Expanding the Data Normalization Strategy to the MACONT Method for Multi-Criteria Decision Making

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Received: 8 January 2023 | Revised: 16 February 2023 | Accepted: 20 February 2023

ABSTRACT

The Mixed Aggregation by Comprehensive Normalization Technique (MACONT) is a well-known Multi-Criteria Decision-Making (MCDM) method with significant benefits compared to traditional approaches. The key difference that distinguishes this method from most others is the use of data normalization techniques and aggregation approaches. MACONT uses three different data normalization techniques simultaneously along with two aggregation approaches throughout its evaluation process. This reduces the derivation of evaluation values and enhances the reliability of the final decision results, making the process more precise and convergent. However, the original MACONT emphasizes the integration of multiple normalization techniques of the same type of criteria that might perform badly in some circumstances. This paper proposes combination strategies of six normalization techniques to be coupled with the MACONT to help the normalized data synthetically reflect the original information and solve different types of data, criteria, and alternatives. The proposed approach was applied in four case studies. In all studies, the ranking results were compared with the other MCDM methods, producing the same best alternatives and overcoming the cases when the original MACONT did not work properly.

Keywords-MCDM; MACONT method; data normalization

I. INTRODUCTION

Multi-Criteria Decision-Making (MCDM) is a common action in various fields to select the best option among available alternatives [1-4]. Data normalization is one of the most important tasks in the MCDM process. However, since the process of data normalization in each MCDM method differs, the final ranking of alternatives based on different MCDM methods also varies [5]. In addition, using the same MCDM method but combining different data normalization algorithms could produce different outcomes [6]. Mixed Aggregation by Comprehensive Normalization Technique (MACONT) is a recent MCDM method that differs from most others, especially in data normalization. In contrast to the majority of other MCDM methods, the MACONT utilizes three data normalization procedures simultaneously: linear sum-based normalization (N1), linear ratio-based normalization (N2), and linear max-min normalization (N3). With this distinction, the MACONT can reduce mistakes in comparison to other MCDM systems that employ a single data normalization method [7, 8]. This strategy has been successfully applied to the selection of supply chain management [7] and retirement service providers [8]. However, the N1 and N2 normalization procedures cannot be utilized if there is a criterion that is as minimal as feasible and whose value at some variant is zero. If the highest value of a particular as large as the feasible criterion is zero, N2 will likewise not be applied. Therefore, the MACONT approach cannot be used by just employing N1, N2, and N3. To overcome these issues, this paper proposes combination strategies from six normalization methods for coupling with the MACONT. The proposed approaches were examined and compared in 4 case studies, with different types of data, criteria, and alternatives.

II. LITERATURE REVIEW

Data normalization plays an important role in MCDM. This process is conducted using mathematical formulas to transform the factors that have different units into dimensionless [9]. The 6 normalization methods (N1 to N6) that have been widely used for MCDM problems are [10]:

- Linear sum-based normalization (N1).

  For criteria where the biggest value is the best:

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

  For criteria where the smallest value is the best:

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

- Linear ratio-based normalization (N2).

  For criteria where the biggest value is the best:

$$n_{ij}^2 = \frac{y_{ij}}{\max y_{ij}} \quad (3)$$

  For criteria where the smallest value is the best:

$$n_{ij}^2 = \frac{\min y_{ij}}{y_{ij}} \quad (4)$$

- Linear max-min normalization (N3).

  For criteria where the biggest value is the best:

$$n_{ij}^3 = \frac{y_{ij} - \min y_{ij}}{\max y_{ij} - \min y_{ij}} \quad (5)$$

  For criteria where the smallest value is the best:

$$n_{ij}^3 = \frac{y_{ij} - \max y_{ij}}{\min y_{ij} - \max y_{ij}} \quad (6)$$

- Linear max normalization (N4)

  For criteria where the biggest value is the best:

$$n_{ij}^4 = \frac{y_{ij}}{\max y_{ij}} \quad (7)$$

  For criteria where the smallest value is the best:

$$n_{ij}^4 = 1 - \frac{y_{ij}}{\max y_{ij}} \quad (8)$$

- Half-linear vector normalization (N5).

