,818

Japan	1,000	1,000	1,000	1,000	1,000	1,000	0,818
Mexico	0,750	0,813	0,364	0,786	0,500	0,231	0,364
Saudi Arabia	0,917	0,813	0,727	0,929	0,900	0,769	0,727
Russia	0,000	0,188	0,091	0,071	0,000	0,000	0,000
South Africa	1,000	0,813	0,636	1,000	1,000	0,538	0,455
South Korea	0,917	0,813	0,727	0,929	0,900	0,769	0,727
Turkey	0,417	0,500	0,182	0,286	0,100	0,077	0,000
United Kingdom	1,000	1,000	0,909	0,929	1,000	0,846	0,909
United States	0,833	0,875	0,727	0,929	0,900	0,692	0,818
Mean	0,816	0,783	0,651	0,774	0,716	0,595	0,603
Mean of Mean				0,705			

In the third step of the SRCBECM method, Equation 12 was used to determine the values of V_j for the criteria, Equation 13 for VV, Equation 14 for MDV_j, and Equation 15 for MSV_j. For illustrative purposes, the values of V_j, VV, MDV_j, and MSV_j for FIW1 relative to the mean values are calculated below, and the MDV_j and MSV_j values for the other criteria are presented in Table 6.

Case 1: Calculation of the mean value for each normalized criterion (V_{FIW1})

$$V_{FIW1} = \frac{0{,}917+1+0{,}8833+1+0+1+1+1+0{,}917+1+1+0{,}750+0{,}917+0+1+0{,}917+0{,}417+1+0{,}833}{19} = 0{,}816$$

Case 2: Calculation of the mean value of the normalized criteria relative to the overall mean value (VV)

$$VV = \frac{0{,}816 + 0{,}783 + 0{,}651 + 0{,}774 + 0{,}716 + 0{,}595 + 0{,}603}{7} = 0{,}705$$

Case 3: Measure the deviation value of each criterion from the mean value (MDV_{FIW1})

For each criterion, the divergence value:

$$MDV_{FIW1} = |0{,}816 - 0{,}705| = 0{,}111$$

Case 4: Measure the inverse of the deviation value of each criterion from the mean value (MSV_{FIW1})

For each criterion, the similarity value

$$MSV_{FIW1} = \frac{1}{0{,}111} = 9{,}026$$

Table 6. Separation (Deviation (MDV_j)) and Similarity (MSV_j) Values of Criteria

Criteria	FIW1	FIW2	FIW3	FIW4	FIW5	FIW6	FIW7
MDV_j	0,111	0,078	0,054	0,069	0,011	0,110	0,102
MSV_j	9,026	12,838	18,422	14,402	92,683	9,103	9,792

In the fourth step of the method, the rho correlation coefficients between the criteria are first calculated using Equations 1, 2, and 3, and the correlation matrix is created. The calculated rho correlation values between the criteria are shown in Table 7.

Table 7. rho correlation matrix

Criteria	FIW1	FIW2	FIW3	FIW4	FIW5	FIW6	FIW7
FIW1	1,000	0,952	0,883	0,912	0,872	0,801	0,780
FIW2	0,952	1,000	-0,227	-0,244	-0,235	-0,183	-0,137
FIW3	0,883	-0,227	1,000	-0,389	-0,421	-0,388	-0,337
FIW4	0,912	-0,244	-0,389	1,000	-0,306	-0,215	-0,199
FIW5	0,872	-0,235	-0,421	-0,306	1,000	-0,296	-0,279
FIW6	0,801	-0,183	-0,388	-0,215	-0,296	1,000	-0,360
FIW7	0,780	-0,137	-0,337	-0,199	-0,279	-0,360	1,000
Mean	0,886	0,132	0,017	0,080	0,048	0,051	0,067

In the fifth step of the method, the separation (CDV_j) values according to rho correlation analysis were calculated using Equation 16, and the similarity (CSV_j) values were calculated using Equation 17 for the criteria. The corresponding (CDV_j) and (CSV_j) values are presented in Table 8.

Table 8. The separation (CDV_j) and similarity (CSV_j) values of the criteria based on the rho

(CDV_j)	FIW1	FIW2	FIW3	FIW4	FIW5	FIW6	FIW7
FIW1	0,000	0,048	0,117	0,088	0,128	0,199	0,220
FIW2	0,048	0,000	1,227	1,244	1,235	1,183	1,137
FIW3	0,117	1,227	0,000	1,389	1,421	1,388	1,337
FIW4	0,088	1,244	1,389	0,000	1,306	1,215	1,199
FIW5	0,128	1,235	1,421	1,306	0,000	1,296	1,279
FIW6	0,199	1,183	1,388	1,215	1,296	0,000	1,360
FIW7	0,220	1,137	1,337	1,199	1,279	1,360	0,000
Sum (CDV_j)	**0,800**	**6,075**	**6,878**	**6,441**	**6,665**	**6,641**	**6,533**
(CSV_j)	**FIW1**	**FIW2**	**FIW3**	**FIW4**	**FIW5**	**FIW6**	**FIW7**
FIW1	2,000	1,952	1,883	1,912	1,872	1,801	1,780
FIW2	1,952	2,000	0,773	0,756	0,765	0,817	0,863
FIW3	1,883	0,773	2,000	0,611	0,579	0,612	0,663
FIW4	1,912	0,756	0,611	2,000	0,694	0,785	0,801
FIW5	1,872	0,765	0,579	0,694	2,000	0,704	0,721
FIW6	1,801	0,817	0,612	0,785	0,704	2,000	0,640
FIW7	1,780	0,863	0,663	0,801	0,721	0,640	2,000
Sum (CSV_j)	**13,200**	**7,925**	**7,122**	**7,559**	**7,335**	**7,359**	**7,467**

For illustrative purposes, the discrimination CDV_j and similarity CSV_j values for FIW1 were calculated based on the rho correlation values. The calculated values for CDV_j and CSV_j for FIW1, as well as the corresponding situations for other criteria based on rho correlation coefficient values, are presented in Table 8.

