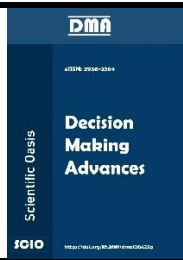




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MAXC2: An Enhanced Iteration of the MAXC Method for Criterion Weight Determination

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ABSTRACT

Determining weights for criteria is a crucial task in multi-criteria decision-making (MCDM) problems. MAXC (MAXimum of Criterion) is an objective weighting method that calculates criterion weights based on the definition of maximum criterion values from the initial matrix and is known as a simple method in the calculation process. However, the data normalization method used in this method cannot be applied if the total value of a certain criterion across all alternatives equals zero. This study improves the MAXC method by creating a new version named MAXC2. MAXC2 improves upon MAXC by changing the normalization formula used in the MAXC method. When both methods are applicable, the maximum difference in the weights calculated by these two methods is only about 4.76%. When only MAXC2 can be used, the calculation of criterion weights using the MAXC2 method ensures high stability in the ranking of alternatives, with the minimum average Spearman correlation coefficient between ranking methods being 0.8667. MAXC2 overcomes the limitations of the MAXC method and can be considered a highly reliable method.

1. Introduction

Ranking alternatives while simultaneously considering multiple criteria is commonly referred to as an MCDM activity, a task occurring across various fields ranging from the stock market [1], business [2], food [3], and many more. In addressing MCDM problems, the determination of criterion weights exerts a profound influence on the ultimate outcomes [4-6]. The process of assigning these weights can be executed through objective methods, subjective approaches, or hybrid frameworks that integrate both perspectives [7, 8]. Among these, objective weighting techniques are more prevalent in existing literature compared to their subjective counterparts [9]. These objective methods are widely adopted because they function independently of the user's specialized knowledge, practical experience, or psychological biases, thereby ensuring impartial results [10]. Rather than analyzing

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the broad characteristics of various objective weighting models, this research concentrates specifically on a recently developed technique known as the MAXC (MAXimum of Criterion) method [11].

Introduced in 2024, the MAXC method derives criterion weights based on the definition of maximum criterion values within the initial decision matrix. Despite its recent inception, this approach has already been utilized by the scientific community to weight criteria across diverse domains. Notable applications include selecting eco-friendly suppliers [12, 13], evaluating sustainable wall cladding materials [14], assessing the financial management performance of banks [15], analyzing the nexus between renewable energy, economic growth, and emissions in Turkey [16], benchmarking G7 nations' efficiency regarding patent applications [17], and evaluating Foreign Direct Investment (FDI) investors in Turkey [18], among others.

Nevertheless, the data normalization technique inherent in the MAXC method follows a sum-based linear normalization approach. This specific mechanism becomes mathematically inapplicable if the aggregate value of a particular criterion across all alternatives is zero. This limitation will be further elucidated in Section 3 during the discussion of the weighting process. To circumvent this constraint, the present study proposes a modified iteration of the MAXC method, designated as MAXC2. The development of MAXC2 builds upon the fundamental logic of the original MAXC while fundamentally transforming the underlying data normalization technique. The primary contribution of this research is the development of the MAXC2 method, which thoroughly resolves the mathematical limitations of the original MAXC method while maintaining superior computational efficiency. This transforms MAXC2 into a criterion weighting approach characterized by high stability and a broader scope of application, even in scenarios where the traditional MAXC method fails to function. The effectiveness of the proposed method is subsequently validated through three distinct practical examples, including wall cladding material selection, deep learning software framework evaluation, and a hypothetical case used to test stability.

The remainder of this paper is structured as follows: Section 2 provides a concise overview of recent refinements in objective weighting methods within the literature. Section 3 introduces the formal methodology for the proposed MAXC2 method. Section 4 presents several illustrative examples to evaluate the efficacy of the new approach. Lastly, Section 5 concludes the paper and offers suggestions for future research directions.

2. Literature Review

As mentioned in the introductory section, employing objective weighting methods to determine the weights of criteria allows for weight values to be calculated independently of the user's knowledge, experience, or subjective opinions. Consequently, to further enhance the effectiveness of objective weighting methods, several distinct approaches have been implemented. In [19], the Mahalanobis distance was integrated with the Entropy method to address inter-criteria dependencies, thereby enhancing the performance of the traditional Entropy approach. Additionally, the Entropy method was modified through integration with the subjective CILOS method to solve problems involving fuzzy sets [20]. In [21], the researchers also refined the conventional Entropy technique by employing a cumulative entropy function predicated on parameters such as the sample mean, variance, and order statistics. This study was implemented to calculate criteria weights within the context of identifying successful bidders. This methodology establishes an objective weighting framework, resolving the deficiencies of the Shannon Entropy method, which inherently fails to comprehensively account for criteria values. Empirical findings indicate that the cumulative Entropy approach enables a more realistic determination of criteria weights relative to actual contractor competency, thereby facilitating a more precise selection of the winning bidder compared to

traditional methods. CRITIC was further enhanced by incorporating distance correlation to account for criterion relationships, resulting in more valid weights and rankings [22]. In [23], a multi-objective non-linear programming model was utilized to synthesize the CRITIC, BWM, and LINMAP methods, creating a novel weighting approach termed OSWMI to mitigate inconsistencies in multi-criteria decision-making. In [24], the WASPAS-IC weighting method was introduced as an evolution of the WASPAS method by accounting for intercriteria correlation. This research also demonstrated that WASPAS-IC serves to enhance both precision and objectivity in the determination of criteria weights.

