Dokuz Eylül University Journal of the Faculty of Business, Volume 22, Number 2, 2021, 217-234

Received: July 25, 2021 doi: 10.24889/ifede.974252
Accepted: December 1, 2021

NORMALIZATION PROCEDURES FOR CoCoSo METHOD: A COMPARATIVE ANALYSIS UNDER DIFFERENT SCENARIOS

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ABSTRACT

The first step in Multiple Criteria Decision Making (MCDM) methods is the normalization processes after the decision matrix was created. Normalization is one of the most important process in MCDM methods, and it affects MCDM ranking results. Therefore, choosing the appropriate normalization technique is very important in decision problems. This study aims to reveal the effect of normalization techniques on the combined compromise solution (CoCoSo) method results under different scenarios. The study determined that the Enhanced accuracy technique, Non-linear normalization and Linear normalization techniques can be used as alternatives to the Weitendorf linear normalization technique in the algorithm of the CoCoSo method. Also, it was concluded that Vector normalization and Linear normalization sum-based techniques are not suitable for the CoCoSo method. In this study, the suitability of different normalization techniques for the CoCoSo method was tested for the first time.

Keywords: *Normalization, MCDM, CoCoSo, Decision Making, Comparative Analysis*.
Jel Codes: *C44, C40, D81*

CoCoSo YÖNTEMİ İÇİN NORMALİZASYON PROSEDÜRLERİ: FARKLI SENARYOLAR ALTINDA KARŞILAŞTIRMALI BİR ANALİZ

ÖZ

Karar matrisinin oluşturulmasının ardından Çok Kriterli Karar Verme (ÇKKV) yöntemlerinde ilk adım normalizasyon işlemidir. Normalizasyon, ÇKKV yöntemlerinde en önemli süreçlerden biridir ve ÇKKV sıralama sonuçları üzerinde etkilidir. Bu nedenle karar problemlerinde uygun normalizasyon tekniğinin seçilmesi çok önemlidir. Bu çalışma, normalizasyon tekniklerinin farklı senaryolar altında Birleşik Uzlaşma Çözümü-Combined Compromise Solution (CoCoSo) yöntemi sonuçları üzerindeki etkisini ortaya koymayı amaçlamaktadır. Çalışma sonunda, Gelişmiş doğruluk yöntemi, Doğrusal olmayan normalizasyon ve Doğrusal normalizasyon tekniklerinin CoCoSo yönteminin kendi algoritmasında bulunan Weitendorf doğrusal normalizasyon tekniğine alternatif olarak kullanılabileceği tespit edilmiştir. Ayrıca Vektör normalizasyon ve Doğrusal toplam tabanlı normalizasyon tekniklerinin CoCoSo yöntemi için uygun olmadığı tespit edilmiştir. Bu çalışmada farklı normalizasyon tekniklerinin CoCoSo yöntemi için uygunluğu ilk kez test edilmiştir.

Anahtar Kelimeler: *Normalizasyon, ÇKKV, CoCoSo, Karar Verme, Karşılaştırmalı Analiz*.
Jel Kodları: *C44, C40, D81*

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INTRODUCTION

Multi-Criteria Decision Making (MCDM) methods help decision-makers to make a selection in the presence of multiple alternatives and criteria, and their use has increased considerably in recent years. An MCDM problem with finite probabilities can be expressed in a matrix format. In this matrix, there are the possible alternatives $Ai(i = 1, \dots, m)$, the *criteria* $cj(j = 1, \dots, n)$, the relative importance of the criteria wj, and the xij, which is degree of the i alternative according to the j criterion, that the decision-makers should choose (Jahan, Bahraminasab and Edwards, 2012, p.648).