Case 1: Divergence of criteria according to rho correlation analysis (CDV_{FIW1})

$CDV_{FIW1} = 0 + 0{,}048 + 0{,}117 + 0{,}088 + 0{,}128 + 0{,}199 + 0{,}220 = 0{,}800$

Case 2**:** Identification of the inverse of the divergence value according to rho correlation analysis (similarity) (CSV_{FIW1})

$CSV_{FIW1} = 2 + 1{,}952 + 1{,}883 + 1{,}912 + 1{,}872 + 1{,}801 + 1{,}780 = 13{,}200$

In the 6th step of the method, the separation values (SE_j) and similarity values SI_j for the criteria are calculated using Equations 17 and 18, respectively. The calculated values for SE_j and SI_j are presented in Table 9.

Table 9. The separation (SE_j) and similarity (SI_j) values of the criteria

Criteria	FIW1	FIW2	FIW3	FIW4	FIW5	FIW6	FIW7	Sum
$(MDV_j.CDV_j)$	0,089	0,055	0,031	0,038	0,005	0,073	0,070	0,361
(SE_j)	0,246	0,153	0,086	0,106	0,015	0,202	0,194	
Criteria	**FIW1**	**FIW2**	**FIW3**	**FIW4**	**FIW5**	**FIW6**	**FIW7**	**Sum**
$(MSV_j.CSV_j)$	34,121	48,601	70,032	54,808	352,760	34,189	37,014	631,525
(SI_j)	0,054	0,077	0,111	0,087	0,559	0,054	0,059	

As an illustrative example, the discrimination values (SE_j) and similarity values (SI_j) for FIW1 have been calculated below.

Case 1: Calculation of divergence values for criteria (SE_{FIW1})

$$SE_{FIW1} = \frac{0{,}111.\,0{,}800}{0{,}361} = 0{,}246$$

Case 2: Calculation of similarity values for criteria(SI_{FIW1})

$$SI_{FIV1} = \frac{9{,}026.\,13{,}200}{631{,}525} = 0{,}054$$

In the final step of the method, the weights of the criteria (w_j) are calculated by evaluating the discrimination (SE_j) and similarity (SI_j) conditions of the criteria with equal importance, as expressed in Equations 19 and 20. The resulting weight values (w_J) for the criteria are presented in Table 10.

Table 10. Criteria weights

Criteria	EW_J	w	Rank
FIW1	0,150	0,197	2
FIW2	0,066	0,087	4
FIW3	0,071	0,093	3
FIW4	0,062	0,082	7
FIW5	0,282	0,372	1
FIW6	0,063	0,084	6
FIW7	0,064	0,085	5
Sum	0,759		

Upon examining Table 10, the ranking of criteria weight values is as follows: FIW5, FIW1, FIW3, FIW2, FIW7, FIW6, and FIW4. Furthermore, for illustrative purposes, the weight values of the FIW1 criterion have been calculated and are presented below.

Case 1: Taking into account the equal-weight divergence and similarity situations of criteria (EW_{FIW1})

$$EW_{FIW1} = \frac{0{,}246 + 0{,}054}{2} = 0{,}150$$

Case 2: Calculation of weight (w_{FIW1})

$$w_{FIW1} = \frac{0{,}150}{0{,}759} = 0{,}197$$

3.2. Sensitivity analyses

In the scope of this investigation, we performed an evaluation of the SRCBECM approach to scrutinize its methodological sensitivity. Sensitivity analysis, as applied in the context of MCDM, involves the utilization of diverse criteria weighting methods on the same dataset, enabling a comparison of resulting values and rankings. To ascertain the method's sensitivity in calculating weight coefficients, it is expected that the rankings of criteria weights determined using the chosen method for sensitivity analysis will deviate from the weight coefficient rankings obtained through alternative methods [63].

Following this methodology, we employed established objective weighting techniques to compute and organize the weighting coefficients linked to the components of the FIW. These techniques, widely utilized in scholarly literature, encompass ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW. The corresponding numerical outcomes are meticulously presented in Table 11.

Table 11. Findings derived from different methodologies for computing objective weighting coefficients

Criteria	CRITIC	Ranking	SD	Ranking	SVP	Ranking
FIW1	0,024	7	0,145	3	0,132	4
FIW2	0,153	6	0,131	6	0,170	3
FIW3	0,197	4	0,153	2	0,103	7
FIW4	0,193	5	0,142	5	0,183	1
FIW5	0,221	1	0,145	4	0,115	6
FIW6	0,212	2	0,167	1	0,180	2
FIW7	0,199	3	0,118	7	0,117	5
Criteria	**LOPCOW**	**Ranking**	**MEREC**	**Ranking**	**ENTROPY**	**Ranking**
FIW1	0,156	2	0,110	6	0,157	5
FIW2	0,167	1	0,126	4	0,131	6
FIW3	0,140	4	0,097	7	0,178	2
FIW4	0,151	3	0,121	5	0,167	3
FIW5	0,135	5	0,175	3	0,159	4
FIW6	0,123	7	0,177	2	0,209	1

FIW7	0,128	6	0,193	1	0,089	7

An analysis of Table 11 indicates notable disparities in the rankings of FIW weight values when employing the SRCBECM method compared to rankings obtained through other methods for determining FIW criterion weights. This outcome implies that the proposed method exhibits sensitivity to the inherent relationships among the criteria.

3.3. Comparative analyses

The comparative analysis explores both the congruities and divergences between the proposed method and other techniques for calculating objective weight coefficients. The proposed method is expected to possess credibility, reliability, and consistency in alignment with other methodologies, while concurrently exhibiting a positive and significant correlation with various weight coefficient methods [20]. To substantiate this, Figures 1 and 2 provide a visual examination of the weight coefficients determined using the weight measurement methods outlined in Table 12.