The aforementioned studies indicate that there has been highly specialized research dedicated to refining the algorithms of objective weighting methods to produce versions of superior quality compared to their original counterparts. Nevertheless, it must be acknowledged that such approaches are mathematically complex and often extend the computational procedure.

Another strategy, regarded as simpler for refining objective weighting methods, involves replacing the inherent data normalization technique with a new normalization approach. The CRITIC weighting method was modified by altering its data normalization process. Instead of employing linear normalization which causes each data column to exhibit boundary values of 0 and 1, the revised version of CRITIC performs percentage-based normalization by dividing values by the maximum level within the column. This tactic helps reduce fundamental standard deviation and shifts data distribution closer to the ideal value, thereby resolving the traditional CRITIC method's drawback of assigning irrationally low weights to important criteria [25]. In [26], it was reported that SITDE is an objective weighting method where the built-in data normalization technique is Linear. This normalization method becomes unusable if at least one value among the benefit-type criteria equals zero or if the maximum value of a cost-type criterion is zero. An investigation into selecting alternative data normalization methods to replace the Linear style for integration with SITDE was conducted. The results indicated that three normalization methods Enhanced Accuracy, Vector, and Weitendorf were all determined to be suitable for combination with SITDE, effectively overcoming the constraints of the Linear normalization method.

It is observed that modifying the original data normalization technique within a weighting method is a mathematically straightforward approach. However, a normalization method deemed suitable for a weighting technique is not universally applicable in all cases; for instance, in assessing the sustainable development of EU nations within the educational sector, it was shown that vector normalization and sum-based normalization do not alter criteria weights when calculated using the Entropy method [27]. Conversely, other situations have confirmed that the data normalization method, when integrated with the Entropy technique, exerts a significant influence on criteria weights [28, 29]. This suggests a research direction where, for each objective weighting method, specific investigations are required to select the most compatible data normalization approach.

MAXC is a recently introduced objective weighting method that has been applied in various studies, as mentioned in the introduction. MAXC demonstrates advantages over several common objective weighting methods. While the Entropy weighting method occasionally generates overly concentrated weights or is heavily skewed by extreme values, MAXC processes data more equitably, preventing any single criterion from gaining an irrationally dominant influence. Compared to SD, MAXC does not merely examine pure standard deviation but focuses on the "peak" of the data (the Max value), highlighting criteria where alternatives exhibit breakthrough performance. Relative to MEREC, MAXC is less computationally complex yet still effectively reflects the actual significance of the data. However, this method becomes unusable due to its inherent data normalization technique, which fails when the total value across all alternatives for a specific criterion equals zero. This necessitates a modification of the data normalization method within the MAXC framework to create a new version, designated as MAXC2.

3. MAXC2 Methodology

Since the MAXC2 method is an evolution of the MAXC approach, it is essential to first outline the fundamental steps of the original MAXC framework. The weighting process follows a specific sequence as described below [11]:

Step 1: Construct a decision matrix consisting of m alternatives and n criteria. Let x_{ij} represent the performance value of the i -th alternative with respect to the j -th criterion, where $i = 1 \div m$ and $j = 1 \div n$.

Step 2: Normalize the decision matrix entries using Eq. (1).

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (1)$$

Step 3: Determine the maximum normalized value for each criterion according to Eq. (2).

$$n_{ij}(\max) = \max(n_{ij} / 1 \leq j \leq n) \quad (2)$$

Step 4: Calculate the distance between the maximum value and each criterion value via Eq. (3).

$$d_{ij} = n_{ij}(\max) - n_{ij} \quad (3)$$

Step 5: Compute the expected distance value for each criterion using Eq. (4).

$$E_j = \frac{\sum_{i=1}^m d_{ij}}{m} \quad (4)$$

Step 6: Derive the final weights for each criterion following Eq. (5).

$$w_j = \frac{E_j}{\sum_{j=1}^n E_j} \quad (5)$$

It is observed that Eq. (1) becomes mathematically undefined if its denominator is zero specifically, when the sum of values for a given criterion across all alternatives equals zero. Such scenarios can arise when evaluation criteria involve opposing marginal values. For instance, in financial performance analysis, the profit of a product line may be positive (gain), zero (break-even), or negative (loss) due to varying pricing strategies or operational costs. Similarly, in manufacturing quality assessments, complex fabrication processes might result in a balance between acceptable parts and defects, causing the representative value of a criterion to cancel out or reach zero. In such instances, the MAXC method is rendered inapplicable for weight determination. This motivates the necessity of identifying an alternative data normalization technique to replace the sum-based linear normalization approach inherent in the MAXC method. Consequently, vector normalization, as defined in Eq. (6), is proposed as a robust substitute. By integrating vector normalization into the MAXC framework, a new iteration is developed and designated as MAXC2.

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (6)$$

Vector normalization was selected for this study due to its universal applicability, including cases where a specific criterion contains zero values or where the sum of values for a criterion across all alternatives is zero. Furthermore, the vector normalization style is employed because it shares similarities with the sum-based linear normalization inherent in the MAXC method, such as maintaining a direct proportional relationship between original values; specifically, any value that is larger before normalization remains larger afterward. This is vital as it preserves the comparative essence of the raw data. Even more notably, research has revealed that integrating both of these data normalization types with the Entropy method does not result in a change to the criteria weights [30]. Furthermore, this technique is a cornerstone of several well-established MCDM methods, such as TOPSIS [31], PIV [32], and MOORA [33].

