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Research Article

Correlation based sensitivity analysis and suitability evaluation of multi-criteria decision-making methods according to different normalization techniques

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ABSTRACT

Using multi-criteria decision-making (MCDM) methods and the most appropriate normalization techniques significantly affects the accuracy of the ranking results obtained. The study's primary purpose is to present new robust and practical evaluation strategies for both the suitability of normalization techniques and the sensitivity of MCDM methods. In this study, new strategies created with metrics different from those used in previous studies (Spearman correlation, mean absolute deviation and variation coefficient) are proposed to evaluate the suitability and sensitivity of nine different MCDM methods with seven different normalization techniques. *Strategy 1* is presented among the proposed strategies to evaluate the suitability of normalization techniques, and *Strategy 2* assesses MCDM methods' sensitivity. The most important advantage of the proposed strategies compared to other studies is they provide a more reliable and practical experience by testing the consistency of the results. The compatibility of the results obtained by applying the proposed strategies shows that they are dependable, practical, and robust. According to the effects of Strategy 1, the most suitable normalization technique for each examined MCDM method is the Linear normalization technique, whereas the most unsuitable technique is the Logarithmic normalization technique. According to the results of Strategy 2, the most sensitive methods affected by the change of normalization techniques are TOPSIS (The Order Preference by Similarity Ideal Solution) and CODAS (COmbinative Distance-based Assessment), and the least sensitive methods are COCOSO (Combined Compromise Solution) and VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje). For the first time, more than one MCDM method was evaluated in terms of both the sensitivities of MCDM methods and the suitability of normalization techniques comparatively, and for this purpose, the new robust and practical strategies with reliable metrics (strategies 1 and 2) are presented.

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INTRODUCTION

Decision-making is one of the most critical stages in management, strategy development, planning and similar issues. Multi-criteria decision-making (MCDM) methods are the methods used effectively in decision-making stages. Many objective and subjective MCDM methods in the literature can be applied depending on the problem, and new ones are added to the existing methods. The results obtained with MCDM methods vary depending on the parameters used during the analysis phase. These are generally normalization techniques and criterion weighting methods. The focused factor in this study is the normalization techniques used in MCDM methods. When studies in the literature are examined, the generally used normalization techniques are; linear, non-linear, max, max-min, sum, vector and logarithmic normalization technique, and studies on the evaluation of these techniques for different MCDM methods are given below.

In their study, Lakshmi and Venkatesan evaluated the TOPSIS method with the relative closeness coefficient metric using five different normalization techniques [1]. They compared their use with TOPSIS for each normalization technique in terms of time and space complexity. Similarly, Çelen, who used four different normalization techniques for the TOPSIS method, evaluated 13 foreign Turkish deposit banks in his study and used the FAHP (Fuzzy Analytical Hierarchy Process) method in criterion weighting. The study used descriptive statistical values, Kolmogorov-Simirnov test statistics, and correlation coefficients to measure and evaluate the suitability of normalization techniques with the TOPSIS method [2]. Vafaei et al. proposed an evaluation approach to evaluate the compatibility of five normalization techniques with AHP using Pearson and Spearman correlation coefficients [3]. Mathew et al. evaluated the WASPAS method with six different normalization techniques in the industrial robot selection case study. They used the average Spearman correlation coefficient as a metric [4]. TOPSIS and SAW methods were evaluated in separate analyses for six different normalization techniques, with metrics such as RCI (Rank Consistency Index), Pearson and Spearman correlation coefficients and descriptive statistics values [5, 6]. Kosareva et al. evaluated the compatibility of five different normalization techniques for the SAW method for different scenarios with decision-making matrices created using the Monte Carlo method [7]. In another study, the WSM (Weighted Sum Method), TOPSIS and ELECTRE methods were compared with the WPM (Weighted Product Method) method, which does not require normalization, and were evaluated using the correlation coefficient for three different normalization methods [8]. In two separate studies conducted in 2021, the compatibility of SAW and TOPSIS methods with varying techniques of normalization was evaluated with RCI, standard deviation, Euclidean distance, mean square error and average correlation values, using data taken from the literature [9, 10]. In her study, Ersoy interpreted the ROV (Range of Value) method for eight different normalization techniques with standard deviation, Euclidean distance, RCI and average correlation values, using the 2020 data of the top 10 companies on the FORTUNE 500 list. In another study, using seven artificial data sets, she examined the compatibility of six different normalization techniques with the COCOSO method using the Pearson correlation coefficient [11, 12]. Pandya and others conducted a study in the field of public health during the pandemic crisis in 2021 [13]. In the study, they presented a deep learning and sensor fusion-based approach that helps reduce the spread of coronavirus. Considering the pandemic crisis, Vafaei et al., who examined the SAW method for six different normalization techniques through the case study of ICU patients sorting and resource allocation, used metrics such as standard deviation, MSE, RCI, and average correlation in their evaluations [14]. Tran et al., in their study in 2023, evaluated the compatibility of 12 different normalization techniques with the Preference Selection Index (PSI) method. In the study, analyzes were carried out on 4 different scenarios and datasets and as a result, the normalization techniques most compatible with PSI were; It has been concluded that there are Linear normalization, Max linear normalization, Jüttler-Körth normalization and Z-score normalization techniques [15]. Baydaş and his colleagues emphasized the effect of using the correct normalization technique on the ranking result quality and presented a special evaluation approach to financial data. Using the evaluation approach presented, they carried out analyses of different financial data and showed that the evaluations can change dynamically depending on the data structure and time [16]. Esangbedo and Wei pointed out in their study that using different normalization techniques created differences in the rankings obtained with MCDM methods. They addressed this uncertainty problem in terms of performance value measurement of alternatives, criterion weighting and normalization and they proposed a hybrid normalization technique based on the Grey relationship. For the practical application of the method, 48 cities ranked with the data of a Chinese electric vehicle manufacturer between 2019 and 2021 [17]. In another study, Baydaş et al. examined the effects of normalization techniques on MCDM results and the effects of fuzzy and crisp data structures. In the study, ten different data showing the economic performance of G-20 countries were analyzed and evaluated with ten different MCDMs. Multiple normalization techniques and correlation methods were used to evaluate and compare the results. According to the analysis results, the most compatible combination that shows the best performance; was the fuzzy-based CODAS method with the maximum normalization technique [18]. In their study, Jagtap and Karande used the ELECTRE-1 method integrated with the m-polar fuzzy set approach presented as a solution approach to the multi-polar uncertainty problem. In the study, along with this method, the AHP method and the Shannon's entropy weighting method were applied in criterion weighting, and the compatibility of the different normalization techniques used was evaluated comparatively with the Spearman correlation coefficient [19]. Unlike other studies, Raszkowska and Wachgwicz investigated the effects of different normalization techniques on criterion weights by using the entropy weighting method. For the analysis, the entropy method was applied together with the Helwigs method to the 2021 education and sustainability data of European countries and the results were evaluated [20].

Unlike other studies, the new strategies presented not only obtain the appropriate result with the similarity relationship but also evaluate the consistency of the result with the coefficient of variation. Therefore, this strategy (strategy 1) also tests the accuracy of the result and increases its reliability. In this way, the strategies presented provide more reliable and more practical results than other studies. On the other hand, unlike other studies, for the first time in this study, the sensitivity of MCDM methods to different normalization techniques was evaluated with the proposed strategy (strategy 2). Sensitivity analyses were carried out with this strategy and it was shown that the sensitivities of the MCDM methods also had an impact on the different rates of variation in the ranking results.

When existing studies are examined, it is observed that the evaluations are conducted based on a single MCDM method and with similar metrics for different numbers of normalization techniques. Due to the different data, results must be objectively compared for the relevant MCDM method. This is because the methods are costly in terms of calculation and time. This study conducted analyses using Python programming and the results were obtained quickly and easily. Differently from the studies in the literature, in this study, for the first time, the sensitivities of nine different MCDM methods: ARAS, COCOSO, CODAS, MABAC, MAIRCA, MARCOS, OCRA, TOPSIS, VIKOR, for the normalization techniques, using seven different normalization techniques; Min-max, Max, Sum, Vector, Linear, Non-linear and Logarithmic, were evaluated comparatively in a measurable way, by using a new proposed evaluation strategy (Strategy 2), and the suitability of the normalization techniques for the MCDM methods used was evaluated with another newly proposed method (Strategy 1). The strategies proposed in the study for these evaluations are new evaluation strategies focused on similarity and variability, using the Spearman correlation coefficient, average absolute deviation and coefficient of variation metrics.

Normalization techniques are methods that facilitate the application of many methods, not only MCDM methods, and ensure that analysis and evaluations give accurate and reliable results without any loss of information in the data. There are many normalization techniques in the literature, and the main purpose of all of them is to transform the data set to be used into the most suitable form for analysis. The use of a normalization technique that is not suitable for the method or data used will significantly affect the reliability and accuracy of the study results. For this reason, it is very important to determine which method gives the most reliable results with which normalization technique and to examine the sensitivity of the methods used when different normalization techniques are used. The main motivation of this study is to provide reliable and practical evaluation strategies for determining the most appropriate normalization methods for MCDM methods and examining their sensitivities. The presented strategies aim to increase the accuracy and reliability of the results obtained by the methods by determining appropriate normalization techniques for MCDM methods.

In the rest of the study; details about the data set, MCDM methods, normalization techniques and evaluation strategy metrics used in the study are given in the methodology section, evaluations of the analysis results along with graphs and tables are included in the results and discussion section, and the conclusion section evaluates, the general result of the study.