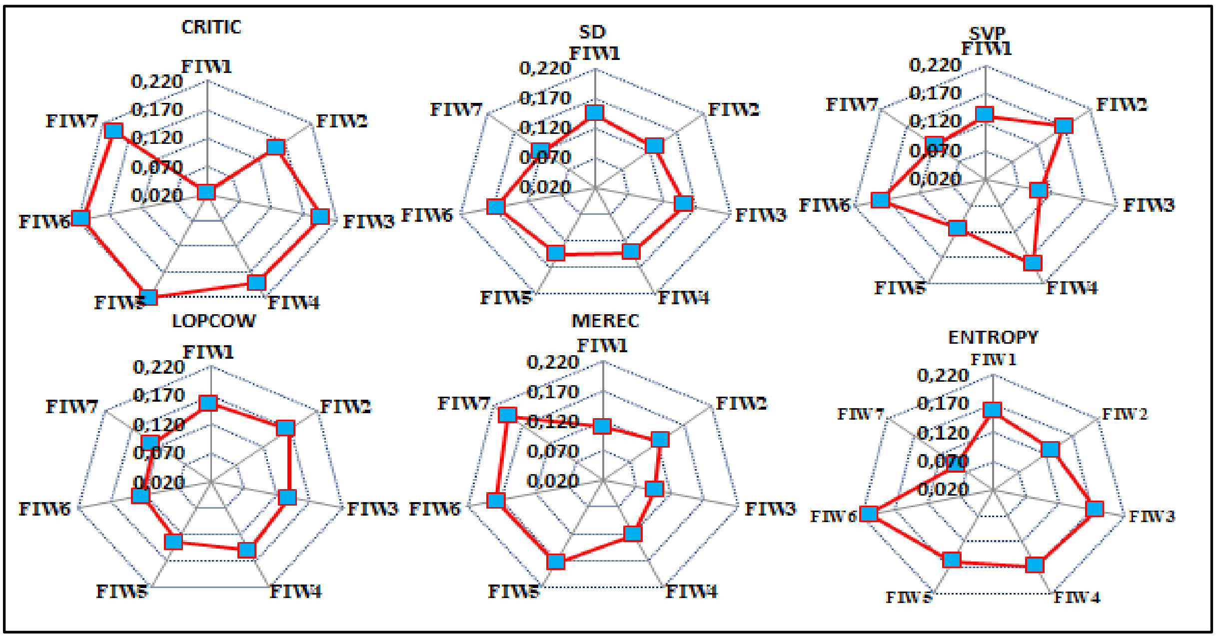

Figure 1. Positions of the ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC methods