  For criteria where the biggest value is the best:

$$n_{ij}^5 = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{m} y_{ij}^2}} \quad (9)$$

  For criteria where the smallest value is the best.

$$n_{ij}^5 = 1 - \frac{y_{ij}}{\sqrt{\sum_{i=1}^{m} y_{ij}^2}} \quad (10)$$

- Linear max-min sum-based normalization (N6).

  For criteria where the biggest value is the best:

$$n_{ij}^6 = 1 - \frac{max y_{ij} - y_{ij}}{\sum_{i=1}^{m}(max y_{ij} - y_{ij})} \quad (11)$$

  For criteria where the smallest value is the best:

$$n_{ij}^6 = 1 - \frac{y_{ij} - min y_{ij}}{\sum_{i=1}^{m}(y_{ij} - min y_{ij})} \quad (12)$$

In these methods, y_{ij} is the value of criterion j in the alternative i, i=1÷m, j=1÷n, and n_{ij}^k is the normalization method number k. Previous studies combined more than one normalization methods in coupling with different MCDMs to solve certain decision-making problems. Methods N1 to N5 were used in combination with Combinative Distance-based Assessment (CODAS) to rank robots, air quality in an office, and lathe processing, while the results showed that N1, N2, N3, and N5 were suitable for use with the CODAS method [11]. The Proximity Indexed Value (PIV) method was used with N1, N3, N4, and N5 in [12], and the results showed that the PIV method provided reliable decisions only when combined with N3 [12]. In a study on ranking the financial state of companies, the results showed that all methods were not suitable using the Range of Value (ROV) method [13]. Among N1, N3, N4, and N5, only N4 was proven to be suitable for coupling with the Analytic Hierarchy Process (AHP) method to rank smart car parking [14]. In food processing decisions, N1, N2, N3, and N5 were used with Weighted Aggregates Sum Product Assessment (WASPAS) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods [15]. N1, N3, and N5 were applicable in coupling with the Weighted Sum Product (WISP) method when studying the rank of random numeric sets [16]. In a study to investigate the landing methods of unmanned autonomous vehicles, of the considered N1, N2, N3, and N5, only N2 was compatible with TOPSIS [17]. When combining the N2, N3, and N5 with the "Vlsekriterijumska optimizacijaI Kompromisno Resenje" (VIKOR) method to rank a wifi network, the results showed that only N3 was applicable [18]. However, when ranking products based on the responses of the clients, only N5 among N1, N2, N3, and N5 was suitable for coupling with the VIKOR method [19]. In a study to combine N1, N3, N4, and N5 with WASPAS to classify different types of robots, N3 was determined as the most suitable [20].

Using a data normalization method in a certain MCDM process is a complex problem, as normalization methods only solve the problem in certain cases. Therefore, investigating the suitability of combination normalization methods with certain MCDM methods is important and must be carried out before applying it to rank alternatives. The MACONT has been recently developed as an MDCM method with numerous advantages. However, this technique uses simultaneously three normalization methods, and therefore it is necessary to study the suitability of the normalization methods for MACONT.

III. MACONT METHOD

This section presents the MACONT method for ranking alternatives as follows [7]:

- Establish a decision-making matrix with m alternatives and n criteria. Supposing y_{ij} is the value of criterion j in the alternative m, where i=1÷m and j=1÷n.
- Normalize data using N1, N2, and N3.
- Calculate normalized balance values using:

$$n_{ij} = \lambda.n_{ij}^1 + \mu.n_{ij}^2 + (1 - \lambda - \mu).n_{ij}^3 \quad (13)$$

  where $\lambda \geq 0$ and $\mu \leq 1$. Normally, $\lambda = \mu = 1/3$.