MATERIALS AND METHODS

The purpose of this study is to comparatively evaluate the sensitivity of MCDM methods to the change of the normalization techniques using the proposed evaluation strategies and to analyze the compatibility of normalization techniques for the MCDM methods used. The sensitivity of a method expresses how and how much the results change depending on the change of any parameter or used techniques. A significant difference in the results in response to a specified parameter or technique means that the method's sensitivity to the relevant parameter or technique change is high. In contrast, a small or no change in the results indicates that the method is insensitive to the relevant parameter or technique change. In this study, while analyzing the compatibility and sensitivity of MCDM methods on a method basis through the normalization techniques, the same data set was used for all MCDM methods, and all criteria were weighted equally for a healthy comparison and reliability of the results.

Dataset

The data set created with 2020 data from data.un.org, the United Nations data platform, was used in the study [21]. This data set includes 39 European countries considered alternatives and comprises ten features evaluated as criteria. In this study, European countries are ranked according to their environmental and infrastructure data for each MCDM method. In the study, some criteria were accepted as benefit-oriented and some as cost-oriented. These criteria (features) are indicator variables containing environmental and infrastructure information of countries. They are as follows:

1. Individual internet consumption: benefit criteria,

2. Research and development expenditures: benefit criteria,
3. Number of endangered species: cost criteria,
4. Forested area: benefit criteria,
5. CO2 emission estimate: cost criteria,
6. Primary energy production: benefit criteria,
7. Energy supply: benefit criteria,
8. Number of tourists and visitors: benefit criteria,
9. Areas protected for biodiversity: benefit criteria,
10. Official development aid spent: benefit criteria.

MCDM Methods

MCDM methods are the decision-making processes and can obtain different results depending on changing parameters or used techniques. In this study, the techniques used in the normalization process of data in MCDM methods, which are focused on, were evaluated on a method basis regarding compatibility (Strategy 1). The MCDM methods' sensitivity to the changing normalization techniques was made measurable and comparable for the first time with the presented strategy (Strategy 2). Nine different MCDM methods were used to be examined in the study. The Additive Ratio Assessment (ARAS) method determines the relative efficiency of alternatives proportionally according to the optimal alternative value through a utility function, considering the criterion weights [22]. The CoCoSo (Combined Compromise Solution) method, in which SAW (Simple Additive Weighting) and WPM (Weighted Product Model) methods are used in an integrated manner for the relative evaluation of alternatives in the solution stages, was proposed by Yazdani [23]. The CODAS (COmbinative Distance-based Assessment) method tries to achieve an objective ranking by calculating Euclidean and Taxicab distances over negative ideal solutions at various stages when evaluating alternatives [24]. MABAC (Multi-Attributive Border Approximation Area Comparison) is a MCDM method in which ideal and anti-ideal solutions are obtained with comparative distances to the border approximation area [25]. MAIRCA (MultiAtributive Ideal-Real Comparative Analysis), which considers the gap between ideal and empirical ratings and determines the alternative with a low gap value as the best and the alternative with a high gap value as the worst alternative, is a method based on theoretical and empirical ratio comparisons of alternatives [26]. The MARCOS (Measurement of Alternatives and Ranking according to COmpromise Solution) method evaluates and ranks based on the relationship of all alternatives with ideal and anti-ideal alternatives determined by a utility function [27]. OCRA (Operational Competitiveness Rating Analysis) is an MCDM method that intuitively performs preference ratings of criteria and both cardinal and ordinal evaluation of available options [28]. TOPSIS (The Order Preference by Similarity Ideal Solution), one of the most popular MCDM methods, evaluates and ranks alternatives according to their distance to ideal and anti-ideal solutions using Euclidean distance [29]. VIKOR method, on the other hand, is highly preferred in the presence of conflicting situations in the multi-criteria optimization of complex systems, which performs a compromise solution and ranking based on proximity to the ideal solution [30].

Normalization Techniques

Generally, the criteria in the data used in MCDM problems have different units and measurements. Therefore, for the applied methods to yield healthy results, it is crucial to normalize the data with a suitable normalization technique. Although there are many normalization techniques of different classifications in the literature, the most commonly used normalization techniques for optimization problems are normalization techniques depending on the optimization orientation, and the suitability of the chosen technique depends on both the problem structure and the MCDM method to be applied [31]. In many studies in the literature, the suitability of different normalization techniques for different MCDM methods has been examined. Among these techniques; vector, linear max-min, linear sum, linear max, and logarithmic normalization techniques are the most frequently used techniques, and metrics such as Pearson correlation, Spearman correlation, ranking consistency index, Euclidean distance have been preferred for conformity evaluations. In this study, analysis and evaluations were carried out for seven different normalization techniques that are widely used, and the formulations of the techniques according to the criterion types are given in Table 1. Here is x_{ij}; the value in i. column and j. row, x_{max}; maximum value in decision matrix, x_{min}; minimum value in decision matrix, $max_i x_{ij}$; maximum value in i. column, x_j^*; maximum value in j. column, x_j^-; minimum value in j. column.

Proposed Evaluation Strategies and Metrics

Evaluation metrics generally used in studies evaluating which normalization technique is more suitable for MCDM methods; are Spearman correlation coefficient, Pearson correlation coefficient, Rank Consistency Index (RCI), Standard deviation, Euclidean distance [4, 2, 11, 12]. Vafaei et al. proposed a 3-stage evaluation strategy, including these metrics and the mean square error (MSE), and carried out the compliance evaluations of normalization techniques for MCDM methods using this strategy in their studies [10, 14, 3]. In their proposed evaluation strategy, the data type is determined in the first stage, the normalization techniques to be evaluated are determined and applied in the second stage. In the last stage, the results are evaluated from different perspectives using many metrics. The metrics used aim to compare results in terms of similarity and spread.

Two different strategies are recommended for two purposes in this study. The stages of the proposed evaluation strategies are shown in Figure 1. The stages of these two proposed strategies are the same, but they differ in terms of evaluation. *In the first stage* for both strategies, criterion types are determined and the data set is ready. *In the second stage*, for each MCDM method, applications are conducted

Table 1. Normalization techniques were used in the study with benefit and cost criteria formulas.

Normalization	*Benefit criteria*	*Cost criteria*
Min-max [32].	$n_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}}$	$n_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}}$
Max [33].	$n_{ij} = \frac{x_{ij}}{max_i x_{ij}}$	$n_{ij} = 1 - \frac{x_{ij}}{max_i x_{ij}}$
Sum [34].	$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$	$n_{ij} = \frac{1/x_{ij}}{\sum_{i=1}^{m} 1/x_{ij}}$
Vector [35].	$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} \lvert x_{ij} \rvert^2}}$	$n_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} \lvert x_{ij} \rvert^2}}$
Linear [32].	$n_{ij} = \frac{x_j^* - x_{ij}}{x_j^* - x_j^-}$	$n_{ij} = \frac{x_{ij} - x_j^-}{x_j^* - x_j^-}$
Non-linear [34].	$n_{ij} = \left(\frac{x_{ij}}{max_i x_{ij}}\right)^2$	$n_{ij} = \left(\frac{x_{ij}}{max_i x_{ij}}\right)^3$
Logarithmic [35].	$n_{ij} = \frac{ln x_{ij}}{ln\left(\prod_{i=1}^{m} x_{ij}\right)}$	$n_{ij} = \frac{1 - \frac{ln x_{ij}}{ln\left(\prod_{i=1}^{m} x_{ij}\right)}}{m - 1}$