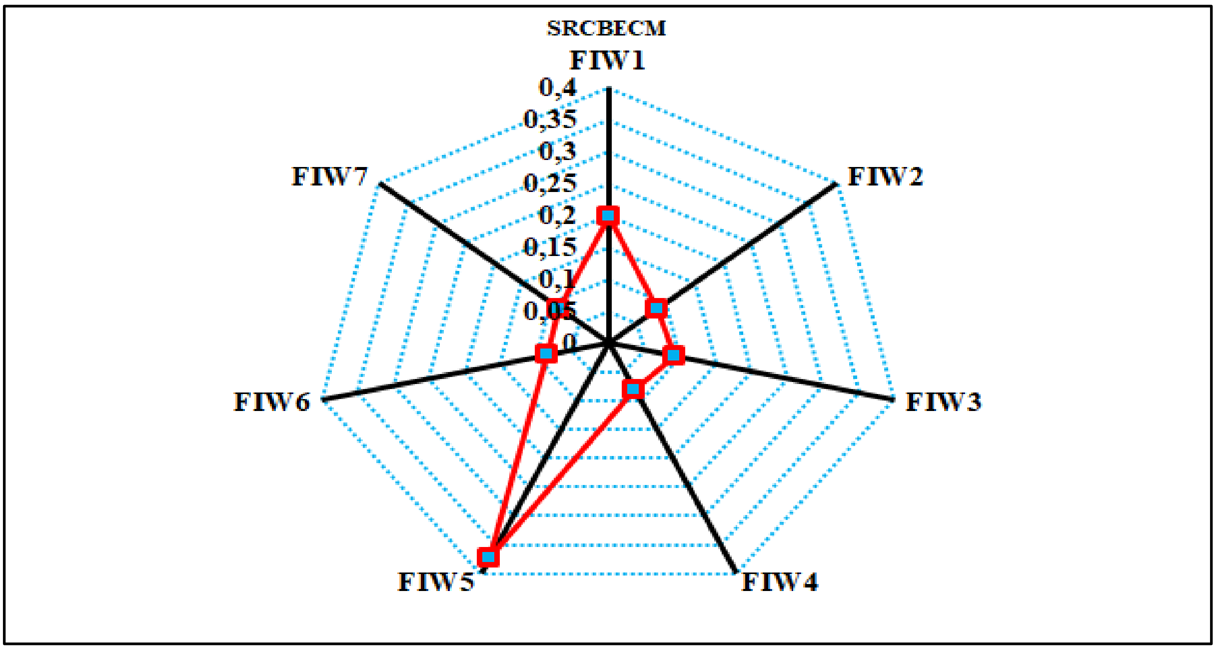

Figure 2. Positions of the SRCBECM method

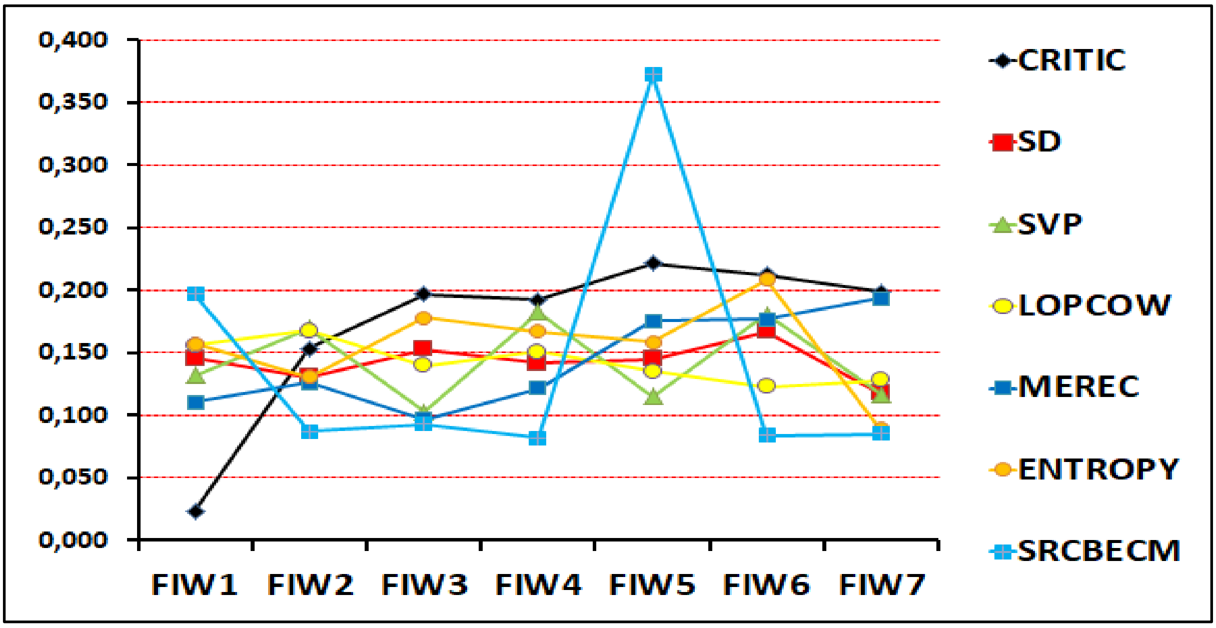

Figure 3. Positions of the Methods 1

When Figure 3 is examined, it is determined that the characteristic properties of FIW1 and FIW5 criteria are reflected more in the SRCBECM method than in other methods. In particular, these criteria are observed to reflect both the separation and similarity of criteria, which constitute the logic of the proposed method, simultaneously. This shows that it explains better which criteria are more important than other methods. In addition, according to Figure 3, it is determined that the differences between the positions of the criterion values of the SRCBECM method are different from other methods. Thus, it is evaluated that the SRCBECM method does not have a positive correlation with other methods. Although it is stated in the MCDM literature that the high level of positive relationship between any objective weighting method and other methods indicates that the credible and reliable level of the proposed method is high, it is the desired result that the SRCBECM method has a low positive and negative correlation with other methods, since the criterion weighting logic in the method (SRCBECM) takes into account both separation and similarity levels (both contrast conditions), unlike other methods. Therefore, in this case, the low positive and negative correlation of the SRCBECM method with other methods shows that the proposed method is credible and reliable. The rho correlation coefficient values between the methods are explained in Table 13, since the data of the methods do not show normal distribution.

Table 13. rho correlation values of the SRCBECM method with other methods

Criteria	CRITIC	SD	SVP	LOPCOW	MEREC	ENTROPY
SRCBECM	-0,047	0,089	-0,434	-0,071	0,211	0,044

When Table 13 is examined, it is observed that none of the relationships between the SRCBECM method and other objective criterion weighting methods are significant. Based on these quantitative results, it is concluded that the SRCBECM method is different from other methods because the criterion weights are calculated based on both separation and similarity levels (both contrast conditions), and accordingly, the proposed method is reliable and credible.

3.4. Simulation Analyses

To assess the robustness of the proposed method, a simulation analysis is undertaken, involving various scenarios created by assigning different values to decision matrices. As the number of scenarios increases, the proposed method is expected to diverge from other methodologies, showcasing its stability. In the subsequent step, the average variance of criterion weights determined by the proposed method across the scenarios should exceed that of one or more alternative objective weighting methods. This signifies the superior discriminative capability of the proposed method in distinguishing between criterion weights. Finally, it validates the consistency of criterion weight variances across methods within the scenarios [20].

To evaluate the coherence of the SRCBECM method with alternative objective weighting methods, a simulation analysis was executed. The simulation involved the generation of 20 distinct scenarios, categorized into 2 groups, each characterized by a unique set of decision matrix values. For each scenario, correlation coefficients between the SDBHA method and other methodologies were computed. The results of the simulation analysis are presented in Tables 14 and 15, and visualized in Figures 4 and 5.

Table 14. *rho* correlation coefficients of the SDBHA method with other methodologies across the range of scenarios-A (First Category)

Group	Scenarios	ENTROPY	CRITIC	SD	SVP	LOPCOW	MEREC
First group	**1. Scenario**	0,048	-0,065	0,095	-0,450	-0,065	0,250
	2. Scenario	0,043	-0,055	0,100	-0,400	-0,080	0,270
	3. Scenario	0,045	-0,070	0,090	-0,460	-0,075	0,200
Group	**Scenarios**	**ENTROPY**	**CRITIC**	**SD**	**SVP**	**LOPCOW**	**MEREC**
Second group	**4. Scenario**	0,044	-0,066	0,075	-0,500*	-0,065	0,240
	5. Scenario	0,040	-0,060	0,080	-0,480	-0,085	0,190
	6. Scenario	0,042	-0,070	0,065	-0,490	-0,090	0,210
	7. Scenario	0,037	-0,075	0,070	-0,510*	-0,080	0,195
	8. Scenario	0,039	-0,065	0,060	-0,520*	-0,085	0,200
	9. Scenario	0,033	-0,080	0,070	-0,500*	-0,075	0,180
	10. Scenario	0,028	-0,077	0,050	-0,480	-0,090	0,185
Mean		0,040	-0,068	0,076	- 0,479	-0,079	0,212

