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Selecting the Best Normalization Technique for ROV Method: Towards a Real Life Application

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Highlights

- This study focuses on the effect of different normalization methods on results.
- Based on financial ratios, a real case is analyzed to select the best data normalization technique.
- This is the first study to test the suitability of normalization techniques for the ROV method.

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Abstract

Normalization is one of the stages that have an impact on the results of MCDM problems. Choosing the right normalization technique leads the decision maker to the right results. Accordingly, the purpose of this study is to determine the most appropriate normalization technique for the ROV method. In this study, a real case is analyzed, eight different normalization methods are compared with each other on the basis of a multi-stage framework. The findings show that the model used in this study can be successfully applied in the selection of normalization technique. This study provides a decision support and reference for the selection of nomalization technique for MCDM methods in terms of the framework used. Another importance of this study is the first testing the suitability of different normalization techniques for the ROV method.

1. INTRODUCTION

The need for various decision-making methods to deal with different design problems has encouraged researchers to develop new techniques. Accordingly, it is seen as an opportunity to use MCDM methods as part of the engineering design process to produce better products [1].

MCDM methods, which have a wide area of use, offer a suitable framework for the decision maker to reach a solution in the presence of many alternatives and criteria. In some cases, the large number of alternatives and criteria can cause difficulties in the process steps. Many studies have been conducted to find a solution to this problem. [2] proposed a model for picture fuzzy Dombi aggregation operators to solve multiple attribute decision making (MADM) problems. They determined the most favorable emerging technology enterprises using picture fuzzy Dombi weighted average (PFDWA) and picture fuzzy Dombi weighted geometric (PFDWG). [3] developed a model for bipolar fuzzy Dombi aggregation operators to solve MADM problems. Five possible emerging technology enterprises and four attributes were used to assess the emerging technology enterprises. They determined the most favorable emerging technology enterprises using bipolar fuzzy Dombi weighted averaging operator (BFDWA) and bipolar fuzzy Dombi weighted geometric operator (BFDWGA). [4] used Interval Trapezoidal Neutrosophic Number Weighted Arithmetic Averaging (ITNNWAA) operator and the Interval Trapezoidal Neutrosophic Number Weighted Geometric Averaging (ITNNWGA) operator to solve the MADM problem. Five viable emerging technology enterprises were evaluated under the four attributes.

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In the MCDM problems, the criteria must be defined on the same scale to make an effective comparison. Pretreatment to define the criteria on the same scale is called normalization. The normalization procedureis the first step in most MCDM methods, and the use of different normalization techniques can lead to differential sequencing of alternatives, which results in deviation from optimal sequencing. Therefore, the selection of appropriate normalization techniques plays an important role in the final results of decision problems [5].

In the literature, the effects of different normalization techniques on the decision results of a particular MCDM method have been investigated by various studies. [6] examined the effects of three popular normalization procedures on SAW, TOPSIS and ELECTRE methods. It was concluded that the normalization procedure affects the options. [7] tested the five different normalization procedures on the TOPSIS method in their study on the selection of gear material for power transmission. They concluded that different normalization procedures produce quite different proximity coefficients. [8] used nonlinear vector as well as linear normalization (proposed by [9]) procedures for the TOPSIS method. It has been shown that the accuracy of the results is not only affected by errors in the initial property values but also depends on the solution properties and normalization methods used. [10]tested normalization procedures by suggesting a new method, MOORA. It was concluded that the best choice is the square root of the sum of squares of each alternative per attribute. [11] used different normalization procedures for the WASPAS method and determined max-min as the best normalization technique for the WASPAS method. [12] compared four commonly known normalization procedures using the SAW method. It was concluded that vector normalization and linear scale transformation (max method) performed better than other normalization procedures. [13] compared different normalization procedures for the TOPSIS method. This study supported the use of vector normalization for the TOPSIS method. [14] evaluated the appropriateness of five normalization procedures for AHP and TOPSIS methods in a study evaluating the financial performance of 13 Turkish deposit banks. It was concluded that vector normalization technique generated the most consistent results.

In this study, real life application is carried out by focusing on the effects of different normalization techniques on ROV method results.It is aimed at measuring the financial performance of the top 10-ranked companies in the FORTUNE 500 list by 2020 with the ROV method based on different normalization techniques.This study contributes to the literature as it is the first study to investigate the suitability of different normalization techniques for the ROV method.