In summary, while the original MAXC weighting procedure sequentially applies Eqs. (1) through (5), the proposed MAXC2 method follows the sequence of Eqs. (6), (2), (3), (4), and (5). The fundamental distinction between the proposed MAXC2 method and the traditional MAXC approach lies in the input data processing technique, specifically the transition from sum-based linear normalization to vector normalization. This refinement completely eradicates the mathematical 'dead point' phenomenon occurring when the denominator equals zero, while simultaneously enhancing the method's generalizability in handling decision matrices containing both negative and positive values.

To evaluate the effectiveness of MAXC2, the following section presents three distinct illustrative examples. The first two examples facilitate a comparative analysis between MAXC2 and MAXC across various scenarios. In the third example, where the original MAXC fails, the performance of MAXC2 is validated by assessing the stability of weight values across different contexts and examining the rank correlation coefficients of alternatives when integrated with multiple MCDM ranking algorithms.

4. Performance Evaluation of the MAXC2 Method

4.1. Case Study 1

The dataset for this example is retrieved from a recent publication concerning five types of eco-friendly wall cladding materials, denoted from A1 to A5. Each material is evaluated against six criteria: Thermal Conductivity (C1), Density (C2), Compressive Strength (C3), Flexural Strength (C4), Hardness (C5), and Hardness (C6). The data for Case Study 1 is summarized in Table 1 [14].

Table 1
Dataset for Case Study 1 [14]

Alt.	C1	C2	C3	C4	C5	C6
A1	0.15	600	8.47	14.5	1.98	870
A2	0.2	800	6.76	14.3	1.82	1290
A3	0.13	550	6.58	13.8	1.66	985
A4	0.17	695	7.45	14.89	1.9	1311
A5	0.16	750	6.96	13.095	2.04	1288

The criterion weights were determined by applying Eqs. (1) through (5) for the original MAXC method and Eqs. (6), (2), (3), (4), and (5) for the proposed MAXC2 method. The comprehensive results are compiled in Table 2.

Table 2
Criterion weights for Case Study 1

	C1	C2	C3	C4	C5	C6
MAXC	0.2718	0.2065	0.1961	0.0634	0.0986	0.1636
MAXC2	0.2712	0.2062	0.1968	0.0639	0.0991	0.1628
Deviations	0.22%	0.15%	0.36%	0.79%	0.51%	0.49%

It is observed that for all six criteria, the values calculated using the MAXC2 method are closely aligned with those obtained via the MAXC method; the discrepancy in value for each criterion between these two approaches is minimal, as summarized in the final row of Table 2. The maximum deviation between these two techniques occurs in criterion C4, amounting to only approximately 0.79%. This can be explained by the fact that both MAXC and MAXC2 determine criteria weights based on the distance between the maximum normalized value and the normalized values of the alternatives, as shown in formula (3). Furthermore, it should be reiterated that both the sum-based

linear normalization inherent in MAXC and the vector normalization utilized in the MAXC2 method share a commonality: they maintain a direct proportional relationship among the original values. Specifically, any value that is larger prior to normalization remains larger afterward. Consequently, whether the data is normalized using the linear or the vector approach, there is no significant impact on the resulting criteria weights. Consequently, it can be concluded that in this instance, MAXC2 demonstrates equivalent efficacy to the MAXC method in weight determination. However, the assessment of a newly proposed methodology is incomplete without a rigorous sensitivity analysis [34]. In this study, sensitivity analysis was conducted by generating multiple scenarios based on the systematic removal of alternatives. Specifically, four scenarios were established. Scenario S1, the baseline scenario using the original data from Table 1 (containing all five alternatives), as performed above. Scenario S2, A5 is excluded, leaving alternatives A1, A2, A3, and A4 in the decision matrix. Scenario S3, Both A5 and A4 are removed, leaving only A1, A2, and A3. Scenario S4, A5, A4, and A3 are excluded, resulting in a decision matrix with only two alternatives, A1 and A2.

The weighting process for both MAXC2 and MAXC was executed for Scenarios S2 through S4, following the same procedure as in S1. Table 3 presents the criterion weights derived from both methods across these scenarios. Additionally, Figure 1 illustrates the percentage discrepancies in weights calculated by the two approaches.

Table 3

Criterion weights across different scenarios in Case Study 1

Scenarios	Method	C1	C2	C3	C4	C5	C6
S1	MAXC	0.2718	0.2065	0.1961	0.0634	0.0986	0.1636
	MAXC2	0.2712	0.2062	0.1968	0.0639	0.0991	0.1628
S2	MAXC	0.2600	0.2364	0.1779	0.0406	0.0857	0.1993
	MAXC2	0.2593	0.2363	0.1787	0.0410	0.0864	0.1983
S3	MAXC	0.2537	0.2342	0.1675	0.0214	0.0892	0.2339
	MAXC2	0.2525	0.2338	0.1684	0.0217	0.0901	0.2335
S4	MAXC	0.2227	0.2227	0.1750	0.0108	0.0656	0.3031
	MAXC2	0.2230	0.2230	0.1759	0.0109	0.0663	0.3009

Analysis of Table 3 reveals that within each scenario from S1 to S4, the weight values for each criterion remain highly consistent between MAXC2 and MAXC. Furthermore, as shown in Figure 1, the variance in weight values is minimal. The maximum discrepancy, observed in criterion C4, is only approximately 1.4%. This reinforces the finding that the two methods possess equivalent effectiveness across all four simulated scenarios.