The determination of criterion weights and the normalization process differs according to MCDM methods. Therefore, the final selection and ranking for a given problem may vary. The normalization of decision matrix elements, which converts all criterion values to dimensionless form, is a crucial step in most MCDM techniques (Jahan & Edwards, 2015, p. 335). When the selection criteria have different units, all performance values for each alternative should be normalized and processed into the comparability array (Chatterjee and Chakraborty, 2014, p.143). The process of bringing the ratings of different alternatives into the same range is called normalization. Normalization is mainly used to remove the units of each criterion so that all criteria become dimensionless (Lakshmi and Venkatesan, 2014, p.257). The process of normalizing the ratings of different alternatives into the same range is known as 'normalization'. Normalized performance values are dimensionless (independent of the unit). The different criteria dimensions are converted into dimensionless criteria. The aim here is to make comparisons independent of the unit of measurement (Özden, 2011, p.221). Criteria are independent qualifications that must be met by several alternatives. Each criterion can be measured in different units such as degrees, kilograms or meters; however, to allow aggregation in a final score, criteria in different units need to be normalized to make them dimensionless and obtain a common numerical range/scale (Vafaei, Ribeiro and Camarinha-Matos, 2016, p.261). The normalization process for comparing the alternatives on each attribute is usually built on a column-by-column basis, and the normalized value takes a positive value between 0 and 1. Thus, the problem is eliminated by making the different measurement units in the decision matrix similar (Yazdani, Jahan and Zavadskas, 2017, p.60). However, some techniques such as Vector and Decimal provide normalization in the range of -1 and 1 (Aytekin, 2021). In some cases, the normalized values may be higher than 1 in the techniques of this category. This situation is generally undesirable in some MCDM methods (Jahan and Edwards, 2015, p.338). In general, normalized values are expected to be within a certain range in all criteria as a result of normalization. At this point, it is more preferred that the normalized values are in the range of 0-1 (Aytekin, 2021, p.16).

On the other hand, the weight of each criterion plays an important role in the MCDM process, since it reflects the importance over others and, therefore, influences the final decision-making (Altintas, Vayvay, Apak and Cobanoglu, 2020, p.2). This first step of normalization is mandatory for the whole set of indicators to: (1) be on the same scale of values. (2) express an equivalent semantic. These two points make it possible for the aggregation operator to work on a set of values of equivalent scale and semantics (Rizzolo, Abichou, Voisin and Kosayyer, 2011, p.1008). But, some methods such as the Weighted Product Method (WPM), Weighted Sum Method (WSM), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) and ELimination Et Choix Traduisant la REalité-ELimination and Choice Expressing the REality (ELECTRE) III, can compare two alternatives without using any normalization technique. Depending on the nature of the problem and the range of features, some situations may do not require a normalization process.

The MCDM models may not be able to provide the optimum solution, but they can choose the best one among some predetermined alternatives. The selection of a suitable normalization technique is important to make the right decision. While the normalization operation scales the criterion values to approximately the same size, different normalization procedures may produce different solutions (Chatterjee and Chakraborty, 2014, p.148). Researchers often underestimate the importance of choosing the appropriate normalization technique to solve a given decision-making problem. However, normalization techniques are very important in the decision process and can change the ranking of alternatives (Kosareva, Krylovas and Zavadskas, 2018, p.160).

The purpose of this study is to determine the most suitable normalization technique for the combined compromise solution (CoCoSo) method under different scenarios. CoCoSo method is highly reliable for the calculation of the optimal consensus score using an integrated framework (Torkayesh, Ecer, Pamucar and Karamaşa, 2021, p.6). Due to its structure, CoCoSo allows to build a more robust model and make more accurate decisions (Torkayesh, Pamucar, Ecer and Chatterjee, 2021, p.5). This method has been chosen because it has not been used in a similar problem before and it is advantageous. The advantages and contributions of the proposed decision-making approach are as follows:

i. The subject of this study was examined for the first time with the CoCoSo method.
ii. CoCoSo, which consists of the integration of methods such as the weighted aggregated sum product assessment (WASPAS), Simple Additive Weighting (SAW) and Exponentially Weighted Product (EWP), allows to build a more robust model and make more accurate decisions.
iii. This study is important in terms of showing the effect of normalization techniques on MCDM results and it can be a reference for researchers in the future.

The rest of this paper is organized as follows: Section 2 includes the discussion of the literature review. The mathematical model used in the application is described in Section 3. The findings of the study are included in Section 4. Finally, the discussion, concluding remarks and future research directions are given in Section 5.

LITERATURE REVIEW

MCDM methods are developed to assist decision-makers regarding multiple alternatives and conflicting criteria. MCDM methods, which have become increasingly important in recent years, are considered as solution methods in different issues such as supplier selection (Stević, Pamučar, Puška and Chatterjee, 2020), personnel selection (Krishankumar, Premaladha, Ravichandran, Sekar, Manikandan and Gao, 2020), location selection (Tadić, Krstić, Roso and Brnjac, 2020), project evaluation (Mahmoudi, Deng, Javed and Yuan, 2020) and performance evaluation (Abdel-Basset, Ding, Mohamed and Metawa, 2020).