The motivation and superiority of the proposed method in this paper are outlined as follows:

1- Determining the criterion weights by Entropy method,independently of the subjective evaluations of decision makers, is considered important in terms of making a sound evaluation,

2- The current study is the first in which the suitability of different normalization techniques was tested for the ROV method. In addition, it is also the first study that is used the ROV method for measuring financial performance.

3- It is thought that this study will motivate and guide researchers to try a similar application for different MCDM methods.

4- The obtained results with 8 different normalization methods are considered important in terms of enabling comparison and showing the effect on the results.

The rest of this paper is organized as follows: In Section 2, mathematical models used in the application aredescribed. The real case application and a sensitivity analysis are given in Section 3. Finally, the discussion, concluding remarks and future research directions are involved in Section 4.

2. MATERIAL METHOD

2.1. Entropy Method

The entropy method was developed by [15] to measure the amount of useful information provided with the available data [16]. The steps of the entropy method are as follows [17]:

Step 1: Decision matrix is created.

$$\begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}$$

Step 2: The decision matrix elements are normalized using Equation (1)

$$P_{ij} = \frac{x_{ij}}{\sum_j x_{ij}}. \tag{1}$$

Step 4: The Entropy value for each units in the decision matrix is calculated using Equation (2)

$$e_j = -k\sum_{j=1}^{n} P_{ij} In(P_{ij}) \tag{2}$$

where

$k = (\ln(m))^{-1}$

m indicates the number of the alternative.

Step 5: The degree of differentiation of the criteria is found with the help of Equation (3)

$$div_j = 1 - e_j. \tag{3}$$

The more the div_j is, the more important the criterion jth is.

Step 6: The normalized weight values for each criterion are found with the help of Equation (4)

$$w_j = \frac{div_j}{\sum_j div_j}. \tag{4}$$

2.2. Range of Value (ROV) Method

The "Range of Value" (ROV) method was introduced by [18]. The ROV method offers the decision maker a fairly simple calculation procedure compared to other MCDM methods [19]. The processing steps of the ROV method are as follows [20].

Step 1: Decision matrix is created

A decision matrix is created with alternatives in rows and criteria in columns

$$X = \left[x_{ij}\right]_{mxn} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix},$$

x_{ij} is the performance measure of i-th alternative with respect to j-th criterion, m is the number of alternatives and n is the number of criteria.

Step 2: Decision matrix units are normalized.
Benefit-oriented criteria are normalized using equality (5), and cost-oriented criteria are normalized using Equation (6)

$$\bar{x}_{ij} = \frac{x_{ij} - x_{ij}^{\min}}{x_{ij}^{\max} - x_{ij}^{\min}} \tag{5}$$

$$\bar{x}_{ij} = \frac{x_{ij}^{\max} - x_{ij}}{x_{ij}^{\max} - x_{ij}^{\min}}. \tag{6}$$

Step 3: The best and worst utility functions are calculated.
In the last step, the best and worst benefit functions of each alternative are calculated. To perform this process, separate utility functions are created for utility and cost direction criteria. Benefit functions (ui +, ui-) for utility-side and cost-side criteria are shown in Equations (7) and (8), respectively

$$Max: u_i^{+} = \sum_{j=1}^{n} \bar{x}_{ij}.w_j \tag{7}$$

$$Min: u_i^{-} = \sum_{j=1}^{n} \bar{x}_{ij}.w_j, \tag{8}$$

wj; indicates criteria weights. Weights must meet the following two conditions;

$$\sum_{j=1}^{n} w_j = 1$$

$$w_j \geq 0$$

if $u_i^{-} > u_i^{+}$; alternative i can be said better than i alternative regardless of the total score. If this does not happen, the Equation (9) is used to find the middle point and sort accordingly.

$$u_i = \frac{u_i^{-} + u_i^{+}}{2}. \tag{9}$$

The alternative with the highest value is determined as the best alternative.

2.3. Normalization Instruments

Numerous normalization techniques have been proposed, and as mentioned in the literature section above, most MCDM methods use one of these techniques. In this study, the eight normalization techniques introduced by [1] are used and are presented in Table 1.