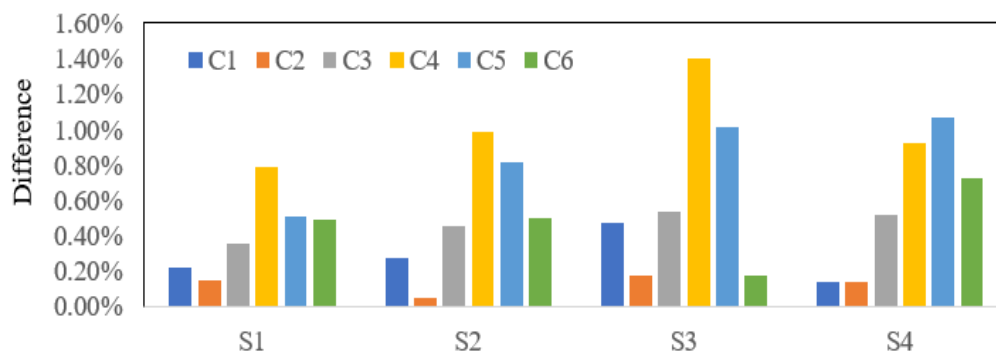


Fig. 1. Weight discrepancies across different scenarios in Case Study 1

In summary, Case Study 1 demonstrates that the weights produced by MAXC2 are nearly identical to those of the original MAXC across all test cases. This confirms the successful implementation of MAXC2 and establishes its parity with the MAXC method in standard applications.

4.2. Case Study 2

The data for this example is sourced from a recent study involving 19 deep learning software frameworks, denoted as A1 to A19. Twelve evaluation criteria were utilized to characterize each alternative: Problem Type (C1), Data Availability and Quality (C2), Computational Resources (C3), Explainability (C4), Scalability (C5), Multi-input Handling (C6), Time Constraints (C7), Domain Expertise (C8), Installation Cost (C9), GPU Size (C10), Storage Size (C11), and RAM Size (C12). The dataset for Case Study 2 is compiled in Table 4 [11].

Table 4

Dataset for Case Study 2 [11]

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	7.4	6.2	7.6	6.6	6.2	7.2	7.2	6.2	6.6	6.6	6.6	7.2
A2	6.2	6.2	7	6.2	6.2	7	7.2	6.2	6.6	6.2	6.2	7.2
A3	7	7	6.2	7	7	6.2	7	7	6.6	7	7	6.2
A4	7	7	7	7	7	7	7	7	7	7	7	7
A5	6.4	6	6.4	6.4	6	6.4	7.4	6	6.8	7	6.2	7
A6	6.2	7	6	6.2	7	6	7.2	7	7.2	6.6	7	6.2
A7	8	6.4	7	7.8	6.4	7	7.4	6.6	7	8	7	7
A8	6.2	6	6.4	6.2	6	6.4	7.2	6	6.8	6.2	6	7
A9	7	6.2	7	6.8	6.2	7	7.4	6.2	7	7	6.6	7
A10	7	6.2	6	7	6.2	6	7	6.2	7.2	7	6.6	6.2
A11	6.4	5.4	6	6.4	5.4	6	7.4	5.4	7.2	7	5.6	6
A12	7	5.4	7	7	5.4	7	7	6	7	7	6	7
A13	7	6.2	8	7	6.2	8	7	6.2	6.8	7.2	6.2	8
A14	7	5.2	6.4	7	5.2	6.4	7	5.2	6.8	7.2	5.2	7
A15	7	7	8	7	7	8	7	7	6.8	7	7	8
A16	7	7	6.2	7	7	6.2	7	7	7	7.2	7	6.2
A17	8	7	8	8	7	8	7	7	6.8	8	7.2	8
A18	7.6	8	7.6	8	7.6	8	7	7.4	6.8	7.2	8	8
A19	7.2	6.2	7.2	7.2	6	7.2	7.2	6.4	6.4	7.2	6	7.4

The weighting process in this example follows the same methodology as Case Study 1, comparing the MAXC2 and MAXC methods across various scenarios. Scenario S1 considers the complete dataset of 19 alternatives. Scenario S2 involves the removal of A19, and S3 excludes both A19 and A18. This iterative reduction continues until Scenario S18, where only A1 and A2 remain in the decision matrix. Table 5 summarizes the criterion weights calculated by both methods across all 18 scenarios.

According to the data in Table 5, in Scenario S17, the weight of C9 becomes zero for both MAXC2 and MAXC. This is attributed to the fact that in S17, only alternatives A1, A2, and A3 remain, and their values for C9 are identical (all equal to 6.6). In Scenario S18, the weights for criteria C2, C5, C7, C8, C9, and C12 also drop to zero. This occurs because, in S18, the values for these specific criteria are identical for the remaining alternatives A1 and A2 (refer to Table 4 for verification).

Furthermore, the results in Table 5 indicate that within each scenario, the weight values for each criterion derived from MAXC2 and MAXC are highly consistent. For ease of observation, these weights are illustrated in the chart in Figure 2.