The normalization process is usually the first step in MCDM problems and is very important. The normalization techniques used in MCDM methods affect the results and differ according to the structure of the problem and the algorithm of the method. For example, in the presence of negative and zero values in the decision matrix, not all normalization techniques can be used (Aytekin, 2021; Vafaei et al., 2016). Table 1 gives information about the normalization techniques used in MCDM methods.

Table 1: The Normalization Techniques for MCDM Methods

Methods	Normalization technique	Source
TOPSIS	Vector normalization	Triantaphyllou (2000)
PIV	Vector normalization	Mufazzal and Muzakkir (2018)
MOORA	Vector normalization	Brauers and Zavadskas (2009)
ELECTRE I	Vector normalization	Huang and Chen (2005)
GRA	Weitendorf linear normalization	Wu (2002)
VIKOR	Weitendorf linear normalization	Opricovic and Tzeng (2004)
ROV	Weitendorf linear normalization	Madić and Radovanović (2015)
PROMETHEE	Weitendorf linear normalization	Brans and Vincke (1985)
COPRAS	Sum based linear normalization	Zavadskas, Kaklauskas and Sarka (1994)
AHP	Sum based linear normalization	Saaty (1980)
ARAS	Sum based linear normalization	Zavadskas and Turskis (2010)
WASPAS	Linear normalization	Chakraborty and Zavadskas (2014)
SECA	Linear normalization	Keshavarz-Ghorabaee, Amiri, Zavadskas, Turskis and Antucheviciene (2018)
MARCOS	Linear normalization	Stević et al. (2020)
CODAS	Linear normalization	Ghorabaee, Zavadskas, Turskis and Antucheviciene (2016)

As shown in Table 1, normalization techniques vary according to MCDM methods. Weitendorf linear normalization techniques are used in Grey Relational Analysis (GRA) and VIsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methods, but GRA, which has a different normalization procedure for the criteria desired to be in the optimum direction, differs from the VIKOR method. In methods such as Weight Product Method (WPM) and Weight Sum Method (WSM) which are not given in Table 1, alternatives are compared without the need for any normalization technique.

The effects of different normalization techniques were examined for many MCDM methods in the literature. Pavlicic (2001) examined the effects of three popular normalization procedures on the SAW, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and ELECTRE methods. It was concluded that the normalization procedure affected the options. Mathew, Sahu & Upadhyay (2017) used different normalization procedures for the WASPAS method and determined max-min was the best normalization technique for the WASPAS method. Chakraborty and Yeh (2007) compared four commonly known normalization procedures using the SAW method. It was concluded that linear scale transformation and vector normalization performed better than other normalization techniques. Chakraborty and Yeh (2009) tested the suitability of different normalization techniques for the TOPSIS method. It was determined that vector normalization was most suitable for the TOPSIS method. Similarly, Celen (2014) determined the effects of various normalization procedures on the Fuzzy Analytical Hierarchy Process (FAHP) and TOPSIS methods. It was determined that the most coherent results were obtained by vector normalization. Milani, Shanian, Madoliat & Nemes (2005) examined the effect of five normalization techniques on the TOPSIS method. It was concluded that different normalization procedures produced different rankings. Brauers and Zavadskas (2006) proved the appropriateness of five normalization procedures for the Multi-objective Optimization By Ratio Analysis (MOORA) method. It was concluded that the vector normalization technique generated the most consistent results. Yazdani et al. (2017) measured the effects of different normalization techniques on the COmplex PRoportional ASsessment (COPRAS)-G model. It was determined that the logarithmic normalization was the most suitable technique for the COPRAS-G method. Kosareva et al. (2018) tested the suitability of five different normalization techniques for the SAW method. They found that of all the five techniques, none was the best or worst in all cases and that the logarithmic normalization technique was the worst in some cases. Vafaei et al. (2016) examined the effects of the most appropriate normalization techniques for the Analytical Hierarchy Process (AHP) method. It was revealed that the logarithmic normalization technique could not be used in the AHP method, as it leads to zero or infinite values in the normalized decision matrix. Ersoy (2021) tested the suitability of eight normalization techniques for the Range of Value (ROV) method. It was determined that non-linear normalization was the most suitable technique for the ROV method.