- Determine $S_{1(a_i)}$, $S_{2(a_i)}$ as:

$$S_{1(ai)} = \delta \frac{p_i}{\sqrt{\sum_{i=1}^{m}(p_i)^2}} + (1 - \delta)\frac{Q_i}{\sqrt{\sum_{i=1}^{m}(Q_I)^2}} \quad (14)$$

$$S_{2(ai)} = \vartheta.max\left(w_j(n_{ij} - \bar{n}_{ij})\right) + (1 - \vartheta).\min\left(w_j(n_{ij} - \bar{n}_{ij})\right) \quad (15)$$

  where and $\delta \geq 0$ and $\vartheta \leq 1$. Normally choose $\delta = \nu = 0.5$. The factors p_i and Q_i in (14) and (15) are calculated using:

$$p_i = \sum_{j=1}^{n} w_j . (n_{ij} - \bar{n}_{ij}),\ i = 1 \div m \quad (16)$$

$$Q_i = \frac{\Pi_{\gamma=1}^{n} (n_{ij} - \bar{n}_{ij})^{w_j}}{\Pi_{\eta=1}^{n} (n_{ij} - \bar{n}_{ij})^{w_j}},\ i = 1 \div m \quad (17)$$

where $\gamma=1 \div n$ are the criteria that satisfy $n_{ij} < \bar{n}_{ij}$, and $\eta=1 \div n$ are the criteria that satisfy $n_{ij} \geq \bar{n}_{ij}$.

- Calculate the score of the alternative using:

$$S_{(a_i)} = \frac{1}{2}\left(S_{1(a_i)} + \frac{S_{2(a_i)}}{\sqrt{\sum_{i=1}^{m} \left(S_{2(a_i)}\right)^2}} \right) \quad (18)$$

- Rank the alternatives using the rule that the higher score, the better the alternative.

IV. COMBINING STRATEGIES OF NORMALIZATION METHODS

In the original MACONT, the N1, N2, and N3 data normalization methods were used simultaneously. Nonetheless, these methods cannot be used if the value of y_{ij} becomes zero. This paper proposes normalization combination strategies for coupling with the MACONT to solve the alternative ranking problems. Each combination strategy *T* involves three independent techniques selected from N1 to N6. Table I shows the detailed combinations, where the combination T1 belongs to the original MACONT version.

TABLE I. STRATEGIES FOR COMBINING NORMALIZATION TECHNIQUES

Combination Strategy	**Noramlization Techniques**					
	N1	**N2**	**N3**	**N4**	**N5**	**N6**
T1 (Original MACONT)	√	√	√			
T2	√	√		√		
T3	√	√			√	
T4	√	√				√
T5		√	√	√		
T6		√	√		√	
T7		√	√			√
T8			√	√	√	
T9			√	√		√
T10			√		√	√
T11				√	√	√

V. CASE STUDIES AND DISCUSSION

In the case studies, the criteria were divided into two categories: Category B defines the criteria related to benefit and positive effectivity with high optimal value, while category C defines the criteria related to cost and negative aspects with low optimal value.

A. Case Study 1

Table II shows the information on 8 logistics providers [7]. Three groups of criteria were applied to evaluate the general quality of these providers. A series of evaluation criteria were established from three dimensions of sustainability as follows:

- The basis group: quality (C1), lead time (C2), cost (C3), delivery and services (C4), relationship (C5), and innovativeness (C6).
- The expanding group: pollution controls (C7), resource consumption (C8), remanufacture and reuse (C9), green technology capability (C10), and environmental management system (C11).
- The human care group: health and safety (C12), employment stability (C13), customer satisfaction (C14), reputation (C15), respect for the policy (C16), and contractual stakeholders' influence (C17).

Only C2, C3, and C8 belong to category C where the optimal value is small, while the rest belong to category B. The weights of these criteria were calculated as 0.048, 0.067, 0.085, 0.026, 0.017, 0.034, 0.098, 0.087, 0.065, 0.113, 0.046, 0.079, 0.047, 0.025, 0.072, 0.080, and 0.011, respectively [7]. The objective of MCDMs was to identify a logistics provider that simultaneously ensured that C2, C3, and C8 were the smallest variables while the remaining criteria were considered the highest (Category B). This procedure was completed using the T1 normalization strategy [7]. In addition, this case study also employed ten more combination strategies (T2-T11). Steps to rank the options according to MACONT were applied, and Table III and Figure 1 present their ranking results. The order of the alternatives with different strategies was extremely similar. In particular, all 11 combination strategies implied that option A8 was the best and option A7 was the second best. In other words, they can be applied to find the optimal solution in this case.