Table 1. *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. [7]; Shanian and Savasdogo[21]; Delft and Nijkamp [22]

	Cost criteria	$n_{ij} = 1 - \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^{2}}}$	Zavadskas and Turskis [23]; Delft and Nijkamp [22]
Linear Normalization sum based method (N2)	Benefit criteria	$n_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$	Milani et al. [7]; Jee and Kang [24];Wang and Luo[25]
	Cost criteria	$n_{ij} = \frac{1/r_{ij}}{\sum_{i=1}^{m} 1/r_{ij}}$	Wang and Luo [25];Stanujkic et al.[26]
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 et al. [27]
	Cost criteria	$n_{ij} = 1 - \frac{r_{ij} - r_j^{\min}}{\sum_{i=1}^{m} (r_{ij} - r_j^{\min})}$	Zeng et al. [27]
Non-linear normalization (N4)	Benefit criteria	$n_{ij} = (\frac{r_{ij}}{r_j^{\max}})^2$	Zavadskas and Turskis [23];Peldschus et al. [28]
	Cost criteria	$n_{ij} = (\frac{r_j^{\min}}{r_{ij}})^3$	Zavadskas and Turskis [23];Peldschus et al. [28]
Linear max min normalization method (N5)	Benefit criteria	$n_{ij} = \frac{r_{ij} - r_j^{\min}}{r_j^{\max} - r_j^{\min}}$	Asgharpour [29]; Zavadskas and Turskis [23] ;Tzeng and Huang [30] ;Shih et al. [31];Chakraborty and Yeh [12]
	Cost criteria	$n_{ij} = \frac{r_j^{\max} - r_{ij}}{r_j^{\max} - r_j^{\min}}$	Asgharpour [29]; Zavadskas and Turskis [23] ;Tzeng and Huang [30] ;Shih et al. [31] ;Chakraborty and Yeh [12]
Linear normalization (N6)	Benefit criteria	$n_{ij} = \frac{r_{ij}}{r_j^{\max}}$	Milani et al. [7]- Asgharpour [29]-Farag [32]; Tzeng and Huang [30]
Linear normalization (N6)	Cost criteria	$n_{ij} = 1 - \frac{r_{ij}}{r_j^{\max}}$	Milani et al. [7] ;Asgharpour [29];Farag[32]
Linear normalization (N6a)	Cost criteria	$n_{ij} = \frac{r_{ij}^{\min}}{r_{ij}}$	Milani et al. [7] ; Asgharpour [29]; Zhou et al.[33]
Linear normalization (N6b)	Cost criteria	$n_{ij} = 1 - \frac{r_{ij} - r_j^{\min}}{r_j^{\max}}$	Markovic [34]

Source: Jahan and Edwards [1]

Table 1 shows the normalization methods used in this study. On the other hand, logarithmic normalization method, Lai and Hwang [9] normalization method and Z transformation method introduced by the study of [1] could not be used because they cause negative values in the normalized decision matrix. Zavadskas and Turskis [23] normalization method and linear normalization method could not be included in the study because they cause values greater than 1 in the normalized decision matrix.

3. THE RESEARCH FINDINGS AND DISCUSSION

3.1. Data

In this study, the suitability of the selected normalization techniques for the ROV method is tested. For this purpose, based on real life practice, the 2019 financial performances of firms that ranked top 10 in the FORTUNE 500 list by 2020 are evaluated using MCDM methods on the basis of seven rates determined by literature review. The criteria used in the study were obtained from the financial statements of the companies and are presented in Table 2 and alternatives are included in Table 3.

Table 2. *Criteria*

Rank	Code	Financial Ratios and Disclosures	
Liquidity ratios			Opt.
1	CR	Current ratio= Current Assets / Current Liabilities	max
2	QR	Quick ratio = (Current Assets - Inventories) / Current Liabilities	max
Profitability ratios			
3	ROE	Return on Equity = Net Income (annual)/ Total equity	max
4	ROA	Return on Assets = Net Income (annual)/ Total assets	max
Efficiency Ratios			
5	ATR	Asset Turnover Rate = Net Sales/Total Assets	max
Leverage ratios			
6	LR	Leverage Ratio = Total Liabilities /Total assets	min
7	DTE	Debt to equity ratio= Long term debt / Total *equity*	min

Table 3. *Alternatives*

Rank	Company's Name
1	Walmart
2	Amazon.com
3	Exxon Mobil
4	Apple
5	CVS Health
6	Berkshire Hathaway
7	Unitedhealth Group
8	McKesson
9	AT&T
10	AmerisourceBergen

3.2. Application

In this study, the weights of the criteria are determined by the entropy method, while the ROV method is used for evaluating the performances of the firms. Eight different normalization procedures, described in Table 1, are used to convert different financial ratios into a comparable unit of measurement.

3.2.1. Weighting of criteria with entropy method

The first step of weighting the criteria with the entropy method is meant to create the decision matrix. The decision matrix with the criteria in the rows and the alternatives in the columns is presented in Table 4.