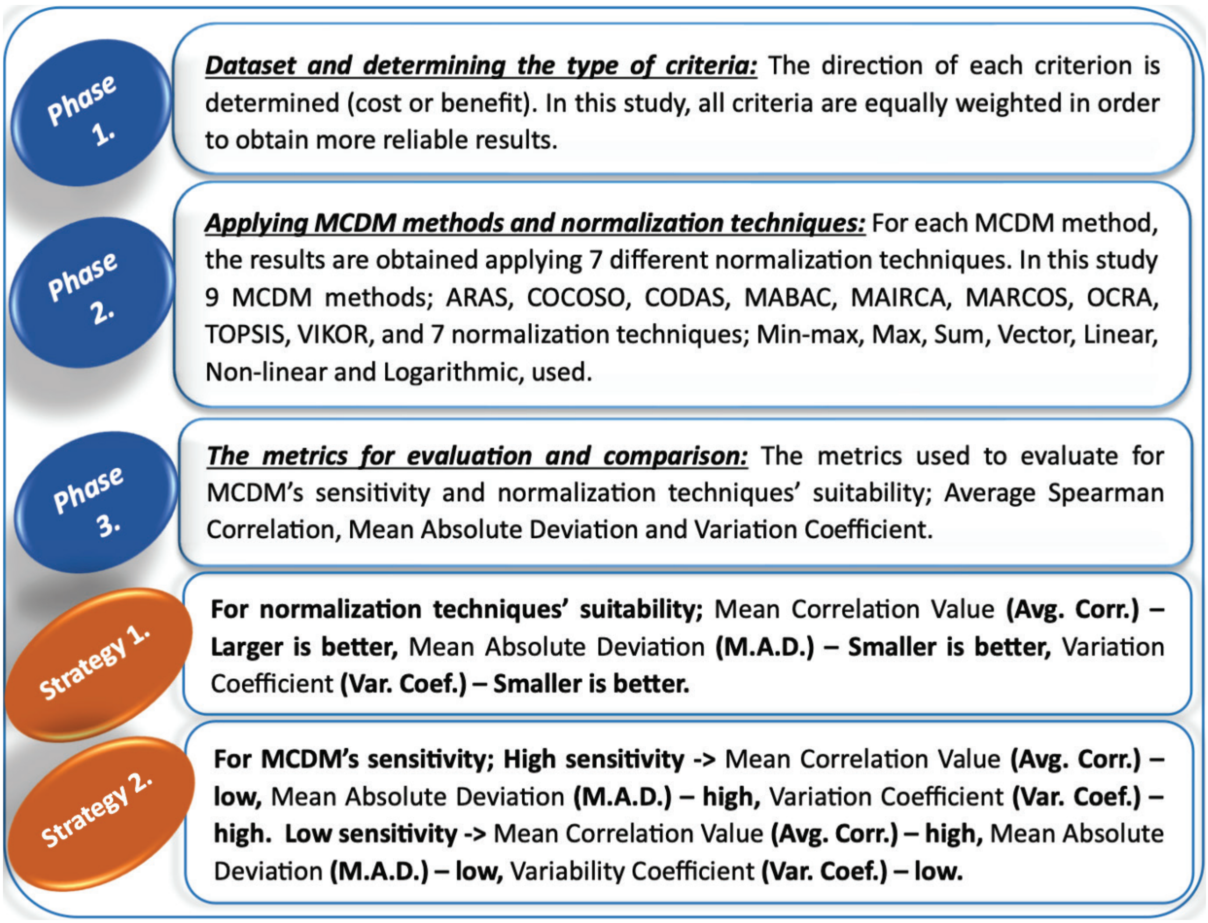

Figure 1. The main phases followed in the study and the proposed evaluation strategies.

Table 2. The metrics' formulas used for proposed evaluation strategies.

Spearman Rank Correlation (Avg. Corr.)	*Mean Absolute Deviation (M.A.D.)*	*Variation Coefficient (Var. Coef.)*
$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$ [36].	$MAD = \frac{\sum\lvert x_i - \bar{x}\rvert}{n}$ [37].	$CV = \frac{\sigma}{\mu} * 100$ [38].

with seven different normalization techniques selected, and the results are obtained as a ranking. *In the third stage*, the ranking results are evaluated comparatively in terms of similarity (Spearman rank correlation coefficient) and variation (Mean absolute deviation, Variation coefficient). The evaluations of metric calculations conducted in the studies in the literature were generally obtained not through the row numbers results, but through the ranked results without row numbers of the alternatives obtained due to the application of the methods.

In this study, all evaluations and calculations were conducted based on the ranking results with row numbers of alternatives, considering it to be more precise and reliable. Spearman correlation coefficient is a non-parametric method that measures the monotonic relationship between variables for ordinal data, regardless of population distribution [36]. Mean absolute deviation (M.A.D.) is a more effective and realistic metric than the standard deviation, least affected by data distribution and erroneous measurements [37]. The coefficient of variation, obtained by dividing the standard deviation of a series by the mean of the series, is one of the most reliable metrics that measures variability without being affected by the difference in the measurement unit of the variables [38]. The formulas of the metrics used in the evaluation phase of the proposed strategies are given in Table 2, and detailed explanations of the evaluation strategies proposed and used in the study are given below. Here is n; the number of observations, d_i; the difference between the two ranks of each observation, x_i; i. observation value, $\bar{x}$; arithmetic mean of the observations, σ; standard deviation of the observations, μ; mean of the observations.

Strategy 1: For normalization techniques' suitability; According to this strategy proposed for the suitability evaluation of normalization techniques, in the correlation matrix created for the rankings obtained with different normalization techniques, corresponding to the row average of the normalization technique with the highest average correlation value (Avg. Corr.), the lowest average absolute deviation (M.A.D.), and the lowest coefficient of variation (Var. Coef.), will be the most suitable normalization technique for the MCDM method. The high average correlation indicates how compatible and similar the relevant and other normalization techniques are regarding results. The change

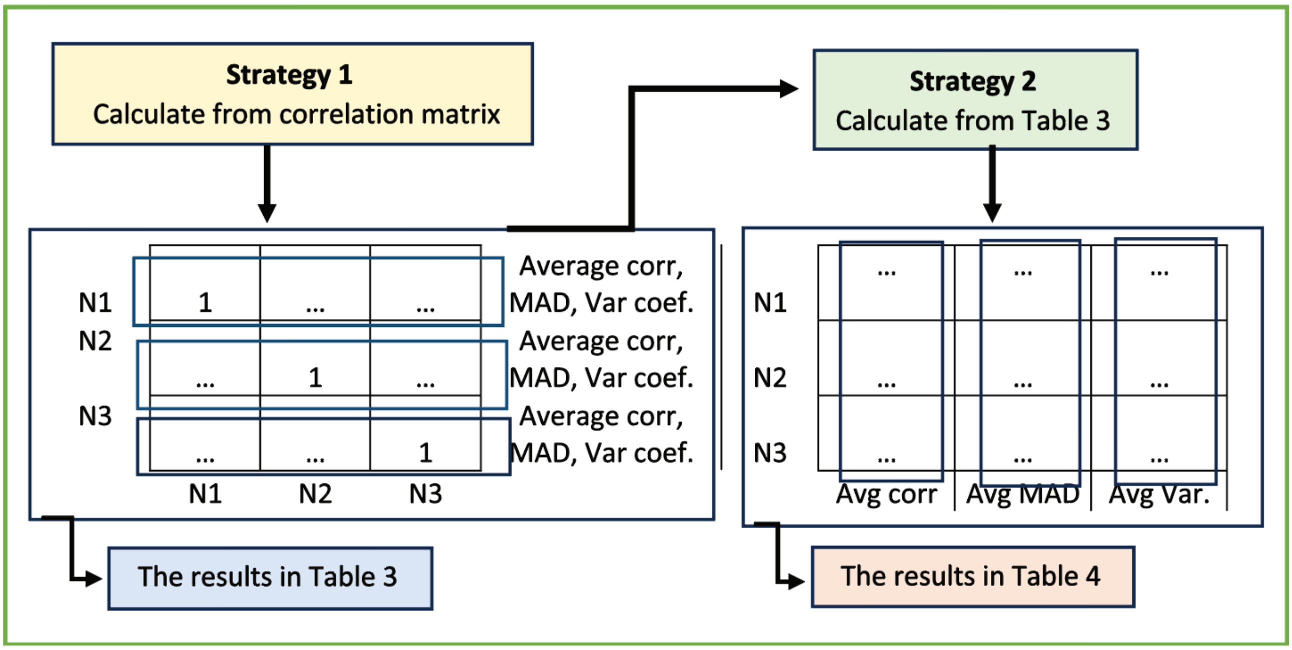

Figure 2. The flow chart of application of proposed evaluation strategies.

observed in the results obtained with a normalization technique that works compatible with the MCDM method should be at a minimum level, and the low average absolute deviation and coefficient of variation here indicate low deviation and low change in correlation values on the basis for the relevant normalization technique. In summary, as the similarity between the results increases, variability and deviation will decrease inversely. Table 6, which contains the correlation matrices created with the Spearman correlation technique used in calculating the metrics and the results obtained for strategy 1, is included in the results and discussion section.

Strategy 2: For MCDM's sensitivity; This strategy proposed to evaluate the sensitivity of MCDM methods according to the changing normalization techniques; in the values created by averaging the results obtained with the metrics based on the relevant MCDM method for the first strategy, the MCDM method which has a low average correlation value (Avg. Corr.) and a high average absolute deviation (M.A.D.) and average coefficient of variation (Var. Coef.), has the highest sensitivity to changing

Table 3. Ranking results for TOPSIS method using 7 different normalization techniques

Countries	*Minmax*	*Max*	*Sum*	*Vector*	*Linear*	*Nonlinear*	*Logarithmic*
Albania	25	19	12	13	25	30	39
Austria	4	3	18	8	8	9	1
Belarus	27	28	21	23	32	37	31
Belgium	9	8	25	12	15	15	5
Bosnia and Her.	34	30	19	16	36	36	38
Bulgaria	30	24	38	29	31	28	28
Croatia	29	29	34	30	35	33	25
Czechia	14	13	29	18	17	18	11
Denmark	3	4	22	9	12	6	6
Estonia	8	6	17	11	9	12	16
Finland	2	2	16	5	4	4	4
France	12	9	4	21	5	5	8
Germany	10	12	9	33	6	8	3
Greece	36	34	31	36	27	26	21
Hungary	22	22	33	27	29	29	15
Iceland	11	16	2	2	2	1	12
Ireland	20	26	36	25	34	25	23
Italy	35	35	10	39	18	22	18
Latvia	16	15	20	17	13	13	30
Lithuania	18	18	28	22	23	21	26
Luxembourg	5	5	3	7	1	2	22
Malta	28	33	6	28	19	20	32
Montenegro	19	14	5	6	7	7	36
Netherlands	7	11	23	15	16	10	9
NorthMacedonia	33	32	26	24	38	38	35
Norway	6	10	8	3	21	27	10
Poland	23	25	30	31	26	24	19
Portugal	38	38	37	37	33	34	17
Moldova	24	23	11	14	24	31	37
Romania	37	36	39	32	37	35	33
RussianFederation	32	31	1	1	10	14	24
Serbia	26	20	15	10	30	32	27
Slovakia	21	21	35	26	28	23	29
Slovenia	13	7	24	20	11	11	13
Spain	31	37	7	34	14	17	20
Sweden	1	1	13	4	3	3	7
Switzerland	15	17	27	19	20	16	2
Ukraine	39	39	32	38	39	39	34
United Kingdom	17	27	14	35	22	19	14

normalization techniques. On the contrary, the MCDM method with a high average correlation value, low average absolute deviation and average coefficient of variation will have the lowest sensitivity to the changing normalization techniques. In other words, the results obtained with changing normalization techniques are similar and the variability is low, which means that the results are least affected by the change in normalization techniques. In contrast, the similarity between the results is low and the variability is high, meaning that the results are most affected by the change in normalization techniques. Table 7, which contains the results for Strategy 2, is included in the results and discussion section.