B. Case Study 2

This study evaluated the quality of several robot models. A series of evaluation criteria were established, including loads (C1), maximum speed (C2), time response (C3), memory storage (C4), and working distance for the operator (C5). In these five criteria, only C3 belongs to category C, and the rest belong to B. The weights of these criteria from C1 to C5 were calculated as 0.036, 0.326, 0.192, 0.326, and 0.120, respectively.

TABLE II. DETAILED FIGURES OF CASE STUDY 1 [7]

Alt.	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**	**C17**
A1	22	22	850	34	3.5	13	17	11039	46	6	7	27	3.8	78	5	57	3.4
A2	34	38	1450	67	7.9	6	4	14326	37	3	2	63	5.9	89	6	66	6.8
A3	27	30	1068	29	5	21	11	12765	41	5	4	64	7.3	80	4	74	4.3
A4	19	41	729	37	4.3	26	9	10343	16	7	5	82	4.1	67	3	85	3.7
A5	15	76	697	45	2.8	8	13	6390	32	4	3	45	6.3	56	4	90	3.2
A6	32	25	1371	74	6.7	5	8	15789	24	2	4	38	5.2	92	7	69	7.5
A7	28	68	1190	63	5.4	23	14	13270	62	8	2	50	6.4	82	5	73	4.6
A8	17	64	798	42	3.1	19	16	8356	58	6	3	57	4.7	34	8	92	3.9

TABLE III. RANK ALTERNATIVES ACCORDING TO DIFFERENT DATA NORMALIZATION STRATEGIES

Alt.	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
A1	4	3	3	3	3	3	3	4	4	4	3
A2	8	8	8	8	8	8	8	7	7	7	8
A3	6	6	6	6	6	6	6	5	5	5	5
A4	3	4	4	4	4	4	4	3	3	3	4
A5	5	5	5	5	5	5	5	6	6	6	6
A6	7	7	7	7	7	7	7	8	8	8	7
A7	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**
A8	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

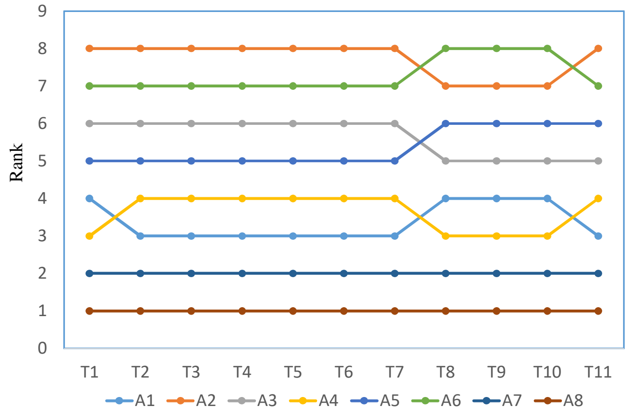

Fig. 1. The graphical of the alternative ranking.

Table IV presents the figures for seven robot models [21, 22]. The best alternative was the one where C3 was the smallest and the other four criteria had the highest values. In this instance, the CODAS [21], Ranking of the attributes and alternatives (R), and Collaborative Unbiased Rank List Integration (CURLI) [22] methods were also used to determine the best one. Table V and Figure 2 illustrate the alternate rankings when the MACONT was combined with 11 data normalization combination methods, along with other MDCMs.

The ranking alternatives using the MACONT with all forms of data normalization combination strategies were identical and correspond to the results obtained by employing R and CURLI. In addition, A2 was determined to be the optimal selection in every circumstance, even when using the CODAS method. When paired with the MACONT method, all these data normalization methods were found to be adequate.