Table 4. *Decision matrix*

Alternatives	Criteria						
	CR	QR	ROE	ROA	ATR	LR	DTE
Walmart	0.80	0.23	0.09	0.03	2.33	0.64	0.78
Amazon.com	1.10	0.86	0.19	0.05	1.25	0.72	1.21
Exxon Mobil	0.78	0.56	0.07	0.04	0.73	0.45	0.50
Apple	1.54	1.50	0.61	0.16	0.77	0.73	1.57
CVS Health	0.94	0.62	0.10	0.03	1.15	0.71	1.64
Berkshire Hathaway	0.39	0.32	0.19	0.10	0.31	0.48	0.24
Unitedhealth Group	0.69	0.58	0.23	0.08	1.39	0.64	0.83
McKesson	1.02	0.58	0.03	0.004	3.59	0.84	1.49

AT&T	0.79	0.79	0.07	0.03	0.33	0.63	2.39
AmerisourceBergen	0.11	0.11	0.29	0.02	4.58	0.92	2.20

In the second step, the normalization process is carried out with the help of Equation (1), and the results are presented in Table 5. **In the third step**, using normalized decision matrix elements, entropy measurements for each criterion are calculated with the help of Equation (2), and **in the fourth step**,differentiation measures of criteria values are determined with the help of Equation (3). The results are presented in Table 6. **Finally**, the weights of each criterion are determined with the help of Equation (4) and presented in Table 7.

Table 5. *Normalized decision matrix*

	CR	QR	ROE	ROA	ATR	LR	DTE
Walmart	0.098	0.037	0.048	0.055	0.142	0.095	0.061
Amazon.com	0.135	0.140	0.102	0.092	0.076	0.107	0.094
Exxon Mobil	0.096	0.091	0.037	0.074	0.044	0.067	0.039
Apple	0.189	0.244	0.326	0.294	0.047	0.108	0.122
CVS Health	0.115	0.101	0.053	0.055	0.070	0.105	0.128
Berkshire Hathaway	0.048	0.052	0.102	0.184	0.019	0.071	0.019
Unitedhealth Group	0.085	0.094	0.123	0.147	0.085	0.095	0.065
McKesson	0.125	0.094	0.016	0.007	0.219	0.124	0.116
AT&T	0.097	0.128	0.037	0.055	0.020	0.093	0.186
AmerisourceBergen	0.014	0.018	0.155	0.037	0.279	0.136	0.171

Table 6. *ej and dj values*

	CR	QR	ROE	ROA	ATR	LR	DTE
ej	0.949	0.923	0.865	0.869	0.865	0.991	0.936
dj	0.051	0.077	0.135	0.131	0.135	0.009	0.064

Table 7. *Criteria weights*

CR	QR	ROE	ROA	ATR	LR	DTE
0.085	0.127	0.224	0.217	0.224	0.015	0.107

According to Table 7, the most important and least important criteria are determined to be “ATR” and “LR”, respectively

3.2.2. Performance evaluation using ROV method

As the first step of ranking the alternatives with the ROV method, the decision matrix in Table 4 is used. **In the second step**, the normalization method (N5) in ROV method's own algorithm is used. Benefit-oriented criteria (CR, QR, ROE, ROA, ATR) are normalized using Equation (5), and cost-oriented criteria (LR, DTE) are normalized using Equation (6). The results obtained are presented in Table 8. **In the third step**, the best and worst benefit functions are calculated using Equation (7) for benefit-oriented criteria and (8) for cost-oriented criteria and the results obtained are presented in Table 9. **In the last step**, performance ranking is obtained using Equation (9) and presented in Table 10.

Table 8. *Normalized decision matrix*

	CR	QR	ROE	ROA	ATR	LR	DTE
Walmart	0.483	0.086	0.103	0.167	0.473	0.596	0.749
Amazon.com	0.692	0.540	0.276	0.295	0.220	0.426	0.549
Exxon Mobil	0.469	0.324	0.069	0.231	0.098	1	0.879
Apple	1	1	1	1	0.108	0.404	0.381

CVS Health	0.580	0.367	0.121	0.167	0.197	0.447	0.349
Berkshire Hathaway	0.196	0.151	0.276	0.615	0	0.936	1
Unitedhealth Group	0.406	0.338	0.345	0.487	0.253	0.596	0.726
McKesson	0.636	0.338	0	0	0.768	0.170	0.419
AT&T	0.476	0.489	0.069	0.167	0.005	0.617	0
AmerisourceBergen	0	0	0.448	0.103	1	0	0.088