p*<.05

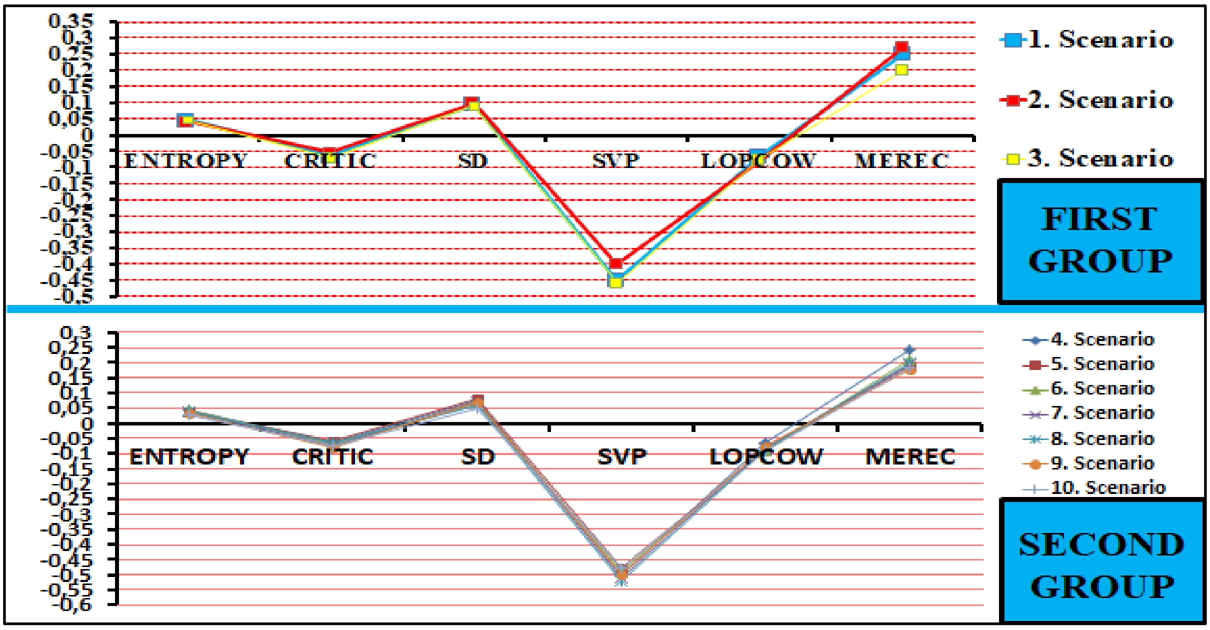

Figure 4. Positions of the Methods 2-A (First Category)

Table 15. *rho* correlation coefficients of the SDBHA method with other methodologies across the range of scenarios-B (Second Category)

Group	Scenarios	ENTROPY	CRITIC	SD	SVP	LOPCOW	MEREC
First group	**1. Scenario**	0,055	-0,078	0,122	-0,5	-0,074	0,324
	2. Scenario	0,059	-0,082	0,132	-0,55	-0,098	0,327
	3. Scenario	0,056	-0,08	0,124	-0,495	-0,087	0,312
Group	**Scenarios**	**ENTROPY**	**CRITIC**	**SD**	**SVP**	**LOPCOW**	**MEREC**
Second group	**4. Scenario**	0,058	-0,077	0,114	-0,455	-0,085	0,308

5. Scenario	0,055	-0,075	0,109	-0,475	-0,077	0,301
6. Scenario	0,048	-0,073	0,102	-0,484	-0,089	0,294
7. Scenario	0,041	-0,067	0,09	-0,501	-0,082	0,299
8. Scenario	0,033	-0,062	0,07	-0,495	-0,078	0,267
9. Scenario	0,031	-0,069	0,06	-0,425	-0,071	0,259
10. Scenario	0,003	-0,066	0,06	-0,412	-0,066	0,239
Mean	0,0440	-0,0730	0,0983	-0,4792	-0,0807	0,293

p<.05*

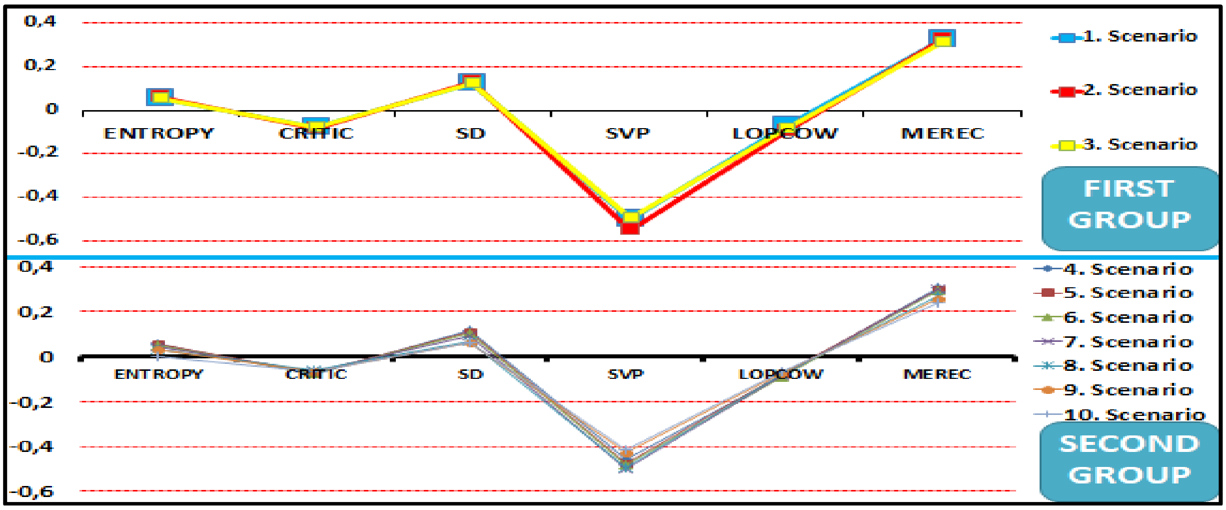

Figure 5. Positions of the Methods 2-B (Second Category)

A simultaneous examination of Tables 14 and 15, and Figures 4 and 5 reveals that the 10 scenarios, categorized into 2 groups, can be further divided into two subgroups. The initial group comprises the first three scenarios, while the subsequent group includes the last seven. When Tables 14 and 15, and Figures 4 and 5 are analyzed together, it is evident that the positive correlation values of the SRCBECM method with the ENTROPY, SD, and MEREC methods decrease as the number of scenarios increases, whereas the correlation values with the CRITIC, SVP, and LOPCOW methods increase negatively. In summary, the SRCBECM method exhibits greater divergence from the other methods as the number of scenarios grows. Consequently, it can be inferred that the distinctive characteristics of the SRCBECM method become more pronounced with an increasing number of scenarios. Additionally, Figures 6 and 7 illustrate the spatial distribution of the relationships between the SRCBECM method and other methodologies within the specified groups across both categories (First Category and Second Category).