The flow diagram explaining the calculation and application of Strategy 1 and 2 is shown in Figure 2 below. Following the flow diagram, it is explained how the necessary calculations for the strategies are made using the TOPSIS method. The results for other MCDM methods are given in the relevant tables.

The calculation steps of the presented strategies are explained below using the TOPSIS method. In the first step, depending on whether the criteria are benefit or cost-oriented, normalization techniques are applied to the data set and made ready for analysis. In the second step, the ranking results obtained with each normalization technique are obtained for the relevant MCDM method. Here, the TOPSIS method was chosen as an example and the rankings obtained with 7 different normalization techniques are given in Table 3 below. The rankings of other MCDM methods examined in the study are included in the appendices section.

In the third step, the similarity relationship coefficient, that is, the Spearman correlation coefficient, between the obtained rankings is calculated and a 7*7 correlation matrix is obtained. Subsequently, each row in the matrix is averaged separately and the average similarity relationship with other normalization techniques is obtained for each normalization technique. Similarly, the average absolute deviation and coefficient of variation values are calculated for each normalization technique, considering each row in the matrix. The results obtained for the TOPSIS method are given in Table 4. In Table 4 above, the Avg. Corr. values are obtained by calculating the row averages in the matrix. M.A.D. values are obtained by taking the average of the sum of the differences between the row elements and the row average. Var. Coef. is obtained by dividing the standard deviation of matrix row by its mean and multiplying by 100.

Table 5. General mean values of average correlations, mean absolute deviations and variation coeeficients for TOPSIS method

	Avg. Corr.	*M.A.D.*	*Var. Coef.*
minmax	**0.7356**	**0.1548**	**28.01**
max	**0.7170**	**0.1578**	**30.34**
sum	**0.4927**	**0.2171**	**55.33**
vector	**0.5933**	**0.1631**	**37.41**
linear	**0.7532**	**0.1286**	**20.66**
nonlinear	**0.7394**	**0.1512**	**23.91**
logarithmic	**0.5457**	**0.224**	**51.54**
General mean values	**0.6538**	**0.1709**	**35.31**

The formulas for the metrics used in these calculations are given in table 2. For strategy 1, the overall average metric values for the relevant MCDM method are found by considering the average of the average correlations, mean absolute deviations and coefficient of variation values obtained as a result of the calculations made for each normalization technique. These general mean values for the TOPSIS method are given in table 5 and the results are used in the sensitivity analysis evaluation of MCDM methods for strategy 2.

RESULTS AND DISCUSSION

This study proposes two strategies to evaluate the suitability of nine different MCDM methods for seven different normalization techniques and to measure their sensitivities comparatively. When looking at the studies in the literature, different results were obtained using different metrics and strategies for the different MCDM methods examined. For

Table 4. Correlation matrix with average corelation values, mean absolute deviations and variation coefficients for TOPSIS method

	Minmax	*Max*	*Sum*	*Vector*	*Linear*	*Nonlinear*	*Logarithmic*	*Avg. Corr.*	*M.A.D.*	*Var. Coef.*
Minmax	1	0.95	0.33	0.64	0.75	0.79	0.7	**0.7356**	**0.1548**	**28.01**
Max	0.95	1	0.29	0.71	0.73	0.74	0.6	**0.7170**	**0.1578**	**30.34**
Sum	0.33	0.29	1	0.51	0.69	0.53	0.1	**0.4927**	**0.2171**	**55.33**
Vector	0.64	0.71	0.51	1	0.57	0.52	0.21	**0.5933**	**0.1631**	**37.41**
Linear	0.75	0.73	0.69	0.57	1	0.96	0.58	**0.7532**	**0.1286**	**20.66**
Nonlinear	0.79	0.74	0.53	0.52	0.96	1	0.64	**0.7394**	**0.1512**	**23.91**
Logarithmic	0.7	0.6	0.1	0.21	0.58	0.64	1	**0.5457**	**0.224**	**51.54**

example, Vafaei et al., who evaluated normalization techniques using different data through the SAW method [10], concluded that the most appropriate normalization technique for this method was Linear sum, while in [14], they concluded that the most appropriate techniques were Linear max and Linear max-min. The results of studies evaluating different normalization techniques through the TOPSIS method have shown that the normalization techniques that work most compatible with this method are fuzzification (Gaussian) [9] and Vector normalization [2, 5]. Evaluating normalization techniques for COCOSO and ROV methods in two studies conducted in [11], Ersoy obtained the results that the most suitable techniques for these methods are Vector and Linear sum for Cocoso and non-linear for ROV, respectively. Vafaei et al., who evaluated normalization techniques for the AHP method in [36], concluded that the most appropriate normalization technique was the Linear max technique. This study analyzed the suitability of normalization techniques for the method by calculating the relevant metrics on the correlation matrices obtained for each method with Strategy 1 recommended for evaluation. The results of the calculations of the average correlation, average absolute deviation and coefficient of variation metrics are shown in Table 6. Correlation matrices calculated with the Spearman correlation technique for method-based normalization techniques are given below, and the evaluation of the most appropriate normalization techniques for the MCDM methods examined according to these matrices is explained separately for each method.

For ARAS, *Linear* is the technique with the highest correlation values with the darkest color tones. In contrast, the techniques with the lowest correlation values with the lightest color tones are *Sum* and *Logarithmic* normalization techniques.

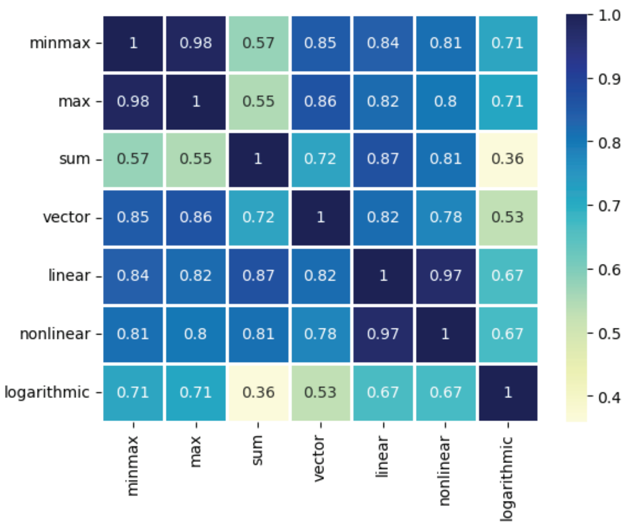

Figure 3. Correlation coefficients with colored matrix for different normalization techniques using the ARAS method.

For MABAC, *Linear* is the technique with the highest correlation values with the darkest color tones. In contrast, the techniques with the lowest correlation values with the lightest color tones are *Sum* and *Logarithmic* normalization techniques.

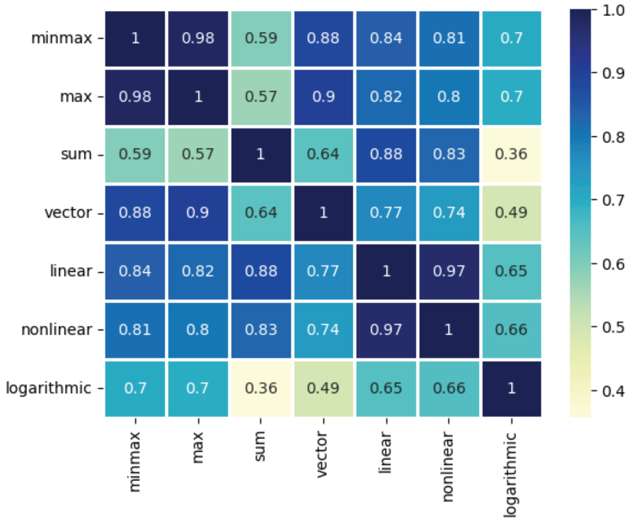

Figure 4. Correlation coefficients with colored matrix for different normalization techniques using the MABAC method.

For OCRA, *Linear* is the technique with the highest correlation values with the darkest color tones. In contrast, the techniques with the lowest correlation values with the lightest color tones are *Sum* and *Logarithmic* normalization techniques.

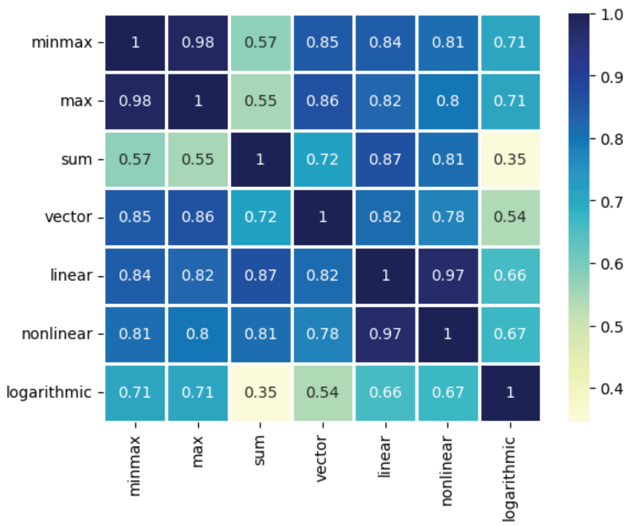

Figure 5. Correlation coefficients with colored matrix for different normalization techniques using the OCRA method.