Table 9. *Weighted normalized decision matrix*

	CR	QR	ROE	ROA	ATR	LR	DTE
Walmart	0.041	0.011	0.023	0.036	0.106	0.009	0.080
Amazon.com	0.059	0.069	0.062	0.064	0.049	0.006	0.059
Exxon Mobil	0.040	0.041	0.015	0.050	0.022	0.015	0.094
Apple	0.085	0.127	0.224	0.217	0.024	0.006	0.041
CVS Health	0.050	0.047	0.027	0.036	0.044	0.007	0.037
Berkshire Hathaway	0.017	0.019	0.062	0.134	0	0.014	0.107
Unitedhealth Group	0.035	0.043	0.077	0.106	0.057	0.009	0.077
McKesson	0.054	0.043	0	0	0.172	0.003	0.045
AT&T	0.041	0.062	0.015	0.036	0.001	0.009	0
AmerisourceBergen	0	0	0.101	0.022	0.224	0	0.009

Table 10. *Benefit functions and ranking*

	u^+	u^-	$u^+ + u^-$	$(u^+ + u^-)/2$	Ranking
Walmart	0.218	0.089	0.307	0.153	7
Amazon.com	0.303	0.065	0.368	0.184	3
Exxon Mobil	0.169	0.109	0.278	0.139	8
Apple	0.678	0.047	0.725	0.362	1
CVS Health	0.204	0.044	0.248	0.124	9
Berkshire Hathaway	0.231	0.121	0.352	0.176	5
Unitedhealth Group	0.318	0.086	0.404	0.202	2
McKesson	0.270	0.047	0.317	0.158	6
AT&T	0.156	0.009	0.165	0.082	10
AmerisourceBergen	0.347	0.009	0.357	0.178	4

According to the results obtained with the entropy based ROV method in Table 10, Apple company had the best performance, while AT&T had the worst performance.

3.2.3. Application of different normalization methods

In this step, an example of normalization calculation is given by taking into consideration the benefit-oriented CR and the cost-oriented LR criteria of Walmart and the results are presented in Table 11.

Table 11. *Normalization sample*

Normalization method	**Condition of use**	**Formula**	**Process**	Value
Vector Normalization (N1)	Benefit criteria	$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$	$\frac{0,80}{\sqrt{0,80^2+1,10^2+0,78^2+1,54^2+0,94^2+0,39^2+0,69^2+1,02^2+0,79^2+0,11^2}}$	0.283
	Cost criteria	$n_{ij} = 1 - \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$	$1-\frac{0,64}{\sqrt{0,64^2+0,72^2+0,45^2+0,73^2+0,71^2+0,48^2+0,64^2+0,84^2+0,63^2+0,92^2}}$	0.707

Linear Normalization sum based method (N2)	Benefit criteria	$n_{ij}=\frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$	$\frac{0,80}{0,80+1,10+0,78+1,54+0,94+0,39+0,69+1,02+0,79+0,11}$	0.098
	Cost criteria	$n_{ij}=\frac{1/r_{ij}}{\sum_{i=1}^{m} 1/r_{ij}}$	$\frac{0,64}{1/0,64+0,72+0,45+0,73+0,71+0,48+0,64+0,84+0,63+0,92}$	0.101
Enhanced accuracy method (N3)	Benefit criteria	$n_{ij}=1-\frac{r_j^{\max}-r_{ij}}{\sum_{i=1}^{m}(r_j^{\max}-r_{ij})}$	$1-\frac{(1,54-0,80)}{\sum(1,54-(0,80+1,1+0,78+1,54+0,94+0,39+0,69+1,02+0,79+0,11))}$	0.898
	Cost criteria	$n_{ij}=1-\frac{r_{ij}-r_j^{\min}}{\sum_{i=1}^{m}(r_{ij}-r_j^{\min})}$	$1-\frac{(0,64-0,45)}{\sum(0,64;0,72;0,45;0,73;0,71;0,48;0,64;0,84;0,63;0,92)-0,45}$	0.916
Non-linear normalization (N4)	Benefit criteria	$n_{ij}=(\frac{r_{ij}}{r_j^{\max}})^2$	$(\frac{0,80}{1,54})^2$	0.270
	Cost criteria	$n_{ij}=(\frac{r_j^{\min}}{r_{ij}})^3$	$(\frac{0,45}{0,64})^3$	0.348
Linear max min normalization method (N5)	Benefit criteria	$n_{ij}=\frac{r_{ij}-r_j^{\min}}{r_j^{\max}-r_j^{\min}}$	$\frac{0,80-0,11}{1,54-0,11}$	0.483
	Cost criteria	$n_{ij}=\frac{r_j^{\max}-r_{ij}}{r_j^{\max}-r_j^{\min}}$	$\frac{0,92-0,64}{0,92-0,45}$	0.596
Linear normalization (N6)	Benefit criteria	$n_{ij}=\frac{r_{ij}}{r_j^{\max}}$	$\frac{0,80}{1,54}$	0.519
Linear normalization (N6)	Cost criteria	$n_{ij}=1-\frac{r_{ij}}{r_j^{\max}}$	$1-\frac{0,64}{0,92}$	0.304
Linear normalization (N6a)	Cost criteria	$n_{ij}=\frac{r_{ij}^{\min}}{r_{ij}}$	$\frac{0,45}{0,64}$	0.703
Linear normalization (N6b)	Cost criteria	$n_{ij}=1-\frac{r_{ij}-r_j^{\min}}{r_j^{\max}}$	$1-\frac{0,64-0,45}{0,92}$	0.793