The visualization in Figure 2 clearly demonstrates that from Scenarios S1 to S17, the weights for each criterion are nearly identical between the two methods. This can also be explained by the fact that both MAXC and MAXC2 determine criteria weights based on the distance between the maximum normalized value and the normalized values of the alternatives. A further point supporting this

explanation is that both sum-based linear normalization and vector normalization share the similarity of maintaining a direct proportional relationship among the original values. However, in Scenario S18, a noticeable divergence in weights is observed, particularly for criterion C1. As explained previously, S18 represents a case with only two alternatives where six criteria (C2, C5, C7, C8, C9, and C12) yield zero weights. Consequently, the total weight is redistributed among the remaining criteria. In this specific boundary case, the different normalization techniques in MAXC and MAXC2 lead to significant variances in the calculated weights. It should be noted, however, that in practical applications, MCDM methods are rarely employed to rank only two alternatives.

Table 5

Criterion weights across different scenarios in Case Study 2

	Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
S1	MAXC	0.081	0.139	0.089	0.085	0.107	0.089	0.020	0.085	0.027	0.077	0.123	0.077
	MAXC2	0.081	0.139	0.089	0.085	0.107	0.089	0.021	0.085	0.027	0.077	0.123	0.077
S2	MAXC	0.082	0.138	0.091	0.087	0.105	0.091	0.021	0.085	0.025	0.077	0.120	0.078
	MAXC2	0.083	0.138	0.091	0.087	0.105	0.091	0.021	0.085	0.025	0.078	0.120	0.078
S3	MAXC	0.106	0.074	0.117	0.114	0.074	0.119	0.025	0.068	0.030	0.096	0.074	0.103
	MAXC2	0.106	0.074	0.116	0.114	0.074	0.119	0.025	0.068	0.030	0.097	0.074	0.103
S4	MAXC	0.111	0.077	0.122	0.099	0.077	0.125	0.023	0.071	0.029	0.101	0.057	0.108
	MAXC2	0.111	0.077	0.122	0.100	0.077	0.125	0.023	0.071	0.029	0.101	0.057	0.108
S5	MAXC	0.110	0.082	0.116	0.100	0.082	0.119	0.022	0.076	0.029	0.101	0.060	0.101
	MAXC2	0.110	0.082	0.116	0.100	0.082	0.119	0.022	0.076	0.029	0.102	0.060	0.101
S6	MAXC	0.106	0.084	0.120	0.097	0.084	0.123	0.020	0.077	0.027	0.097	0.062	0.104
	MAXC2	0.106	0.084	0.120	0.097	0.084	0.123	0.020	0.077	0.027	0.097	0.062	0.104
S7	MAXC	0.111	0.078	0.121	0.102	0.078	0.125	0.019	0.071	0.027	0.103	0.054	0.109
	MAXC2	0.111	0.078	0.121	0.102	0.078	0.125	0.019	0.071	0.028	0.103	0.054	0.109
S8	MAXC	0.134	0.093	0.112	0.124	0.093	0.070	0.021	0.083	0.032	0.125	0.061	0.051
	MAXC2	0.134	0.092	0.112	0.124	0.092	0.070	0.021	0.083	0.032	0.125	0.061	0.051
S9	MAXC	0.138	0.083	0.118	0.129	0.083	0.076	0.020	0.081	0.033	0.128	0.057	0.055
	MAXC2	0.138	0.083	0.118	0.129	0.083	0.076	0.020	0.081	0.033	0.128	0.057	0.055
S10	MAXC	0.143	0.076	0.119	0.136	0.076	0.074	0.023	0.073	0.039	0.140	0.049	0.050
	MAXC2	0.143	0.076	0.119	0.136	0.076	0.074	0.024	0.074	0.039	0.140	0.049	0.050
S11	MAXC	0.150	0.075	0.112	0.144	0.075	0.066	0.021	0.072	0.045	0.147	0.050	0.042
	MAXC2	0.150	0.075	0.112	0.144	0.075	0.066	0.021	0.072	0.045	0.147	0.050	0.042
S12	MAXC	0.152	0.070	0.115	0.145	0.070	0.071	0.024	0.066	0.047	0.148	0.049	0.044
	MAXC2	0.151	0.070	0.115	0.145	0.070	0.071	0.024	0.066	0.047	0.148	0.049	0.044
S13	MAXC	0.152	0.066	0.120	0.147	0.066	0.072	0.026	0.061	0.051	0.148	0.040	0.051
	MAXC2	0.152	0.066	0.119	0.147	0.066	0.072	0.026	0.061	0.051	0.148	0.040	0.051
S14	MAXC	0.126	0.080	0.162	0.080	0.080	0.103	0.039	0.080	0.071	0.048	0.060	0.071
	MAXC2	0.126	0.080	0.162	0.080	0.080	0.103	0.039	0.080	0.071	0.048	0.060	0.071
S15	MAXC	0.114	0.104	0.144	0.070	0.104	0.084	0.043	0.104	0.054	0.046	0.079	0.052
	MAXC2	0.114	0.104	0.144	0.070	0.104	0.084	0.044	0.104	0.054	0.046	0.079	0.052
S16	MAXC	0.114	0.095	0.147	0.070	0.095	0.080	0.022	0.095	0.070	0.070	0.070	0.068
	MAXC2	0.114	0.095	0.147	0.070	0.095	0.080	0.022	0.095	0.071	0.070	0.070	0.068
S17	MAXC	0.108	0.115	0.134	0.084	0.115	0.082	0.013	0.115	0.000	0.084	0.084	0.067
	MAXC2	0.108	0.115	0.133	0.084	0.115	0.082	0.013	0.115	0.000	0.084	0.084	0.067
S18	MAXC	0.129	0.000	0.240	0.183	0.000	0.082	0.000	0.000	0.000	0.183	0.183	0.000
	MAXC2	0.371	0.000	0.173	0.132	0.000	0.059	0.000	0.000	0.000	0.132	0.132	0.000

In conclusion, for 17 out of the 18 scenarios analyzed in this case study, the weights produced by MAXC2 closely align with those from the original MAXC. Across the initial 17 scenarios, the most significant value deviation between the weights determined by the MAXC2 and MAXC methods pertains to criterion C7 in scenario S1. However, even this discrepancy amounts to only

approximately 4.76%. Thus, the MAXC2 method is confirmed to be successful and demonstrates equivalent efficacy to the MAXC method in this context.