For TOPSIS, the technique with the highest correlation values with the darkest color tones is *Linear*, and the technique with the lowest correlation values with the lightest color tones is the *Sum* normalization technique.

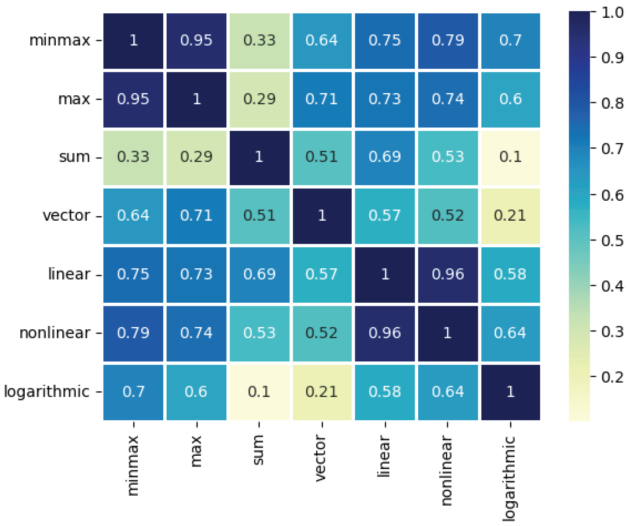

Figure 6. Correlation coefficients with colored matrix for different normalization techniques using the TOPSIS method.

For CODAS, *Linear* is the technique with the highest correlation values with the darkest color tones. In contrast, the techniques with the lowest correlation values with the lightest color tones are *Sum* and *Logarithmic* normalization techniques.

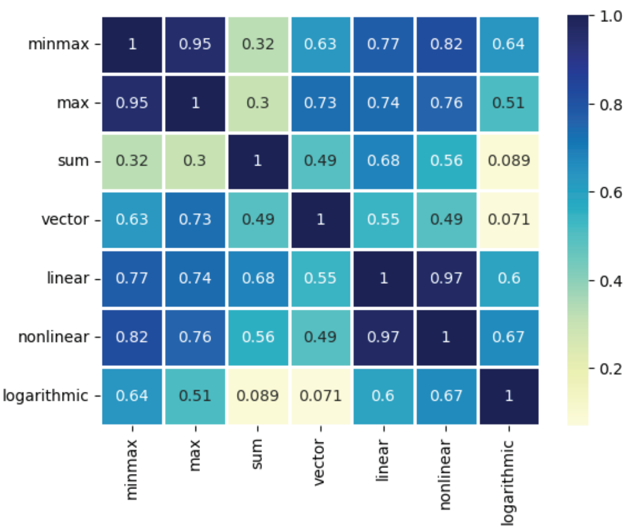

Figure 7. Correlation coefficients with colored matrix for different normalization techniques using the CODAS method.

For MAIRCA *Linear* is the technique with the highest correlation values with the darkest color tones. In contrast, the techniques with the lowest correlation values with the lightest color tones are *Sum* and *Logarithmic* normalization techniques.

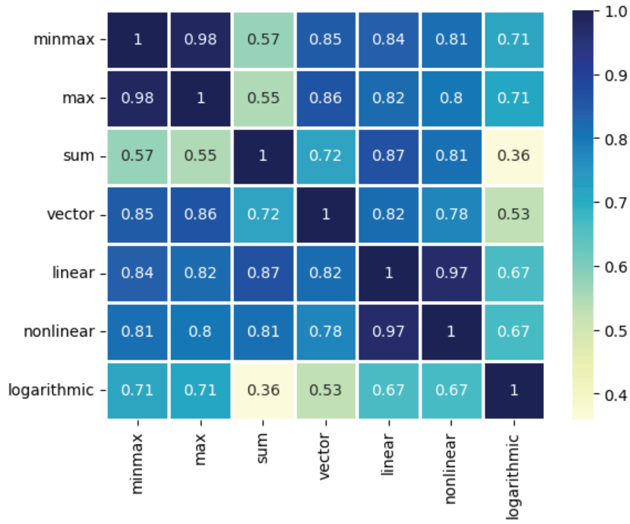

Figure 8. Correlation coefficients with colored matrix for different normalization techniques using the MAIRCA method.

For VIKOR, the technique with the highest correlation values with the darkest color tones is *Vector*, and the technique with the lowest correlation values with the lightest color tones is the *Logarithmic* normalization technique.

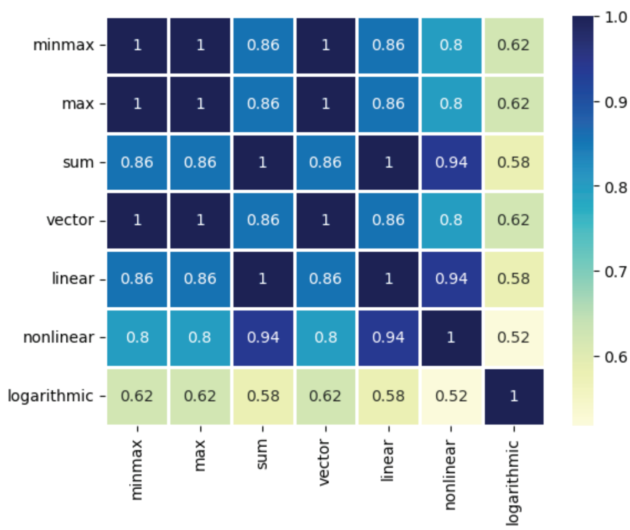

Figure 9. Correlation coefficients with colored matrix for different normalization techniques using the VIKOR method.

For MARCOS, the technique with the highest correlation values with the darkest color tones is *Linear*, and the technique with the lowest correlation values with the lightest color tones is the *Logarithmic* normalization technique.

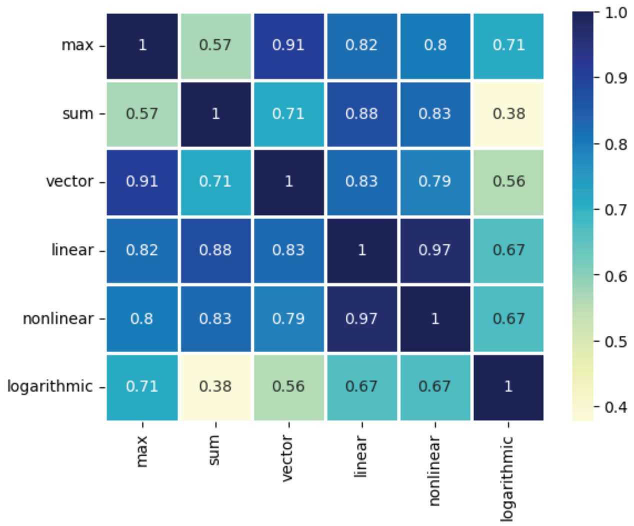

Figure 10. Correlation coefficients with colored matrix for different normalization techniques using the MARCOS method.

For COCOSO, the technique with the highest correlation values with the darkest color tones is *Linear*, and the technique with the lowest correlation values with the lightest color tones is the *Sum* normalization technique.

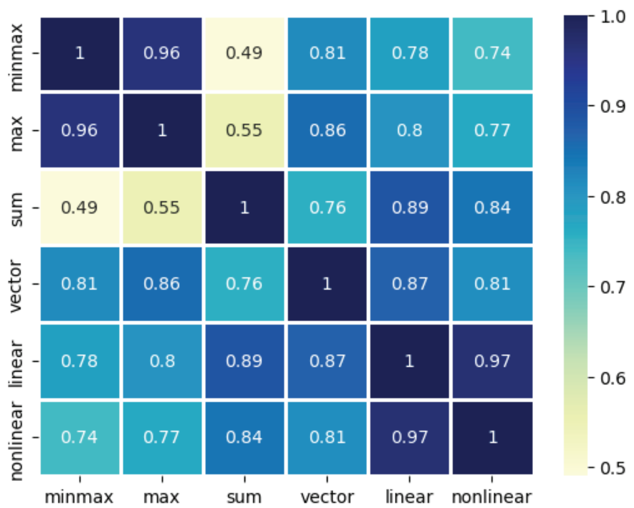

Figure 11. Correlation coefficients with colored matrix for different normalization techniques using the COCOSO method.