Similar steps are repeated for all the units in the decision matrix in Table 4, and the ranking results obtained are given in Table 12.

Tablo 12. *Weights (W) and ranking (R) of the alternatives*

	N1		N2		N3		N4	
	W	R	W	R	W	R	W	R
Walmart	0.134	7	0.040	7	0.447	6	0.053	7
Amazon.com	0.158	4	0.049	5	0.452	3	0.075	6
Exxon Mobil	0.123	8	0.037	8	0.446	8	0.044	8
Apple	0.284	1	0.101	1	0.478	1	0.332	1
CVS Health	0.119	9	0.035	9	0.442	9	0.043	9
Berkshire Hathaway	0.153	5	0.058	2	0.451	4	0.119	3
Unitedhealth Group	0.171	2	0.055	4	0.454	2	0.075	5
McKesson	0.138	6	0.042	6	0.448	5	0.099	4
AT&T	0.095	10	0.027	10	0.435	10	0.038	10
AmerisourceBergen	0.164	3	0.057	3	0.447	7	0.141	2
	N5		N6		N6a		N6b	
	W	R	W	R	W	R	W	R
Walmart	0.153	**7**	0.164	**7**	0.148	7	0.173	**7**
Amazon.com	0.184	**3**	0.194	**3**	0.182	5	0.203	**3**

Exxon Mobil	0.139	**8**	0.149	**8**	0.136	8	0.158	**8**
Apple	0.363	**1**	0.366	**1**	0.359	1	0.375	**1**
CVS Health	0.124	**9**	0.138	**9**	0.132	9	0.147	**9**
Berkshire Hathaway	0.176	**5**	0.186	**5**	0.195	3	0.195	**5**
Unitedhealth Group	0.202	**2**	0.211	**2**	0.195	4	0.221	**2**
McKesson	0.158	**6**	0.170	**6**	0.162	6	0.179	**6**
AT&T	0.082	**10**	0.099	**10**	0.107	10	0.108	**10**
AmerisourceBergen	0.178	**4**	0.191	**4**	0.196	2	0.200	**4**