The effects of different normalization techniques on the SAW, TOPSIS, ELECTRE, WASPAS, MOORA, COPRAS, AHP, and ROV methods were examined. The normalization process is very important in MCDM problems and the effects of different normalization techniques on the CoCoSo method have not been examined until now. These are the motivations for conducting this study.

CoCoSo METHOD

The CoCoSo method was proposed by Yazdani, Zarate, Zavadskas and Turskis (2019). This approach consists of the integration of the WASPAS, SAW and EWP methods (Yazdani et al., 2019). Although the CoCoSo and WASPAS methods have different normalization processes, in the third step of the CoCoSo method, the sum of the power weight (Pi) values are calculated based on the multiplicative property of the WASPAS. The steps of the method are as follows:

Step 1: The initial decision matrix is determined

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \qquad i = 1,2,\ldots,m; j = 1,2,\ldots,n \tag{1}$$

Step 2: The criteria are normalized using the formulas below.

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \qquad \text{for benefit criteria} \tag{2}$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \qquad \text{for cost criteria} \tag{3}$$

Step 3: Si and Pi values are obtained.

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}) \tag{4}$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \tag{5}$$

The Si value is obtained according to the GRA methodology, while the Pi value is determined according to the WASPAS method.

Step 4: Appraisal score strategies are calculated.

The relative weights of each alternative are generated using the following aggregation strategies.

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)}, \tag{6}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i}, \tag{7}$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{(\lambda \max_i S_i + (1-\lambda) \max_i P_i)} \tag{8}$$

Equation (6) expresses the arithmetic mean of WSM and WPM sums, while Equation (7) states the sum of WSM and WPM relative scores. Equation (8) states the balanced reconciliation of WSM and WPM scores. Equation (8), λ is usually chosen by decision makers as $\lambda = 0.5$.

Step 5: The performance scores of alternatives are computed.

The performance scores of options are calculated using equation 9. The highest performance score is desirable.

$$k_i = (k_{ia} + k_{ib} + k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \tag{9}$$

NORMALIZATION INSTRUMENTS

The normalization process aims to evaluate each alternative under the same conditions. However, different normalization techniques can lead to different values and results (Chatterjee and Chakraborty, 2014, p.148). Evaluation of alternatives under the same conditions means that alternatives with different characteristics are evaluated in the same point with similar characteristics. For example, companies can have different sizes such as large, MNE, SME. To make a healthy evaluation, companies with similar characteristics should be evaluated within themselves. On the other hand, alternatives are evaluated based on criteria. Again, criteria with different units are converted into similar measurement units and alternatives are evaluated under similar conditions to make a healthy comparison.

Jahan and Edwards (2015) provided a comprehensive review of existing normalization methods. They identified 31 normalization methods and categorized these methods as sum-based, linear max–min dimensionless methods, linear-ratio-based, and nonlinear dimensionless methods (z-transformation, etc.). This study focuses on the normalization methods presented in Table 2.

Table 2: Normalization Techniques

Normalization method	Condition of use	Formula	Source
Vector Normalization (N1)	Benefit criteria	$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$	Milani et al. (2005); Shanian and Savasdogo (2006); Delft and Nijkamp (1977)
	Cost criteria	$n_{ij} = 1 - \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$	Zavadskas and Turskis (2008); Delft and Nijkamp (1977)
Linear Normalization sum based method (N2)	Benefit criteria	$n_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$	Milani et al. (2005); Jee and Kang (2000); Wang and Luo (2010)
	Cost criteria	$n_{ij} = \frac{1/r_{ij}}{\sum_{i=1}^{m} 1/r_{ij}}$	Wang and Luo (2010); Stanujkic, Dordevic and Dordevic, (2013)