The first three stages explained in Figure 1 were applied for each method, and results were obtained according to Strategy 1. In Table 6, the values of the metrics used according to Strategy 1 are examined, and the normalization techniques that show the best performance in terms of compatibility are colored orange. The normalization techniques that perform the worst are colored green. The similarity of the average correlation values calculated for the methods and the ranking results obtained for each normalization technique is measured. The average absolute deviation and coefficient of variation metrics values show the variability of the correlation values, that is, the similarity ratios, between the rankings. For any method, the more similar the ranking results obtained with a normalization technique are to those obtained with other normalization techniques, the higher the correlation values will be. Similarly, another criterion that shows that the technique works with satisfactory performance is variability, and the similarity ratios of techniques with satisfactory performance will be close to each other. This indicates that variability is low and the technique works consistently and stably. On the contrary, the fact that the similarities, that is, the correlation values, are far from each other and have different values means that the variability between the similarities is high. The working performance of the technique is inconsistent. According to Strategy 1, the normalization technique that has the highest similarity rates with other techniques in terms of ranking results, the similarity rates closest to each other, the lowest variability and therefore the most consistent results, is the most appropriate normalization technique that shows the best performance for the relevant MCDM method. The normalization technique that gives the opposite results is the normalization technique that works most incompatibly with the relevant method. When the results in Table 6 are evaluated according to Strategy 1, it is observed that the normalization technique that shows the best performance for all MCDM methods examined is the Linear normalization technique. Apart from the VIKOR method, the second technique with the best performance for other MCDM methods is the Non-linear normalization technique. When the results in the table are evaluated with strategy 1, it is seen that the normalization techniques with the worst performance for MCDM methods are Logarithmic and Sum normalization techniques. For these two techniques, the correlation values are pretty low, and the deviations and variability between similarities are relatively high. Since calculations could not be made with the Logarithmic normalization technique for the COCOSO method and the Min-max normalization technique for the MARCOS method, these rankings were excluded from the evaluation, and evaluations were made through other normalization techniques.

The general average values of the metrics obtained on a column basis with the data in Table 6 for each method using Strategy 2 are listed in Table 7. As explained before, the purpose of Strategy 2 is to evaluate the sensitivity of the

Table 6. Average Correlations, Mean Absolute Deviations and Variation Coefficients for each MCDM method.

	ARAS			COCOSO			CODAS		
	Avg. Corr.	**M.A.D.**	**Var. Coef.**	**Avg. Corr.**	**M.A.D.**	**Var. Coef.**	**Avg. Corr.**	**M.A.D.**	**Var. Coef.**
Min-max	0.8298	0.1103	16.39	0.7973	0.1271	20.83	0.7328	0.1751	29.07
Max	0.8240	0.1175	17.45	0.8223	0.1158	17.87	0.7142	0.1761	31.49
Sum	0.6941	0.1779	29.25	0.7541	0.1565	24.11	0.4919	0.2181	55.74
Vector	0.7746	0.1312	20.57	0.8514	0.0572	8.91	0.5661	0.1893	46.08
Linear	0.8477	0.0871	12.89	0.8853	0.0662	8.89	0.7587	0.1335	21.16
Non-linear	0.8287	0.0893	13.57	0.8547	0.0861	11.43	0.7511	0.1542	23.95
Logarithmic	0.6508	0.1291	28.32	-	-	-	0.5098	0.2455	60.11
	MABAC			**MAIRCA**			**MARCOS**		
	Avg. Corr.	**M.A.D.**	**Var. Coef.**	**Avg. Corr.**	**M.A.D.**	**Var. Coef.**	**Avg. Corr.**	**M.A.D.**	**Var. Coef.**
Min-max	0.8241	0.1063	16.66	0.8241	0.1063	16.66	-	-	-
Max	0.8173	0.1131	17.72	0.8173	0.1131	17.72	0.8010	0.1093	17.25
Sum	0.6968	0.1738	28.93	0.6968	0.1738	28.93	0.7274	0.1742	28.34
Vector	0.7928	0.1009	16.95	0.7928	0.1009	16.95	0.8003	0.1123	17.61
Linear	0.8545	0.0776	11.92	0.8545	0.0776	11.92	0.8609	0.0883	12.71
Non-linear	0.8343	0.0861	12.68	0.8343	0.0861	12.68	0.8429	0.0947	13.32
Logarithmic	0.6641	0.1255	27.18	0.6641	0.1255	27.18	0.6634	0.1308	28.11
	OCRA			**TOPSIS**			**VIKOR**		
	Avg. Corr.	**M.A.D.**	**Var. Coef.**	**Avg. Corr.**	**M.A.D.**	**Var. Coef.**	**Avg. Corr.**	**M.A.D.**	**Var. Coef.**
Min-max	0.8232	0.1072	16.76	0.7356	0.1548	28.01	0.8763	0.1061	14.71
Max	0.8168	0.1137	17.79	0.7170	0.1578	30.34	0.8763	0.1061	14.71
Sum	0.6948	0.1761	29.51	0.4927	0.2171	55.33	0.8691	0.0945	15.31
Vector	0.7942	0.0992	16.56	0.5933	0.1631	37.41	0.8763	0.1061	14.71
Linear	0.8540	0.0781	12.04	0.7532	0.1286	20.66	0.8691	0.0945	15.31
Non-linear	0.8341	0.0862	12.74	0.7394	0.1512	23.91	0.8274	0.1126	17.81
Logarithmic	0.6613	0.1251	27.61	0.5457	0.224	51.54	0.6496	0.1001	22.67

Table 7. The general mean of the metric values for each MCDM method

Metrics	ARAS	COCOSO	CODAS	MABAC	MAIRCA	MARCOS	OCRA	TOPSIS	VIKOR
Avg. Corr.	0.7785	0.8275	0.6463	0.7834	0.7834	0.7826	0.7826	0.6538	0.8348
M.A.D.	0.1203	0.1015	0.1845	0.1119	0.1119	0.1182	0.1122	0.1709	0.1028
Var. Coef.	19.77	15.34	38.22	18.86	18.86	19.55	19.01	35.31	16.46

MCDM methods examined to the changing normalization techniques. Sensitivity expresses how the results of any method are affected and how much they change depending on a changing parameter or used techniques. By examining the average values in Table 7 according to Strategy 2, the methods with the highest sensitivity for the normalization techniques compared to other methods are colored green, and the methods with the lowest sensitivity compared to other methods are colored orange. When the average results were evaluated, it was concluded that since the COCOSO and VIKOR methods have higher correlation values, lower average absolute deviation and coefficient of variation values than the other methods, it was concluded that these methods were the least sensitive to changing normalization techniques among the MCDM methods examined according to Strategy 2. On the other hand, since CODAS and TOPSIS methods have lower correlation values and higher average absolute deviation and coefficient of variation values than other methods, these methods have been evaluated as the methods that are most sensitive to varying normalization techniques among the MCDM methods that examined according to Strategy 2.

Comments can be made about the sensitivity of the method to the normalization techniques, by looking at the matrices obtained for the MCDM methods examined; in a colored correlation matrix, the fact that dark colors predominate, that is, there are high correlation values, and that there is almost no difference in color tones throughout the matrix, that is, the correlation values are close to each other, means that the relevant MCDM method is less sensitive to the changing parameter or used techniques. In other words, the change in the parameter or used techniques affects the results obtained by the relevant method minimally or not at all, depending on the sensitivity level. However in contrast, it will indicate that the relevant MCDM method is susceptible to changing parameters or techniques. In addition to the evaluations in Table 7, when the MCDM methods examined from this perspective are evaluated, it is observed that the matrices with the highest and closest correlation values belong to the COCOSO and VIKOR methods. In contrast, the matrices with the lowest correlation values and the furthest from each other belong to the CODAS and TOPSIS methods.

CONCLUSION

MCDM methods are mathematical methods that help the decision maker in the decision process when applied with the correct parameters and techniques. One of the most critical factor affecting the results of these methods is the normalization technique applied. Using a normalization technique that works suitable with the method will ensure that the result obtained is more accurate and dependable. This study proposes two strategies with similar stages but different evaluations to perform suitability and sensitivity evaluations for MCDM methods robustly and reliably through the normalization techniques. The first of the proposed strategies evaluates the suitability of normalization techniques for the examined MCDM methods, while the second evaluates the sensitivity of MCDM methods to different normalization techniques. In the study, nine different MCDM methods (ARAS, COCOSO, MABAC, CODAS, MAIRCA, MARCOS, OCRA, TOPSIS, VIKOR) and seven different normalization techniques (Min-max, Max, Sum, Vector, Linear, Non-linear, Logarithmic) were used to analyze the same data to obtain the results by applying calculations and evaluations were made according to the proposed strategies. The metrics in the proposed and implemented strategies are similarity (Avg. Corr.) and variability-oriented (MAD, Var. Coef.) statistical metrics, and these strategies for each method make it practical, dependable and robust in terms of application. As a result of the study, the most suitable and most unsuitable normalization techniques were determined for each method examined and the sensitivity of the used methods to the normalization technique was evaluated comparatively. The results of the study showed that, according to strategy 1, the normalization techniques most suitable with MCDM methods are linear and non-linear methods. On the other hand, the most unsuitable method was determined to be the logarithmic normalization technique. According to Strategy 2, as a result of sensitivity analysis, the MCDM methods that are most sensitive to changes in normalization techniques are CODAS and TOPSIS methods. On the other hand, the least sensitive methods among the examined methods are COCOSO and VIKOR methods. The metrics in the implemented strategies gave results that were compatible with each other, demonstrating the reliability and robustness of these strategies. The MCDM methods used in this study are the methods available in the PyMCDM package in Python programming. This enabled the analysis processes to be carried out more easily and quickly, and the strategies presented could be applied to more than one method. However, there are many MCDM methods that are not available in PyMCDM. Since it is known that the analysis process will be more difficult without using software, future potential studies will include evaluating these methods separately, using the presented strategies. Additionally, in order to demonstrate the reliability and practicality of the presented strategies, studies can be conducted where analyzes are performed using multiple datasets through a single MCDM method. Evaluating different MCDM methods through different weighting techniques using the strategies suggested in this study and examining different MCDM methods through the normalization technique using these strategies are among the planned studies.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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APPENDICES