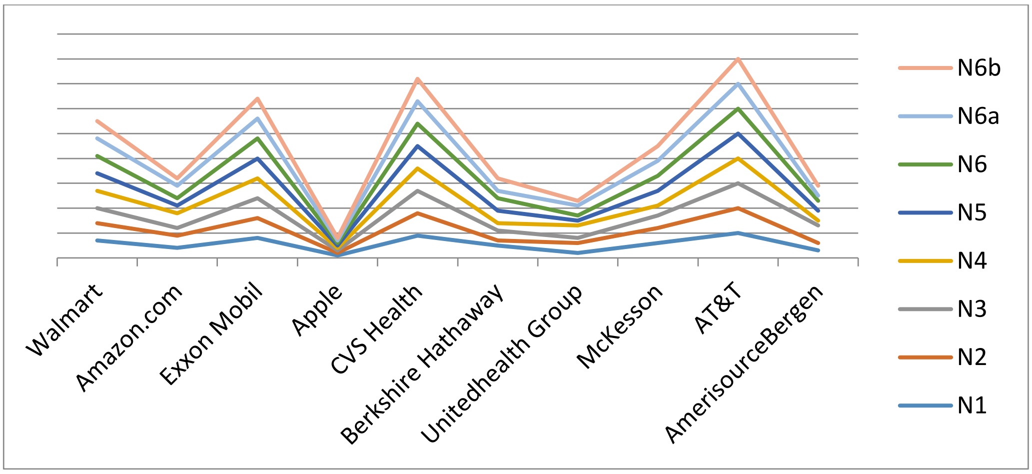

Figure 1. *Ranking results obtained with 8 different normalization methods*

According to Table 12 and Figure 1, N5, N6 and N6b rankings are the same, but it is safe to say that the rankings obtained by the eight different normalization techniques are quite different from each other. According to the results, only the 1st, 8th, 9th and 10th companies remained the same in all rankings. In this situation, it is quite difficult to predict which normalization method is more accurate and reliable for ROV method. For this reason, this study used various approaches to make a better inference.

In the literature, many approaches have been developed to test the suitability of different normalization techniques for MCDM methods. For example, [13] developed the Ranking Consistency Indexed (RCI) approach to test the suitability of four different normalization techniques (max, vector, sum, max-min) for the Topsis method. On the other hand, [14] applied a Pearson correlation for testing the suitability of different normalization methods (vector, max-min, max, sum). [35] added the Spearman correlation approach to the Pearson correlation approach applied by [14]. [11] used Spearman correlation. [36] used ANOVA to compare the effiiciency of three types of normalization techniques (non-monotonic, comprehensive, terget-based normalization method).

In this study, a 4-step process by [35] is followed to decide which of the eight different normalization methods is most suitable for the ROV method. In the first stage, the RCI approach developed by [13] is used. In the second stage, Spearman correlation and their ks [37] are calculated. In addition, contrary to [35]'s approach, Pearson correlation and their ks [14] are calculated. In the third stage, Standard Deviation (STD) [38]; [39]; [40] is calculated using alternative scores. In the last stage, Minkowski distance measurements (Manhattan, Euclidean, Chebyshev) [41]; [42]; [31] are calculated. According to the results obtained in previous studies [35]; [43], the higher the values obtained with the seven approaches (RCI, Spearman Correlation, Pearson Correlation, STD, Manhattan, Euclidean, Chebishev measures) used in this study, the better.

Step 1: Application of RCI from [13]

In this step, ranking consistency index (RCI) application is included. Ranking consistency is used to indicate the similarity between the sequencing produced by a particular normalization procedure and those of other procedures. To measure the ranking consistency index (RCI) of a particular normalization procedure, the number of times the procedure showed similarities/differences in various dimensions with the various procedures applied is calculated. The higher the RCI, the better the procedure is [13].

In this study where 8 different normalization methods are used, the consistency weight (CW) ise used as follows:

1) If a technique is consistent with all other seventechniques, then CW = 7/7 = 1
2) If a technique is consistent with six of the seventechniques, then CW = 6/7
3) If a technique is consistent with five of the seventechniques, then CW = 5/7
4) If a technique is consistent with four of the seventechniques, then CW = 4/7
5) If a technique is consistent with three of the seventechniques, then CW = 3/7
6) If a technique is consistent with two of the seventechniques, then CW = 2/7
7) If a technique is consistent with one of the seventechniques, then CW = 1/7
8) If a technique is not consistent with any other eight techniques, then CW = 0/7 = 0.

The ranking consistency index of **N1** is calculated as;