Enhanced accuracy method (N3)	Benefit criteria	$n_{ij}=1-\frac{r_j^{\max}-r_{ij}}{\sum_{i=1}^{m}(r_j^{\max}-r_{ij})}$	Zeng, Li and Yang (2013)
	Cost criteria	$n_{ij}=1-\frac{r_{ij}-r_j^{\min}}{\sum_{i=1}^{m}(r_{ij}-r_j^{\min})}$	Zeng et al. (2013)
Non-linear normalization (N4)	Benefit criteria	$n_{ij}=(\frac{r_{ij}}{r_j^{\max}})^2$	Zavadskas and Turskis (2008); Peldschus, Vaigauskas and Zavadskas (1983)
	Cost criteria	$n_{ij}=(\frac{r_j^{\min}}{r_{ij}})^3$	Zavadskas and Turskis (2008);Peldschus et al. (1983)
Weitendorf linear normalization method (N5)	Benefit criteria	$n_{ij}=\frac{r_{ij}-r_j^{\min}}{r_j^{\max}-r_j^{\min}}$	Asgharpour (1998); Zavadskas and Turskis (2008); Tzeng and Huang (2011); Shih, Shyur and Lee (2007); Chakraborty and Yeh (2007)
	Cost criteria	$n_{ij}=\frac{r_j^{\max}-r_{ij}}{r_j^{\max}-r_j^{\min}}$	Asgharpour (1998); Zavadskas & Turskis (2008); Tzeng & Huang (2011); Shih et al. (2007); Chakraborty and Yeh (2007)
Linear normalization (N6)	Benefit criteria	$n_{ij}=\frac{r_{ij}}{r_j^{\max}}$	Milani et al. (2005); Asgharpour (1998); Farag (1997); Tzeng and Huang (2011)
	Cost criteria	$n_{ij}=1-\frac{r_{ij}}{r_j^{\max}}$	Milani et al. (2005); Asgharpour (1998); Farag (1997)

Source: Jahan and Edwards (2015, pp. 337-340).

Zavadskas, Zakarevicius, Antucheviciene (2006) tested the suitability of the non-linear normalization technique for the TOPSIS method in their study. The Enhanced accuracy method (N3) was used by Zeng et al. (2013) within the VIKOR method. In this study, the six normalization techniques in Table 1 were preferred because they do not cause outliers in the normalized matrix. On the other hand, Lai and Hwang (1994) method, z-transformation method, and logarithmic normalization methods could not be used because they cause negative values in the normalized matrix. Zavadskas & Turskis method could not be included in the study because they cause values greater than 1 in the normalized decision matrix (Ersoy, 2021, p.596).

APPLICATION OF NORMALIZATION TECHNIQUES FOR CoCoSo METHOD UNDER DIFFERENT SCENARIOS

In this study, the effects of ten normalization techniques on the CoCoSo method were examined. Accordingly, different data sets were created; all normalization techniques were tested for the CoCoSo method, and the ranking results were compared. Basically, for an MCDM problem to occur, there must be at least two alternatives and multiple conflicting criteria (Tabucanon, 1988, p.5). Durucasu, Aytekin, Saraç and Orakçı (2017) examined studies in which the MCDM method was used in 13 different fields, including education, energy, tourism and sustainability. Accordingly, at least two alternatives and two criteria were used in these studies. These numbers increased to over 40 in some cases. In this study, seven different data sets were created according to six alternatives and six different evaluation criteria.

MS Excel program was used to create data sets. In terms of each evaluation criterion, examinations were carried out with different value ranges. MS Excel was used to generate the performance values of the alternatives randomly. For this purpose, the formulas=RANDBETWEEN(lower_bound_value; upper_bound_value) and =RAND() were used. The functions used in creating the six different alternatives and seven different data sets according to the evaluation criteria are shown in Table 3.

Table 3: Functions Used for Each Criterion

Criteria	Function
Criterion 1	=RANDBETWEEN(1;10)
Criterion 2	=RANDBETWEEN(0,1;1)
Criterion 3	=RANDBETWEEN(0,02;0,97)
Criterion 4	=RANDBETWEEN(7500;15000)
Criterion 5	=RANDBETWEEN(3100;6300)
Criterion 6	=RANDBETWEEN(65;280)

The data sets are given in Table 4.