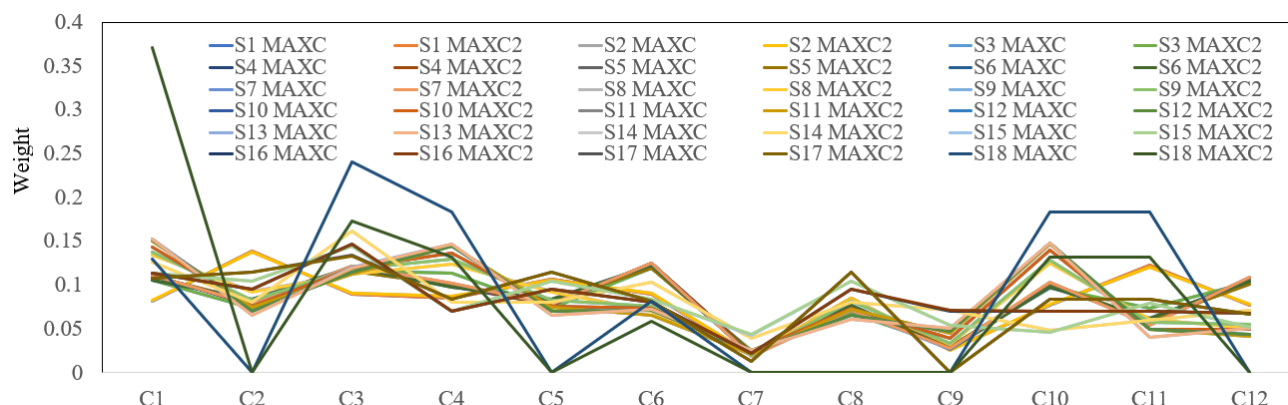


Fig. 2. Comparison of criterion weights across scenarios in Case Study 2

4.3 Case Study 3

While the previous two examples focused on scenarios where both MAXC2 and MAXC were applicable—confirming their equivalent effectiveness—this third case study evaluates the performance of MAXC2 in situations where the original MAXC method fails. We consider a synthetic dataset involving the ranking of ten alternatives (A1 to A10) evaluated against eight criteria (C1 to C8), as shown in Table 6. To ensure an objective assessment, the criteria include both "benefit-type" (the larger the better, C1 to C4) and "cost-type" (the smaller the better, C5 to C8). Crucially, this example intentionally creates a scenario where the MAXC method is mathematically precluded. Specifically, for criterion C7, the sum of its values across all alternatives is zero, rendering Eq. (1) for data normalization unusable and making a direct comparison between MAXC and MAXC2 impossible. In this instance, the efficacy of MAXC2 is appraised through two lenses: first, the stability of weight values across diverse scenarios, and second, the rank consistency of alternatives when integrated with various MCDM ranking algorithms across different contexts.

Table 6
Dataset for Case Study 3

Alt.	C1	C2	C3	C4	C5	C6	C7	C8
A1	100	206	0.5	15	54	0.8	4	4.5
A2	120	220	0.47	14	53	0.7	3	4.2
A3	98	180	0.42	14.5	58	0.62	7	6.4
A4	85	248	0.38	12	46	0.57	3.7	5.5
A5	80	195	0.59	12.5	41	0.68	-1	6.2
A6	92	200	0.82	9.6	49	0.4	-5.4	3.4
A7	106	196	0.9	10	44.8	0.72	-3.6	5.2
A8	76	212	0.66	11.5	52.1	0.64	-8.2	6
A9	86	214	0.72	14.3	48.6	0.7	1	7.2
A10	94	230	0.49	17	46.9	0.59	-0.5	4.9

Following the methodology established in the previous examples, nine scenarios were generated. Scenario S1 utilizes the complete dataset from Table 6; S2 excludes alternative A10; S3 removes A10 and A9; and this process continues until S9, which contains only A1 and A2. The criterion weights derived from MAXC2 for all nine scenarios are summarized in Table 7 and Figure 3.