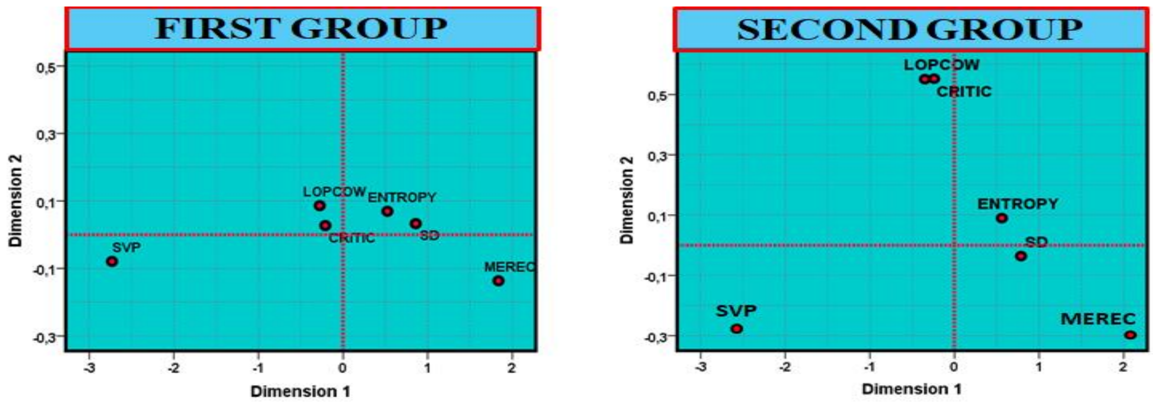

Figure 6. Depicts the discriminant analysis illustrating the rho correlation between the SRCBECM method and alternative methodologies across various scenarios-A (First Category)

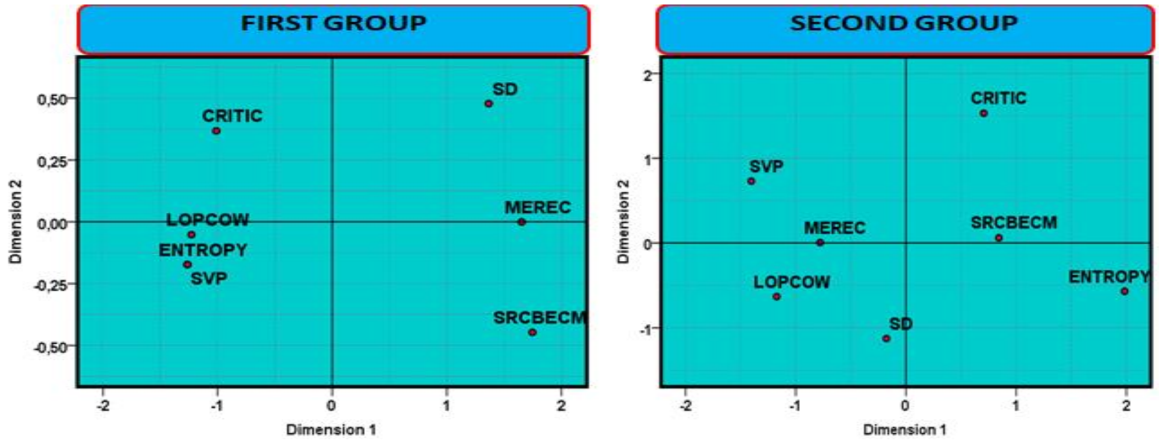

Figure 7. Depicts the discriminant analysis illustrating the rho correlation between the SRCBECM method and alternative methodologies across various scenarios-B (Second Category)

When Figure 6 and Figıre 7 are examined, in scope of first and second categories it is observed that the distribution of the relationships of the SRCBECM method with other objective criterion weighting methods in the 7 scenarios in the 2nd group is more dispersed than the distribution of the relationships of the SRCBECM method with other objective criterion weighting methods in the 3 scenarios in the 1st group. Therefore, it is observed that the rho correlation values of the SRCBECM method with other objective criterion weighting methods change as the number of scenarios increases.

The separation power of any objective criterion weighting method to its own criteria depends on the high variance value of the method [20]. Throughout the simulation analysis, variance values for the methods were computed across diverse scenarios for two categories, and the corresponding values are summarized in Tables 16 and 17.

Table 16. Variance in method outcomes across different scenarios-A (First category)

Scenario	SRCBECM	CRITIC	SD	SVP	LOPCOW	MEREC	ENTROPY
1. Sce.	0,0125	0,0052	0,0002	0,0011	0,0003	0,0014	0,0014
2. Sce.	0,0125	0,0048	0,0001	0,0014	0,0004	0,0019	0,0017
3. Sce.	0,0138	0,0046	0,0003	0,0013	0,0003	0,0027	0,0013
4. Sce.	0,0091	0,0025	0,0003	0,0015	0,0006	0,0011	0,0019
5. Sce.	0,0145	0,0033	0,0003	0,0009	0,0005	0,0018	0,0021
6. Sce.	0,0084	0,0018	0,0002	0,0015	0,0007	0,0028	0,0015
7. Sce.	0,0132	0,0032	0,0004	0,0014	0,0004	0,0026	0,0013
8. Sce.	0,0117	0,0024	0,0005	0,0015	0,0008	0,0029	0,0012
9. Sce.	0,0113	0,0063	0,0003	0,0013	0,0006	0,0022	0,0012
10. Sce.	0,0124	0,0070	0,0002	0,0012	0,0003	0,0016	0,0016
Mean	0,0119	0,0041	0,0003	0,0013	0,0005	0,0021	0,0015

Table 17. Variance in method outcomes across different scenarios-B (Second category)

Scenario	SRCBECM	CRITIC	SD	SVP	LOPCOW	MEREC	ENTROPY
1. Sce.	0,0128	0,0058	0,0003	0,0022	0,0007	0,0024	0,0028
2. Sce.	0,013	0,0051	0,0002	0,0019	0,0006	0,0021	0,0025
3. Sce.	0,0141	0,0049	0,0004	0,0015	0,0005	0,0039	0,0021
4. Sce.	0,0101	0,0028	0,0004	0,0012	0,0007	0,0017	0,0021
5. Sce.	0,0156	0,0036	0,0005	0,001	0,0007	0,0026	0,0023
6. Sce.	0,0099	0,0021	0,0003	0,0018	0,0009	0,0031	0,0017
7. Sce.	0,0149	0,0041	0,0004	0,0016	0,0006	0,0032	0,0019
8. Sce.	0,0131	0,0028	0,0007	0,0017	0,0011	0,0035	0,0016
9. Sce.	0,0128	0,0071	0,0004	0,0017	0,0009	0,0029	0,0015