Table 4. The Decision Matrices for Different Sets

		Criteria					
Sets	Alternatives	C1	C2	C3	C4	C5	C6
		max	max	max	max	min	min
Set1	A1	4	0.226	0.372	13956	3776	257
	A2	1	0.555	0.547	9695	5597	231
	A3	5	0.377	0.291	13587	5661	208
	A4	9	0.645	0.178	14727	4463	127
	A5	4	0.483	0.407	11783	5337	187
	A6	4	0.241	0.687	10496	6242	130
Set2	A1	5	0.470	0.557	12188	4028	168
	A2	8	0.596	0.538	8825	4834	225
	A3	8	0.010	0.834	13236	5041	113
	A4	7	0.428	0.846	10078	6300	126
	A5	6	0.995	0.383	8624	5131	215
	A6	5	0.176	0.193	12825	4362	226
Set3	A1	5	0.678	0.368	10143	3413	274
	A2	9	0.458	0.978	9718	3340	170
	A3	6	0.945	0.810	10396	3786	160
	A4	9	0.439	0.199	11629	4172	105
	A5	6	0.341	0.613	14862	3431	182
	A6	8	0.782	0.023	10046	3975	184
Set4	A1	10	0.111	0.072	10078	5870	228
	A2	7	0.317	0.932	11392	5886	210
	A3	5	0.544	0.390	13021	5343	276
	A4	5	0.598	0.213	11502	3629	217
	A5	4	0.105	0.974	9349	4866	71
	A6	5	0.666	0.560	13215	4400	125
Set5	A1	2	0.462	0.759	10362	4285	186
	A2	7	0.384	0.155	10822	4816	134
	A3	3	0.344	0.233	8649	3568	173
	A4	6	0.501	0.780	14154	4125	165
	A5	5	0.297	0.943	12208	3527	222
	A6	8	0.836	0.802	12338	5300	260
Set6	A1	9	0.449	0.559	9145	4622	208
	A2	9	0.274	0.556	7802	3380	196
	A3	6	0.906	0.579	10116	5531	67

	A4	10	0.451	0.940	13270	4423	196
	A5	2	0.451	0.524	10163	5978	253
	A6	10	0.497	0.084	7576	4207	273
Set7	A1	2	0.748	0.109	9109	5672	234
	A2	8	0.145	0.591	12012	3411	208
	A3	4	0.991	0.660	12899	5068	149
	A4	8	0.034	0.024	9820	3265	117
	A5	10	0.189	0.831	9144	4039	237
	A6	9	0.675	0.842	8839	4953	187

The criteria in MCDM problems can be either benefit or cost-oriented. To reflect a real problem, optimization aspects are determined as a benefit for C1-C4 criteria, and cost for C5-C6 criteria.

Application

In this section, the CoCoSo method was applied using a decision matrix prepared under different scenarios as seen in Table 4. First, the decision matrix data were normalized by using Weitendorf linear normalization technique in the algorithm of the CoCoSo method. For Set 1, the intersection of A1 and C1 and A1 and C5 in the first row was taken into consideration, and the calculations were made as follows.

For benefit criteria (C1); $\frac{4-1}{9-1} = 0{,}375$

For cost criteria (C5); $\frac{6242-3776}{6242-3776} = 1$

Table 5: The Normalized Decision Matrix for Set1

		C1	C2	C3	C4	C5	C6
Set1	A1	0.375	0.000	0.351	0.847	1	0.000
	A2	0.000	0.787	0.351	0.000	0.262	0.200
	A3	0.500	0.361	0.351	0.773	0.236	0.377
	A4	1	1	0.351	1	0.721	1
	A5	0.375	0.613	0.351	0.415	0.367	0.538
	A6	0.375	0,036	0.351	0.159	0	0.977

In the second step, the weighted normalized decision matrix was obtained using the criteria weights. In this study, equal weight was assigned to each criterion using the formula (10) (Jahan et al., 2012, p. 413).

$$w_j = \frac{1}{n} \tag{10}$$

n indicates the number of criteria and the sum of weights should be equal to 1.

Table 6: The Weighted Decision Matrix for Set 1

		C1	C2	C3	C4	C5	C6	S_i	P_i
Set1	A1	0.063	0.000	0.059	0.141	0.167	0.000	0.429	3.674
	A2	0.000	0.131	0.059	0.000	0.044	0.033	0.267	3.473
	A3	0.083	0.060	0.059	0.129	0.039	0.063	0.433	5.106
	A4	0.167	0.167	0.059	0.167	0.120	0.167	0.845	4.947
	A5	0.063	0.102	0.059	0.069	0.061	0.090	0.443	5.258
	A6	0.063	0.006	0.059	0.027	0.000	0.163	0.316	4.157

In the third step, relative weights of the alternatives are computed.
For [A1.C1];

$$k_{ia} = \frac{4,108}{29,459} = 0,139$$

$$k_{ib} = \frac{0,434}{0,329} + \frac{3,674}{3,473} = 2,377$$

$$k_{ic} = \frac{0,5*(0,434)+(1-0,5)*3,674}{0,5*(0,787)+(1-0,5)*5,258} = 0,680$$

$$k_i = (0,139+2,377+0,680)^{1/3} + \frac{1}{3}(0,139+2,377+0,680) = 2,538$$

Table 7: CoCoSo Results and Final Ranking

	k_{ia}	k_{ib}	k_{ic}	k_i	Final rank
A1	0.139	2.377	0.680	2.538	2
A2	0.129	2.000	0.629	2.322	1
A3	0.187	2.720	0.913	2.837	4
A4	0.195	3.817	0.949	3.359	6
A5	0.194	2.911	0.946	2.945	5
A6	0.156	2.488	0.758	2.638	3