TABLE IV. FIGURES OF CASE STUDY 2 [21, 22]

Alt.	C1	C2	C3	C4	C5
A1	60	0.4	2540	500	990
A2	6.35	0.15	1016	3000	1041
A3	6.8	0.1	1727.2	1500	1676
A4	10	0.2	1000	2000	965
A5	2.5	0.1	560	500	915
A6	4.5	0.08	1016	350	508
A7	3	0.1	1778	1000	920

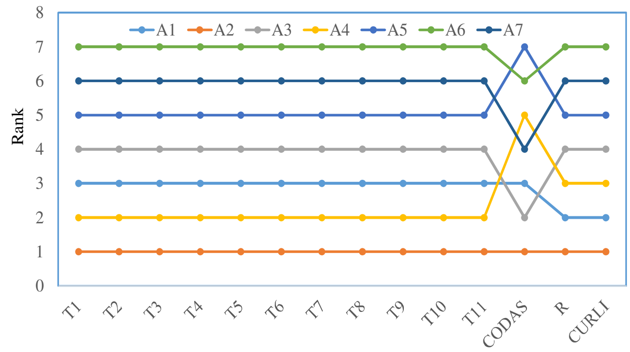

Fig. 2. Graphical representation of the alternative ranking.

TABLE V. RANK ALTERNATIVES ACCORDING TO DIFFERENT DATA NORMALIZATION COMBINATION STRATEGIES

Alt.	MACONT											CODAS	R	CURLI
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11			
A1	3	3	3	3	3	3	3	3	3	3	3	3	2	2
A2	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
A3	4	4	4	4	4	4	4	4	4	4	4	2	4	4
A4	2	2	2	2	2	2	2	2	2	2	2	5	3	3
A5	5	5	5	5	5	5	5	5	5	5	5	7	5	5
A6	7	7	7	7	7	7	7	7	7	7	7	6	7	7
A7	6	6	6	6	6	6	6	6	6	6	6	4	6	6

C. *Case Study 3*

This study was based on data collected from multiple grinding procedures, where the performance was measured and assessed based on three criteria: the arithmetic average of the absolute values of the profile heights (C1), the average value of the absolute values of the heights of the five highest-profile peaks and the depths of the five deepest alleys (C2), and the material removal capacity (C3) (Table VI). C1 and C2 belong to category C, in contrast to C3 which belongs to Category B [23]. The Weighted Sum Model (WSM), the Weighted Product Model (WPM), and TOPSIS were also used for the MCDM with the weights of C1, C2, and C3 being 0.1932, 0.1998, and 0.6070, respectively [23]. Table VII and Figure 3 show the rankings using the MACONT with 11 combination strategies and the WSM, WPM, and TOPSIS methods. Table VII and Figure 3 show that the results of ranking alternatives using the MACONT with different strategies are similar. In addition, A10 was determined to be the optimal choice in every circumstance, even when using the CODAS method. In other words, when paired with the MACONT, all 1 data normalization methods were found to be adequate in this scenario, and equivalent to WSM, WPM, and TOPSIS. Hence, each data normalization combination strategy can be used to precisely identify the optimal solution in this case study.

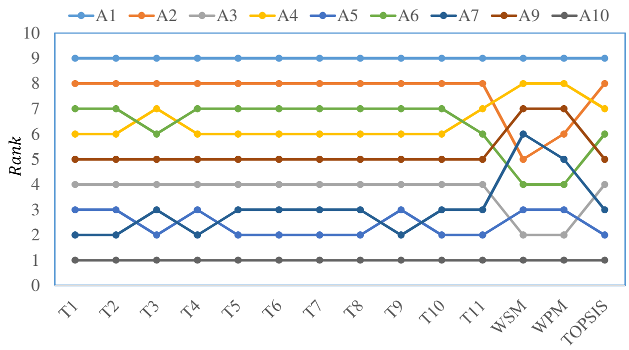

Fig. 3. Graphical representation of the alternative ranking

In general, there are substantial differences between the 3 case studies listed above, including distinct fields, number of possibilities, and number of criteria. However, it is remarkable that the optimal solution was always determined when the MACONT was applied with various strategies. The best choice chosen by the MACONT was similar to the best alternative determined by other decision-making methods. Moreover, the MACONT method was compatible with each strategy, pointing out its applicability and convenience.