Table 7

Criterion weights for Case Study 3 across different scenarios

Scenarios	C1	C2	C3	C4	C5	C6	C7	C8
S1	0.0778	0.0503	0.1381	0.0837	0.0489	0.0680	0.4385	0.0948
S2	0.0837	0.0578	0.1399	0.0566	0.0506	0.0697	0.4438	0.0980
S3	0.0822	0.0609	0.1540	0.0646	0.0512	0.0755	0.4396	0.0720
S4	0.0727	0.0629	0.1626	0.0615	0.0543	0.0762	0.4282	0.0817
S5	0.0842	0.0641	0.1777	0.0533	0.0523	0.0903	0.3888	0.0894
S6	0.1107	0.0835	0.1141	0.0473	0.0691	0.0857	0.4011	0.0884
S7	0.1158	0.0981	0.0790	0.0494	0.0606	0.1149	0.3360	0.1462
S8	0.1047	0.0707	0.0628	0.0274	0.0434	0.1046	0.3741	0.2122
S9	0.2055	0.0746	0.0702	0.0782	0.0212	0.1510	0.3210	0.0782

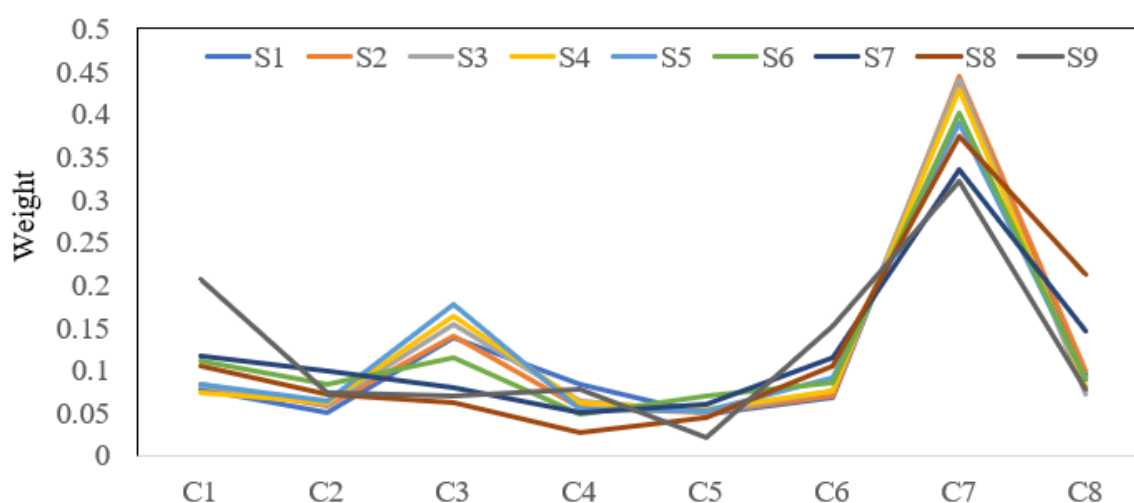


Fig. 3. Comparison of criterion weights in Case Study 3 across scenarios

An examination of Table 7 and Figure 3 reveals that the weight values for each criterion fluctuate minimally across the simulated scenarios. This can also be explained by the fact that MAXC2 determines criteria weights based on the distance between the peak normalized value and the normalized values of the alternatives. Thus, regarding weight stability, the application of MAXC2 effectively maintains consistent criterion importance even when the set of alternatives is altered.

Next, the effectiveness of MAXC2 is evaluated by using its derived weights to rank alternatives via multiple established MCDM methods. The Spearman rank correlation coefficient, calculated using Eq. (7), serves as the primary metric for this assessment. Here, D_i represents the difference in the rank of alternative A_i across different methods.

$$S = 1 - \frac{6 \sum_{i=1}^m D_i^2}{m(m^2 - 1)} \quad (7)$$

Four prominent MCDM methods—TOPSIS, MOORA, ROV, and PIV—were employed to rank the alternatives. Table 8 presents the rankings for Scenario S1. The mean Spearman correlation coefficient among these methods was calculated and recorded in the final row of the table.

The data in Table 8 shows minimal variation in the rankings produced by the four distinct methods. Notably, the rankings yielded by MOORA and PIV are perfectly consistent. The mean Spearman coefficient across the four methods is 0.9818, an exceptionally high value. This confirms that in Scenario S1, utilizing MAXC2 weights significantly bolsters the rank stability of alternatives across different algorithmic frameworks.

Table 8
Ranking of alternatives in Scenario S1 of Case Study 3

Alt.	TOPSIS	MOORA	ROV	PIV
A1	9	8	8	8
A2	7	7	7	7
A3	10	10	10	10
A4	8	9	9	9
A5	4	5	5	5
A6	2	2	1	2
A7	3	3	3	3
A8	1	1	2	1
A9	6	6	6	6
A10	5	4	4	4
Spearman	0.9818			

For the remaining scenarios (S2 through S9), the same ranking and correlation analysis was conducted. Table 9 summarizes the mean Spearman correlation coefficients across all nine scenarios.

Table 9
Mean Spearman correlation coefficients among MCDM methods in Case Study 3

S1	S2	S3	S4	S5	S6	S7	S8	S9
0.9818	0.9722	0.9722	0.9584	0.9714	0.9333	0.8667	1	1

According to Table 9, the average Spearman correlation remains consistently high across all scenarios, with a minimum value of 0.8667 in Scenario S7 and reaching a perfect 1.0 in Scenarios S8 and S9. these figures robustly demonstrate that weights derived from MAXC2 ensure a high degree of ranking consistency regardless of the MCDM method applied.

Thus, considering the nine scenarios executed by removing one alternative in each instance, it has been confirmed that utilizing the MAXC2 method significantly contributes to maintaining the ranking stability of alternatives when evaluated by various MCDM techniques. To further reinforce the stability of the MAXC2 method in determining criteria weights, another approach was implemented by modifying the values of the alternatives. Following this procedure, ten scenarios were generated: the first scenario increased the values of all criteria for A1 by 1%, the second scenario increased all criteria values for A2 by 1%, and similarly for the remaining alternatives, until the tenth scenario where all criteria values for A10 were increased by 10%. Figure 4 illustrates the criteria weights across these ten scenarios, including the case where weights were calculated from the original matrix (the data presented in Table 6).