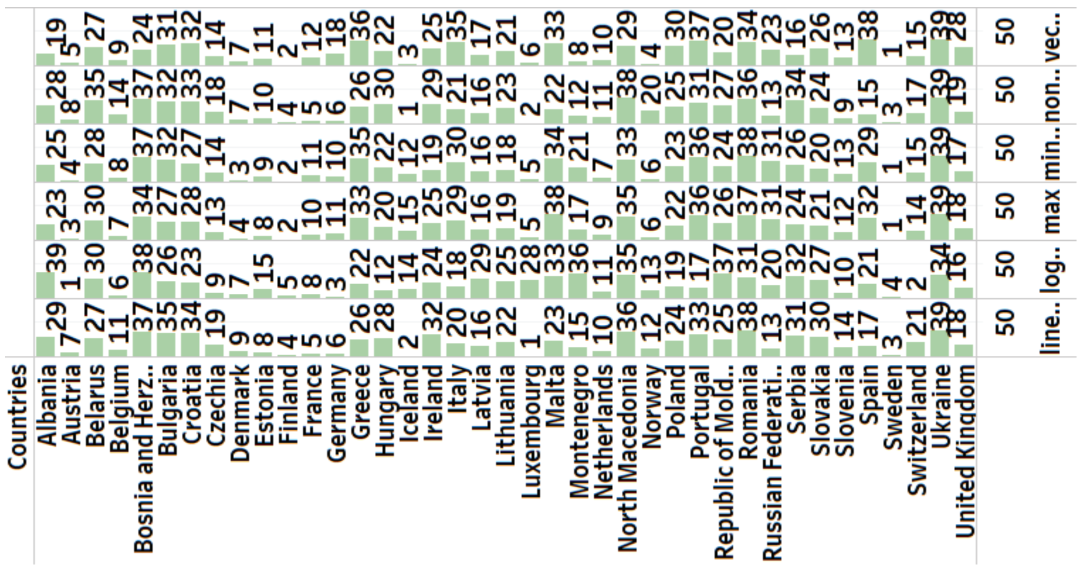

Figure A1. Ranking for ARAS.

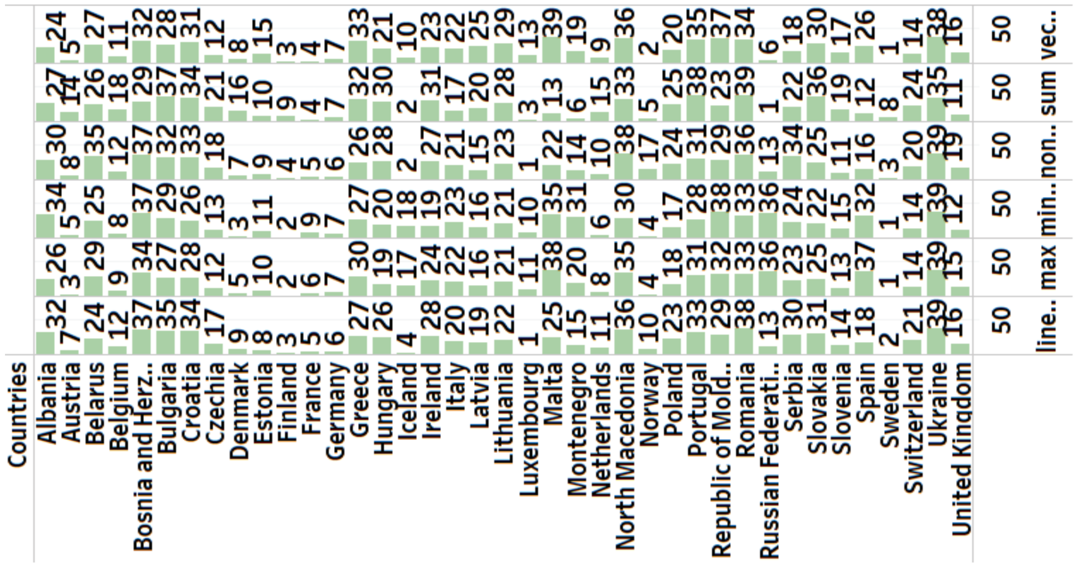

Figure A2. Ranking for COCOSO.

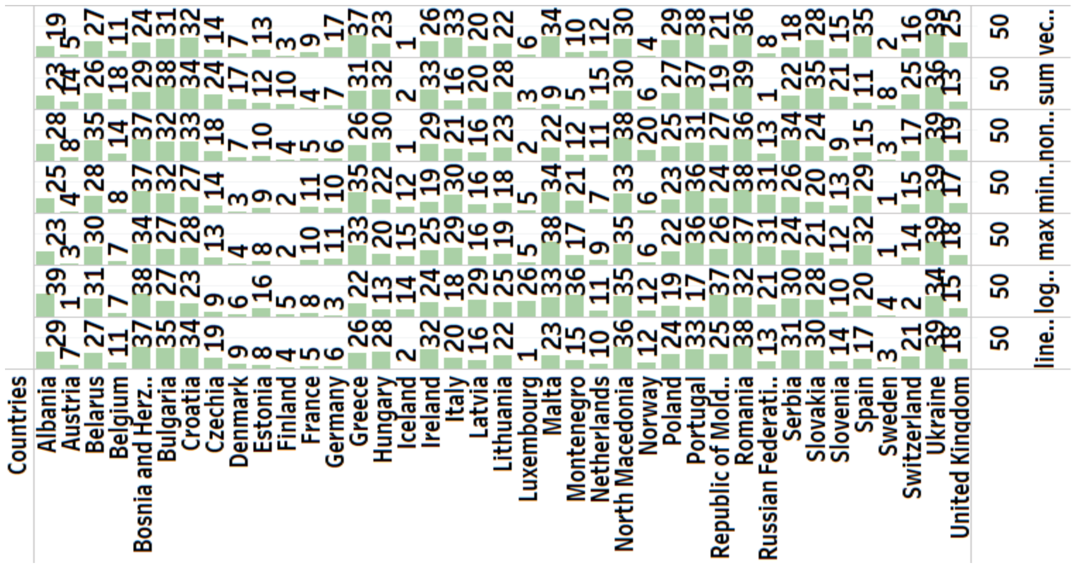

Figure A3. Ranking for MABAC

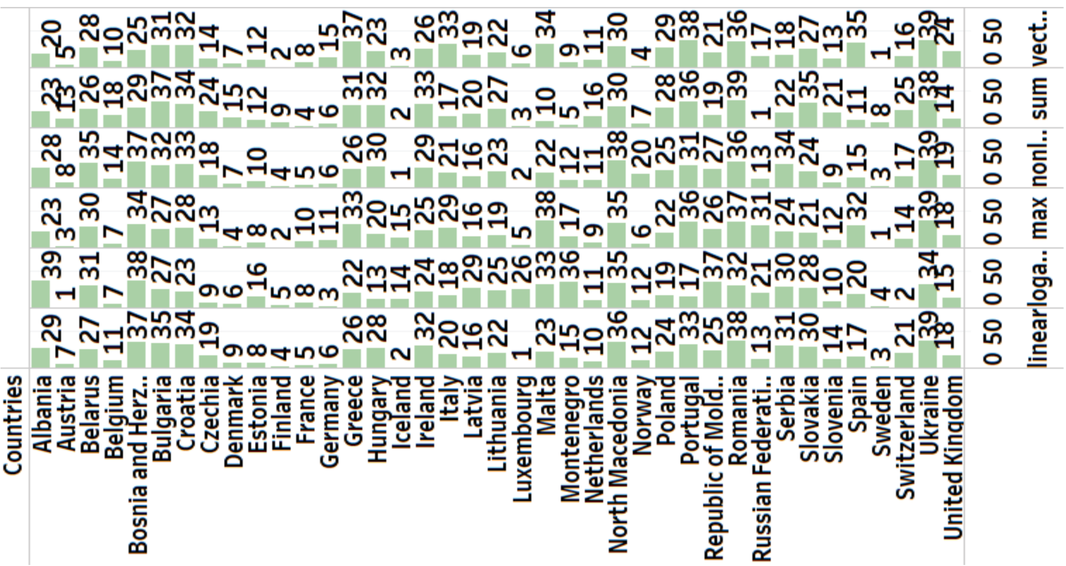

Figure A4. Ranking for MARCOS.

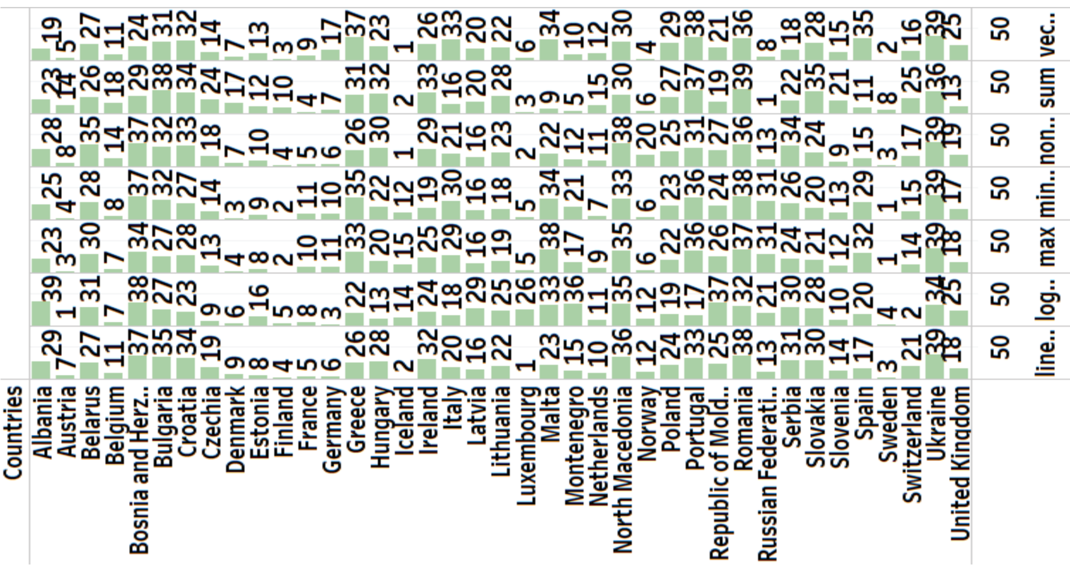

Figure A5. Ranking for OCRA.