TABLE VI. THE FIGURES OF CASE STUDY 3 [23]

Alt.	C1	C2	C3
A1	2.6	12.6	0.75
A2	3.1	14.2	3
A3	3.7	15.3	6.75
A4	1.8	6.4	3
A5	2.3	9.8	9
A6	2.8	12.8	4.5
A7	0.9	4.1	6.75
A8	1.6	7.6	4.5
A9	2.1	9.7	13.5

D. Case Study 4

Assuming that there is a ranking problem for 5 alternatives (A1-A5), each alternative involving 4 criteria (C1-C4). Table VIII presents the calculated values of the criteria. C1 and C2 belong to category B, whereas C3 and C4 belong to C. Without losing generalization, the weights of the 4 criteria were chosen equal to 0.25. As shown in Table VIII, the value of C1 in alternative A2 was zero, which was the highest value among the 5 alternatives. Therefore, neither (3), (7), and (8) nor N2 nor N4 can be used. The normalization combinations T1, T2, T3, T4, T5, T6, T7, T8, T9, and T11 do not function properly due to their dependence on N2 and N4. This phenomenon shows that in some divergent cases, the MACONT method cannot be used to rank the alternatives when only using T1.

TABLE VII. RANK ALTERNATIVES ACCORDING TO DIFFERENT DATA NORMALIZATION COMBINATION STRATEGIES

Alt.	MACONT											WSM	WPM	TOPSIS
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11			
A1	**9**	**9**	**9**	**9**	**9**	**9**	**9**	**9**	**9**	**9**	**9**	**9**	**9**	**9**
A2	8	8	8	8	8	8	8	8	8	8	8	5	6	8
A3	4	4	4	4	4	4	4	4	4	4	4	2	2	4
A4	6	6	7	6	6	6	6	6	6	6	7	8	8	7
A5	3	3	2	3	2	2	2	2	3	2	2	3	3	2
A6	7	7	6	7	7	7	7	7	7	7	6	4	4	6
A7	2	2	3	2	3	3	3	3	2	3	3	6	5	3
A9	5	5	5	5	5	5	5	5	5	5	5	7	7	5
A10	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

TABLE VIII. THE CRITERIA VALUES

Alt.	C1	C2	C3	C4
A1	-4	2.2	5	32
A2	0	1.8	1	19
A3	-3	2.4	4	41
A4	-3	2.5	0	35
A5	-1	1.6	-6	21

Since C3 at A4 is zero, (2) and (4) along with N1 and N2 cannot be used, the combinations T1 through T7 fail. In other words, the MACONT cannot be used to rank alternatives if the T1 normalization combination is used alone. According to the two scenarios analyzed above, only T10 can be coupled with MACONT to rank this problem. To verify the MACONT coupling strategy with T10, the ranking result was compared with the results of the TOPSIS and PIV methods. These methods were chosen because they do not use (2), (3), (4), (7), and (8). Furthermore, TOPSIS is considered the most popular MCDM [24, 25], and PIV was proven to have a lower reverse phenomenon rate [26, 27]. Both TOPSIS and PIV methods are only used (1) for normalizing data. Detailed procedures for these methods can be found in [24-27]. Table IX shows the ranking results for this problem. The comparison shows that the ranking result using the MACONT algorithm with the normalization combination T10 was the same as the TOPSIS and the PIV. This demonstrates the effectiveness of the proposed combination of MACONT and T10 to classify problems when the other methods cannot be used.

TABLE IX. RANKING RESULTS COMPARISON AMONG DIFFERENT METHODS

Alt.	MACONT + T10	TOPSIS	PIV
A1	5	5	5
A2	2	2	2
A3	4	4	4
A4	3	3	3
A5	1	1	1

VI. CONCLUSION

This paper proposed 10 combination strategies of normalization techniques for integration with MACONT. Four case studies were conducted independently, in which the type of data, the number of criteria, and the alternatives varied to assess the efficiency and the response capacity of the proposed methods. The conclusions are drawn as follows:

- When combining all 11 data normalization strategies with the MACONT method, the optimal solution was always the same as the optimal solutions when using the other MCDM methods.
- When $y_{ij} = 0$, the normalization strategy T1 cannot be adapted to determine the final result. To overcome this issue, a new normalization strategy (T10) was presented, which can be applied to rank alternatives.
- This study combined and investigated only 6 data normalizing methods that result in 11 distinct data normalization combination strategies. Future research should focus on other data normalization techniques, such as Jüttler-Korth, Peldschus, and Z-score, to develop more suitable combination strategies and evaluate them with the original MACONT method.

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