Application of Six Normalization Techniques

In this study, six different normalization techniques were used to see their effect on the CoCoSo method. The overall performance scores obtained with the CoCoSo method using six different normalization techniques are presented in Table 8. In Table 8, the largest value produced in each set is indicated in bold, and the smallest value is indicated in red.

Table 8: Overall Performance Scores for Alternatives

		Normalization techniques					
Sets	Alternatives	N1	N2	N3	N4	N5	N6
Set1	A1	2.515	2.521	2.528	2.563	2.538	2.424
	A2	2.498	2.489	2.520	2.448	2.322	2.510
	A3	2.529	2.533	2.526	2.464	2.837	2.573
	A4	**2.618**	**2.762**	**2.539**	**3.137**	**3.359**	**2.902**
	A5	2.545	2.571	2.526	2.538	2.945	2.645
	A6	2.539	2.588	2.525	2.681	2.638	2.513
Set2	A1	2.597	2.725	2.530	2.747	3.164	2.853
	A2	2.599	2.718	2.526	2.665	3.081	2.737
	A3	2.558	2.718	**2.532**	**2.988**	**3.536**	**2.890**
	A4	**2.617**	**2.792**	2.526	2.830	3.150	2.759
	A5	2.603	2.736	2.525	2.636	2.775	2.757
	A6	2.491	2.485	2.522	2.431	2.262	2.403
Set3	A1	2.520	2.517	2.522	2.477	2.319	2.413
	A2	2.615	2.708	**2.533**	**2.890**	3.127	**2.873**
	A3	**2.627**	**2.728**	2.532	2.827	**3.147**	2.860
	A4	2.544	2.589	2.528	2.732	2.765	2.558
	A5	2.563	2.594	2.531	2.670	2.978	2.733
	A6	2.500	2.492	2.524	2.502	2.630	2.567
	A1	2.479	2.466	2.521	2.403	2.405	2.419

Set4	A2	2.618	2.755	2.529	2.771	3.094	2.694
	A3	2.569	2.640	2.525	2.660	2.995	2.550
	A4	2.571	2.663	2.529	2.819	3.388	2.793
	A5	2.581	2.820	2.530	2.903	2.611	2.812
	A6	**2.649**	**2.851**	**2.536**	**3.014**	**3.811**	**3.023**
Set5	A1	2.546	2.617	2.525	2.556	2.599	2.748
	A2	2.526	2.584	2.525	2.675	2.616	2.737
	A3	2.481	2.485	2.521	2.437	2.374	2.613
	A4	2.628	2.794	**2.535**	2.946	**3.270**	**3.013**
	A5	2.588	2.716	2.531	2.838	2.870	2.884
	A6	**2.644**	**2.825**	2.531	**2.965**	2.726	2.686
Set6	A1	2.587	2.682	2.532	2.842	3.409	2.870
	A2	2.568	2.664	2.533	2.956	3.191	2.862
	A3	2.642	**2.946**	2.536	3.365	3.758	3.047
	A4	**2.662**	2.855	**2.541**	**3.401**	**3.981**	**3.121**
	A5	2.489	2.476	2.520	2.399	2.366	2.377
	A6	2.508	2.536	2.526	2.708	2.498	2.509
Set7	A1	2.506	2.488	2.520	2.401	2.233	2.356
	A2	2.607	2.714	2.537	3.106	4.160	3.012
	A3	2.686	**2.887**	**2.538**	**3.312**	**4.426**	**3.199**
	A4	2.477	2.527	2.532	3.041	3.528	2.781
	A5	2.629	2.755	2.535	3.137	3.626	2.890
	A6	**2.689**	2.879	2.537	3.227	3.863	3.181

The approach proposed by Özdağoğlu (2013a, 2013b, 2014) was followed to examine the relationships between the different ranking results obtained with different normalization techniques in Table 8. In this direction, correlation analysis was carried out to determine the relationship between the results by using equation 11. The results are presented in Table 9.

$$r = \frac{n\Sigma xy - \Sigma x \Sigma y}{\sqrt{\left[n\Sigma x^2 - (\Sigma x)^2\right]\left[n\Sigma y^2 - (n\Sigma y)^2\right]}} \tag{11}$$

Table 9: Pearson Rank Correlation Analysis Results

	N1	N2	N3	N4	N5	N6
N1	1	0.953*	0.789*	0.799*	0.762*	0.838*
N2		1	0.790*	0.851*	0.751*	0.859*
N3			1	0.940*	0.880*	0.888*
N4				1	0.883*	0.887*
N5					1	0.890*
N6						1

* indicates significance at the 1 percent level.