10. Sce.	0,0131	0,0082	0,0003	0,0014	0,0006	0,0023	0,0018
Mean	0,01294	0,00465	0,00039	0,0016	0,00073	0,00277	0,00203

Based on the data presented in Tables 16 and 17 for both categories, it is evident that the SRCBECM method consistently exhibits higher average variance values across scenarios compared to the other methods. Consequently, it can be inferred that the SRCBECM method demonstrates a superior ability to discriminate criterion weights, as evidenced by its higher average variance value relative to the other methods.

To meticulously examine the homogeneity of variances within the criterion weights integral to the SDBHA method, an ADM (Analysis of Means for Variances, incorporating the Levene modification) was meticulously executed across a diverse array of scenarios. This analytical approach proffers a cogent visual representation of variance uniformity. The graphical manifestation is composed of three cardinal elements: the global average ADM, which serves as the pivotal axis, bordered by the upper and lower decision limits (UDL and LDL). In the event that the standard deviation of an individual cluster transcends these decision boundaries, it intimates a salient deviation from the global average ADM, thereby portending the existence of variance heterogeneity. Antithetically, if the standard deviations of all clusters are ensconced within the confines of the LDL and UDL, this buttresses the notion of variance homogeneity [20]. A clear visual explanation of the ADM analysis is provided in Figures 8 and 9, encompassing both categories (the first category and the second category).

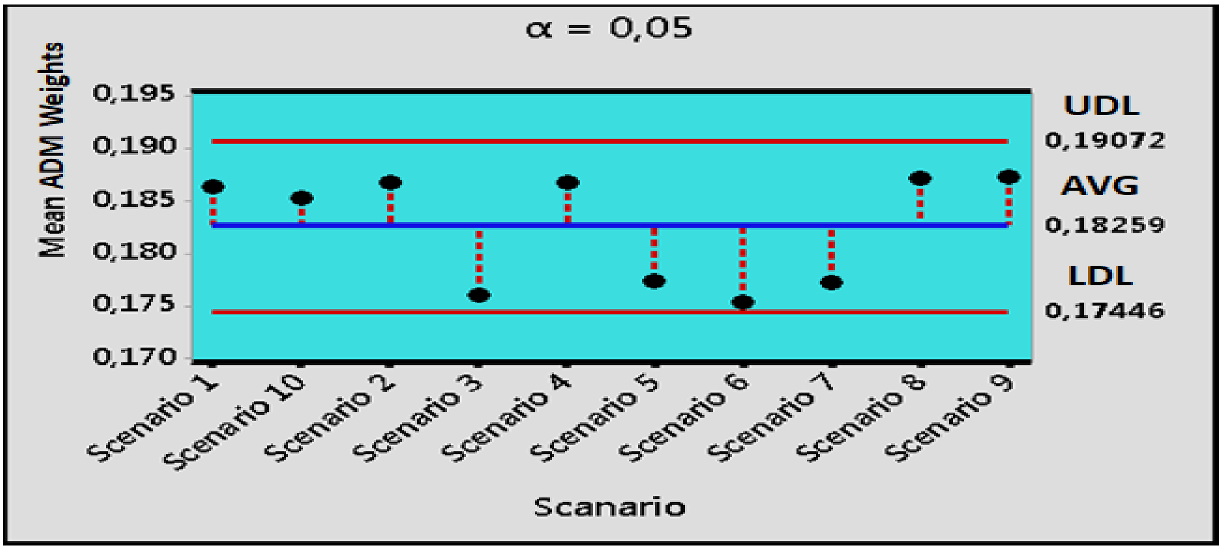

Figure 8. ADM visual-A (First Category)

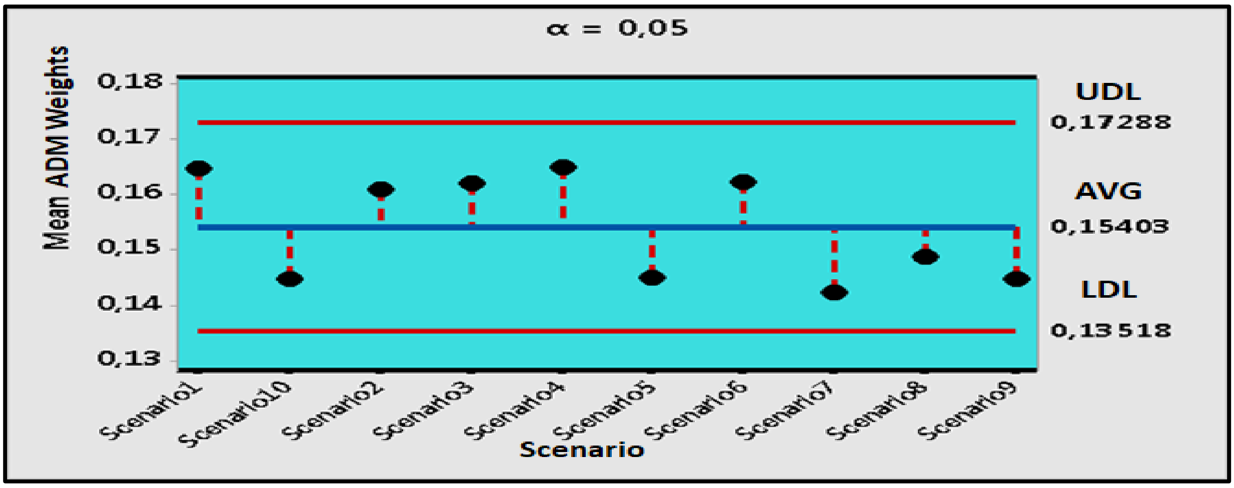

Figure 9. ADM visual-B (Second Category)

Observations from Figures 8 and 9 reveal that for both categories (the first category and the second category), the ADM values for each scenario fall within a range bounded by the UDL and LDL values. This positioning suggests uniformity in the variance of the weights determined for each scenario. This finding is corroborated by the Levene Test, with the essential statistics summarized in Tables 18 and 19 for each category.