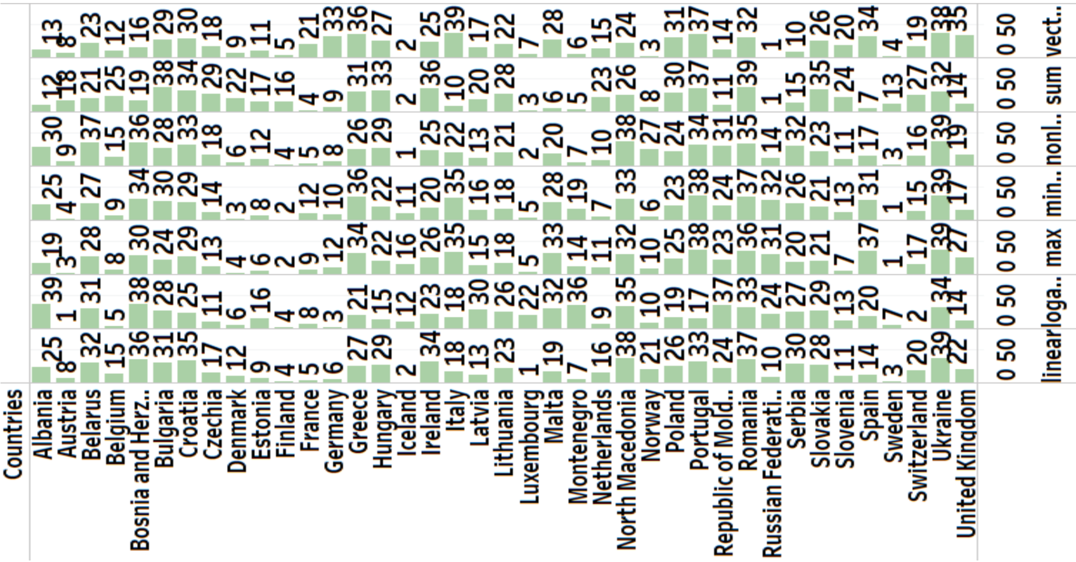

Figure A6. Ranking for TOPSIS.

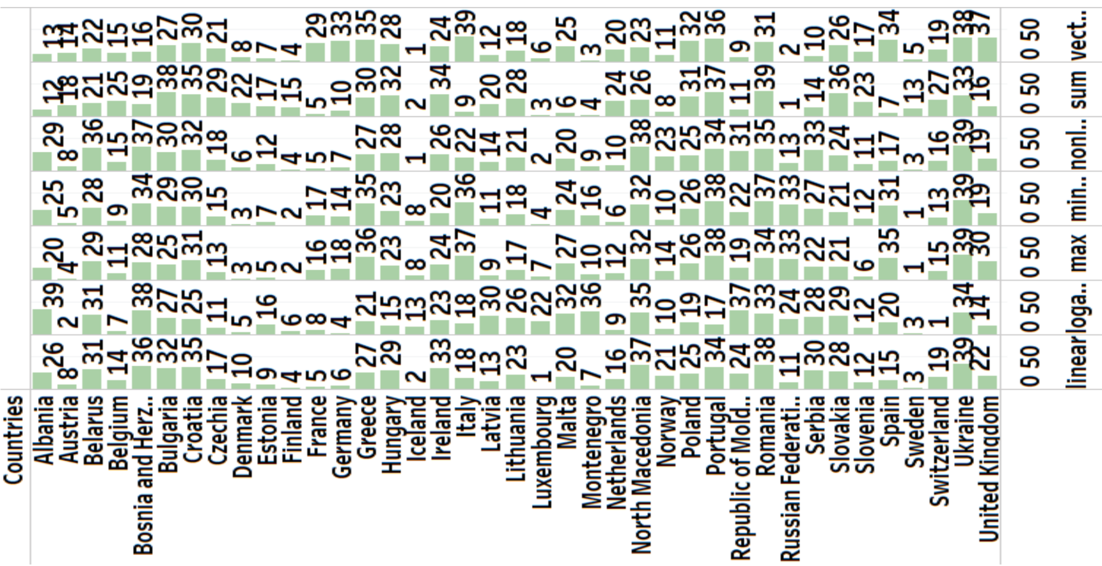

Figure A7. Ranking for CODAS.

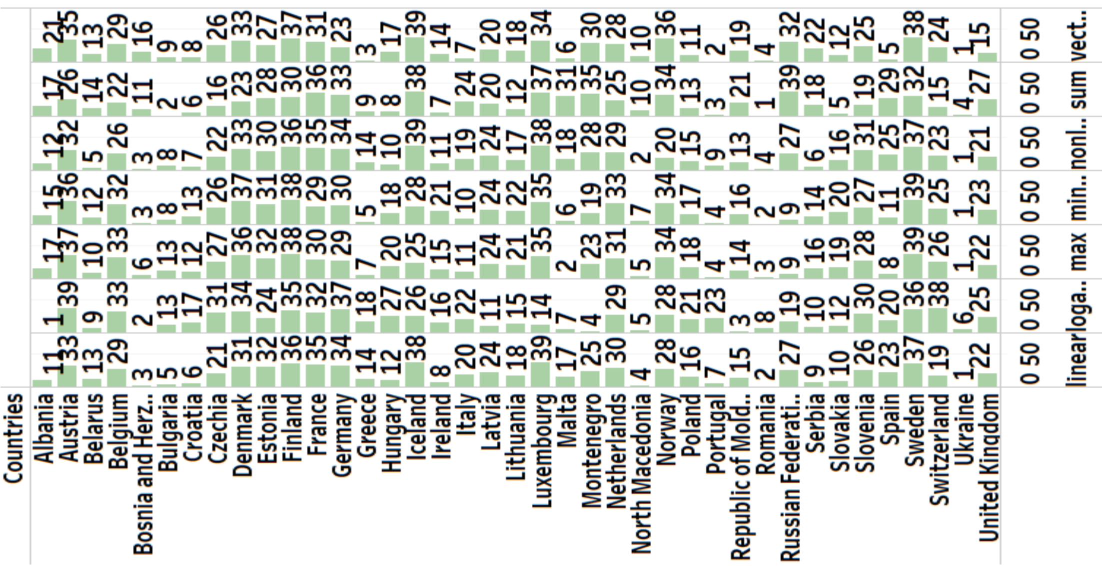

Figure A8. Ranking for MAIRCA.

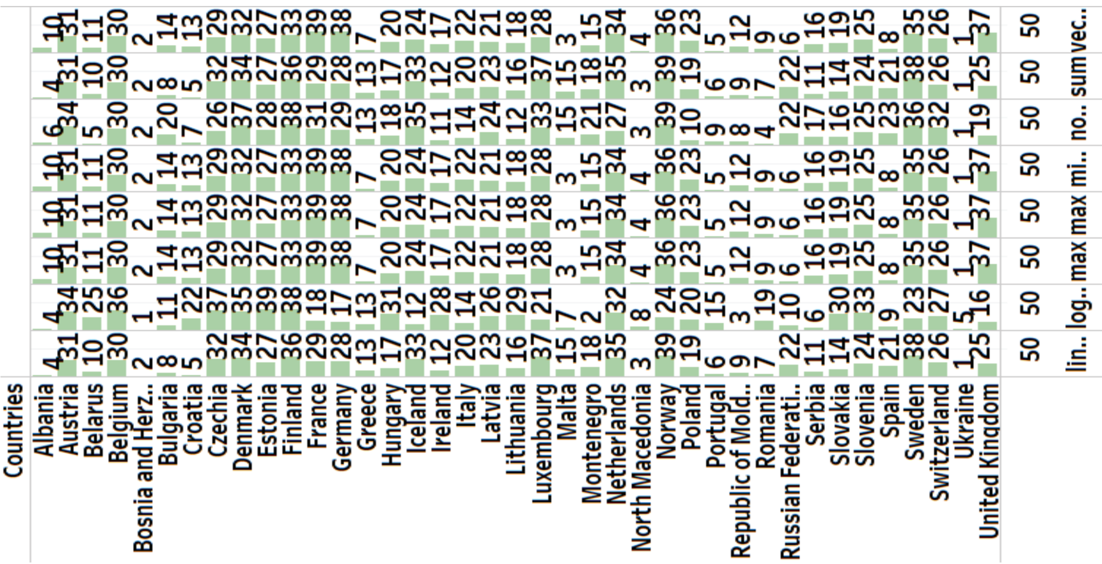

Figure A9. Ranking for VIKOR.