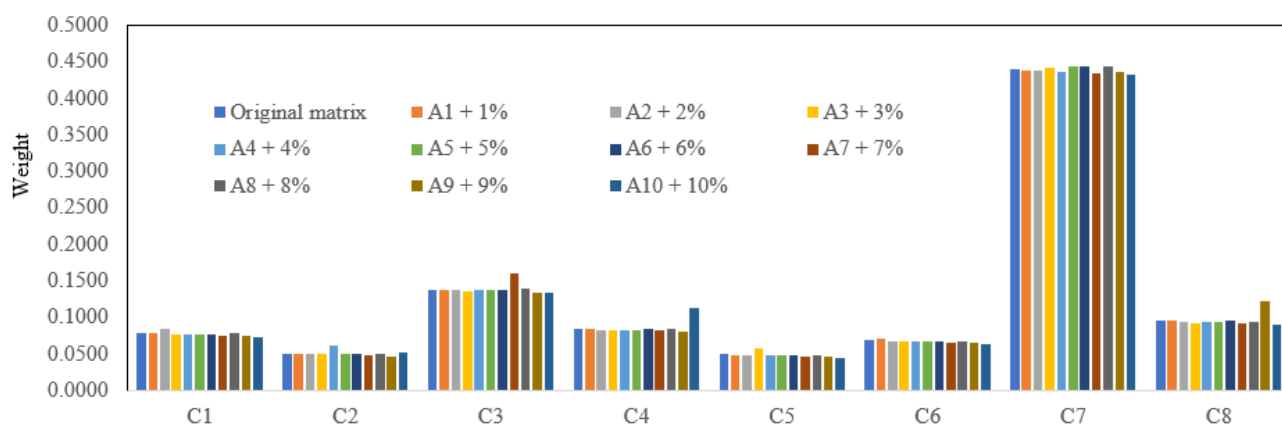


Fig. 4. Criteria weights across scenarios involving changes to the values of the alternatives

Observing Figure 4, it is evident that the weight of each criterion fluctuates very little across the scenarios, despite significant alterations to the values of the alternatives, most notably with the criteria values for alternative A10 increasing by 10% compared to the baseline. The most substantial discrepancy occurs in criterion C4 between the scenario where A9 increases by 9% and the scenario where A10 increases by 10%, which is only approximately 0.033, corresponding to about 2.9%; for all other criteria, the weight value variations across scenarios are negligible. Once again, this outcome is explained by the fact that MAXC2 determines criteria weights based on the distance between the peak normalized value and the normalized values of the alternatives. Modifying the values of all criteria within a single alternative by the same ratio merely causes this distance to expand or contract without disrupting the relative order among the criteria. Consequently, the weights of each criterion across scenarios will increase or decrease in unison, meaning they remain relatively stable between scenarios. This demonstrates that MAXC2 is highly effective in maintaining the weight values of criteria despite major fluctuations in the decision matrix.

In summary, regarding both the stability of individual criteria weight values across scenarios (Figure 3, Figure 4) and the ranking stability of alternatives when evaluated by various MCDM methods (Table 9), the MAXC2 method has consistently confirmed its high level of effectiveness in this example.

When both MAXC and MAXC2 are applicable (as seen in Case Studies 1 and 2), they yield nearly identical results across various scenarios. In cases where the original MAXC is inapplicable (as seen in Case Study 3), MAXC2 maintains high stability and ensures reliable rankings when integrated with multiple MCDM methods. These findings lead to the definitive conclusion that MAXC2 is an accurate and reliable weighting approach. The proposal of the MAXC2 method successfully fulfills the research objective: expanding the applicability and robustness of the original MAXC framework.

While the MAXC2 method has demonstrated superior advantages regarding stability and computational capability, this study still possesses certain limitations. Firstly, MAXC2 is currently a purely objective weighting method; therefore, developing an integrated framework between MAXC2 and subjective weighting techniques to generate hybrid weights is essential to more comprehensively reflect both data attributes and expert experience. Secondly, to more robustly validate the generalizability and effectiveness of the method in complex decision-making scenarios, further empirical research on large-scale datasets or expanding its application to diverse fields such as healthcare, human resource management, and public policy is required.

5. Conclusion

The determination of criterion weights is a fundamental component in addressing Multi-Criteria Decision-Making (MCDM) challenges. This research introduced an advanced weighting technique designated as MAXC2, which serves as a refined iteration of the original MAXC framework. Empirical results demonstrate that when both methodologies are applicable, the criterion weights derived from MAXC2 closely converge with those produced by MAXC. Furthermore, in scenarios where the original MAXC method encounters mathematical limitations, MAXC2 remains highly effective and robust. Based on these findings, MAXC2 is established as a highly accurate and reliable objective weighting method, offering a significant contribution to the field of decision science.

All the formulas in the current versions of the MAXC and MAXC2 methods are designed to calculate criteria weights when the decision matrix consists of real numbers. Developing these methods to determine criteria weights when the decision matrix contains fuzzy sets or qualitative factors, thereby further broadening their scope of application remains a subject for future research. Additionally, integrating MAXC and MAXC2 with subjective weighting techniques to create hybrid

weighting methods, capable of calculating criteria weights that balance both subjective and objective factors, is another study that should be undertaken in the future.

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Conflicts of Interest

The authors declare no conflicts of interest.

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