Table 18. Levene test-A (First Category)

Levene Statistic	df1	df2	*p*
0,240	2	10	0,130

p<.05**

Table 19. Levene test-B (Second Category)

Levene Statistic	df1	df2	*p*
0,298	2	10	0,163

p<.05**

Statistical evidence from Tables 18 and 19 indicates that the p-values for both categories exceed the commonly accepted significance threshold of 0.05. This finding signifies that the variances observed in criterion weights across different scenarios exhibit a remarkable degree of homogeneity. In essence, the simulation analysis produces results that affirm the inherent robustness and consistent stability of the SDBHA method.

4. Conclusion

Navigating intricate problems often necessitates a MCDM approach, where different, and often conflicting, factors come into play. Weighing these criteria fairly is paramount, as their relative importance significantly influences the outcome. Recognizing this, researchers have devised various methods for calculating weight coefficients, enriching the MCDM landscape. This study introduces Spearman Rank Correlation-based Expanded CRITIC (SRCBECM) technique.

In the study, the weight coefficients of the FIW criteria were first measured according to the SRCBECM method and the criterion weights were ranked as FIW5, FIW1, FIW3, FIW2, FIW7, FIW6, and FIW4. In the second stage of the study, the weights of the criteria were also calculated using the CRITIC, ENTROPY, SD, SVP, MEREC, and LOPCOW methods as part of the sensitivity analysis and the criteria were ranked. According to the findings, the FIW ranking determined within the scope of the SRCBECM method was completely different from the FIW criterion rankings within the scope of other objective weighting methods. Based on this result, the SRCBECM method was considered to be sensitive.

In the third stage, a comparative analysis was conducted between the results obtained by the SRCBECM method and the results within the scope of other objective weighting methods. When the findings were examined, it was determined that the characteristics of the criteria identified by the SRCBECM method were more pronounced than the other methods. In addition, the rho correlation coefficient was calculated between the FIW weights within the scope of the SRCBECM method and the FIW weights calculated by other objective criterion weighting methods. According to the findings, no significant positive correlations were observed between the FIW weights obtained by the SRCBECM method and the FIW weights calculated by other objective weighting methods. Although, in the literature, positive and significant relationships with other objective weighting methods are sought for the proposed criterion weighting method to be reliable and credible, it is thought that the SRCBECM method is reliable and credible in that it considers both separation and similarity conditions, which is different from other methods.

Fourthly, two categories were created with different values assigned to the FIW values of countries, providing 10 scenarios (data sets) for each category: 3 scenarios in the first group and 7 in the second group. Correlations between the SRCBECM method and other objective criterion weighting methods were evaluated based on these scenarios. The findings revealed that as the number of scenarios increased, the SRCBECM method diverged from the other methods. Additionally, the average variance values of the methods were calculated according to these scenarios. The results indicate that the SRCBECM method has a higher separation power than other methods, as its average variance values exceed those of the other methods. Furthermore, the homogeneity test of the SRCBECM method (ADM) was applied across the 10 scenarios in both categories. According to the findings, it is concluded that the SRCBECM method exhibits homogeneous variances, thus demonstrating robustness and stability.

The SRCBECM method offers several practical and theoretical benefits based on its unique features. In practical terms, its insensitivity to 0 and negative values enhances its reliability in real-world applications where such values may arise. This avoids the calculation issues seen in methods like ENTROPY or MEREC, resulting in smoother and more reliable computations. Furthermore, the method's flexibility in not assuming a normal distribution of data makes it applicable to a wider range of datasets, particularly in cases where non-parametric relationships are predominant. This allows for better performance across diverse data without the need for complex transformations. Another practical advantage is that the SRCBECM method balances the consideration of both divergence and similarity among criteria, leading to a more holistic assessment. This results in more accurate and meaningful weight assignments in decision-making processes. Additionally, the method emphasizes the characteristic differences between criteria, which helps in distinguishing the most important factors in complex decision-making environments.

5. Discussion

From a theoretical perspective, the SRCBECM method provides a robust alternative to parametric correlation measures by utilizing the rho correlation coefficient. This is especially advantageous when the assumption of normal distribution is not met, making the method more adaptable to a variety of data types. Its comprehensive approach to weighting logic, which includes both divergence and similarity among criteria, makes it more nuanced and reflective of complex relationships between variables compared to methods like ENTROPY and CRITIC, which focus solely on divergence. Finally, the SRCBECM method's ability to generate more distinctive weights based on the characteristic differences between criteria enhances its discriminative power, offering a more precise and granular insight into the decision-making process.

This method is considered an important tool for decision-makers in overcoming various challenges encountered in the criterion weighting process. In real-world scenarios, the presence of zero or negative values during the evaluation of criteria is a common issue, which can lead to invalid calculations in some methods. However, the SRCBECM method is insensitive to zero and negative values, helping to overcome such difficulties. Additionally, since this method does not require the assumption of a normal distribution, it offers a wide range of applicability across different datasets, reducing the complexity of the data. This provides decision-makers with a flexible and reliable solution for the various situations they may face. Furthermore, by evaluating both the similarities and differences among criteria in a balanced manner, it enables the determination of more accurate and meaningful weights. Therefore, the SRCBECM method can contribute to more effective outcomes in complex decision-making processes.

It is considered that the criterion weighting logic of the ENTROPY, SD, SVP, LOPCOW, and MEREC methods, which are other objective weighting methods, can be expanded and improved by considering the similarity logic of criteria in addition to the opposition logic, as in the DEMATEL method, in future research. It is considered that the criterion weighting logic of the ENTROPY, SD, SVP, LOPCOW, and MEREC methods, which are other objective weighting methods, can be expanded and improved by considering the similarity logic of criteria in addition to the opposition logic, as in the DEMATEL method, in future research.

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