According to the results in Table 9, the relationship between the results obtained with the N1 and N2 methods was found to be 95.3%. This shows that the results obtained with the two different normalization techniques are almost the same. Similarly, the correlation between the results obtained with N3 and N4 normalization techniques was determined as 94%, which is the second-highest value. The relationships between the results obtained with other normalization techniques are below 90%. The lowest values were found between the results obtained with N2 and N5 normalization techniques (75.1%) and N1 and N5 normalization techniques (76.2%). Note that N3, N4, N5 and N6 normalization techniques with high correlation values take into account the max and min directional criteria in the relevant column during the normalization phase. In N1, and N2 normalization techniques, the calculation is made by considering the total value of the relevant column.

According to Table 9, it is also possible to use N3, N4 and N6 techniques instead of the Weitendorf linear normalization technique in the algorithm of the CoCoSo method. On the other hand, N1 and N2 normalization techniques should not be used instead of the Weitendorf linear normalization technique in the algorithm of the CoCoSo method. As stated above, N1 and N2 normalization techniques consider the total values of the criteria in the relevant column instead of the benefit and cost aspects of the criteria during the normalization phase. In N3, N4, N5 and N6 normalization techniques, the normalization process is performed by considering the benefit or cost aspect of the criteria.

CONCLUSION

Normalization is one of the most important processes in MCDM problems and has an impact on MCDM results. In most MCDM methods, the first step is the normalization procedure. Using different normalization techniques may result in different rankings of the alternatives. This can lead to deviation from the optimal ranking. Therefore, the selection of appropriate normalization techniques plays an important role in the final results of decision problems (Vafaei, Ribeiro and Camarinha-Matos, 2020, p.43).

In this study, seven different datasets containing six alternatives and six criteria were created to examine the effect of normalization techniques on MCDM results. Six different normalization techniques were applied to the seven different data sets created, and the results were subjected to correlation analysis. While creating the data sets, suitability for real-life problems was taken as a basis, and values in different ranges, min and max directional criteria values were considered.

According to the results of the correlation analysis, a high positive correlation was determined between the values obtained with the six different normalization techniques. The highest value obtained (95.3%) was found between the result of N1 and N2 normalization techniques. The second highest value (94.0%) was found between the result of N3 and N4 normalization techniques. The lowest correlations were found between the results obtained with N2 and N5 normalization techniques (75.1%) and N1 and N5 normalization techniques (76.2%). N3, N4, N5 and N6 normalization techniques with high correlation values consider the max and min directional criteria in the relevant column during the normalization phase. In N1, and N2 normalization techniques, the calculation is made by considering the total value of the relevant column.

The results obtained from this study can be summarized as follows;

i. The use of different normalization techniques affects MCDM results. The ranking results changed according to the normalization technique used.

ii. N3, N4, and N6 normalization techniques can also be used instead of the Weitendorf linear normalization technique in the algorithm of the CoCoSo method.
iii. N1 and N2 techniques should not be used instead of the Weitendorf linear normalization technique in the algorithm of the CoCoSo method.
iv. The rankings obtained with the normalization techniques that consider the benefit and cost-oriented criteria (N3, N4, N5, N6), are similar to each other, and the same applies to the rankings obtained with the normalization techniques that consider the total value of the relevant column in the decision matrix (N1, N2).

Cases with negative and zero values in the decision matrix are very rare in MCDM methods. In this study, suitability for real-life problem is taken as the basis, and values in different ranges, min and max directional criteria values are considered. To test more normalization methods, negative and zero-valued data are not included in the decision matrix. On the other hand, the rank reversal problem was not addressed in this study. These are the limitations of the study. In future studies, the suitability and effect of normalization techniques under different scenarios can be examined by considering different MCDM techniques. In addition, a larger data set can be used in the studies considered.

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