$$\text{RCI} =[(T_{12345678}*(CW=1))+(T_{1234567}*(CW=6/7))+(T_{1345678}*(CW=6/7))+(T_{1245678}*(CW=6/7))+(T_{1235678}*(CW=6/7))+(T_{1234678}*(CW=6/7))+(T_{1234578}*(CW=6/7))+T_{1234568}*(CW=6/7))+(T_{123456}*(CW=5/7))+(T_{123457}*(CW=5/7))+(T_{123458}*(CW=5/7))+(T_{134567}*(CW=5/7))+(T_{134568}*(CW=5/7))+(T_{123678}*(CW=5/7))+(T_{123567}*(CW=5/7))+(T_{123478}*(CW=5/7))+(T_{124567}*(CW=5/7))+(T_{124568}*(CW=5/7))+(T_{125678}*(CW=5/7))+(T_{135678}*(CW=5/7))+(T_{145678}*(CW=5/7))+(T_{134678}*(CW=5/7))+(T_{125378}*(CW=5/7))+(T_{125478}*(CW=5/7))+(T_{135478}*(CW=5/7))+(T_{135268}*(CW=5/7))+(T_{142367}*(CW=5/7))+(T_{142368}*(CW=5/7))+(T_{143678}*(CW=5/7))+(T_{12345}*(CW=4/7))+(T_{12346}*(CW=4/7))+(T_{12347}*(CW=4/7))+(T_{12348}*(CW=4/7))+(T_{12356}*(CW=4/7))+T_{12357}*(CW=4/7))+(T_{12358}*(CW=4/7))+(T_{12368}*(CW=4/7))++(T_{12367}*(CW=4/7))++(T_{12378}*(CW=4/7))+(T_{12456}*(CW=4/7))+(T_{12457}*(CW=4/7))+(T_{12458}*(CW=4/7))+(T_{12478}*(CW=4/7))+(T_{12468}*(CW=4/7))+(T_{12567}*(CW=4/7))+(T_{12568}*(CW=4/7))+(T_{12578}*(CW=4/7))+(T_{12678}*(CW=4/7))+(T_{12467}*(CW=4/7))+(T_{13456}*(CW=4/7))+(T_{13457}*(CW=4/7))+(T_{13458}*(CW=4/7))+(T_{13467}*(CW=4/7))+(T_{13468}*(CW=4/7))+(T_{13478}*(CW=4/7))+(T_{13567}*(CW=4/7))+(T_{13568}*(CW=4/7))+(T_{13578}*(CW=4/7))+(T_{13678}*(CW=4/7))+(T_{14567}*(CW=4/7))+(T_{14568}*(CW=4/7))+(T_{14678}*(CW=4/7))+(T_{14578}*(CW=4/7))+(T_{15678}*(CW=4/7))+(T_{1234}*(CW=3/7))+(T_{1235}*(CW=3/7))+(T_{1236}*(CW=3/7))+(T_{1237}*(CW=3/7))+(T_{1238}*(CW=3/7))+(T_{1345}*(CW=3/7))+(T_{1346}*(CW=3/7))+(T_{1347}*(CW=3/7))+(T_{1348}*(CW=3/7))+(T_{1456}*(CW=3/7))+(T_{1457}*(CW=3/7))+(T_{1458}*(CW=3/7))+(T_{1245}*(CW=3/7))+(T_{1246}*(CW=3/7))+(T_{1247}*(CW=3/7))+(T_{1248}*(CW=3/7))+(T_{1356}*(CW=3/7))+(T_{1357}*(CW=3/7))+(T_{1358}*(CW=3/7))+(T_{1467}*(CW=3/7))+(T_{1468}*(CW=3/7))+(T_{1478}*(CW=3/7))+(T_{1567}*(CW=3/7))+(T_{1568}*(CW=3/7))+(T_{1578}*(CW=3/7))+(T_{1678}*(CW=3/7))+(T_{1256}*(CW=3/7))+(T_{1257}*(CW=3/7))+(T_{1258}*(CW=3/7))+(T_{1367}*(CW=3/7))+(T_{1368}*(CW=3/7))+(T_{1378}*(CW=3/7))+(T_{1267}*(CW=3/7))+(T_{1268}*(CW=3/7))+(T_{1278}*(CW=3/7))+(T_{123}*(CW=2/7))+(T_{124}*(CW=2/7))+(T_{125}*(CW=2/7))+(T_{126}*(CW=2/7))+(T_{127}*(CW=2/7))+(T_{134}*(CW=2/7))+(T_{135}*(CW=2/7))+(T_{136}*(CW=2/7))+(T_{137}*(CW=2/7))+(T_{145}*(CW=2/7))+(T_{146}*(CW=2/7))+(T_{147}*(CW=2/7))+(T_{156}*(CW=2/7))+(T_{157}*(CW=2/7))+(T_{128}*(CW=2/7))+(T_{138}*(CW=2/7))+(T_{148}*(CW=2/7))+(T_{158}*(CW=2/7))+(T_{167}*(CW=2/7))+(T_{168}*(CW=2/7))+(T_{178}*(CW=2/7))+(T_{12}*(CW=1/7))+(T_{13}*(CW=1/7))+(T_{14}*(CW=1/7))+(T_{15}*(CW=1/7))+(T_{16}*(CW=1/7))+(T_{17}*(CW=1/7))+(T_{18}*(CW=1/7))+(TD_{12345678}*(CW=0))/TS] \tag{N1}$$

where

RCI(X) RCI for normalisation procedure ($X = N_1, N_2, \ldots, N_8$)
TS Total number of times the simulation was run (in this study TS = 1)
$TD_{12345678}$ Total number of times N_1, N_2, N_3, N_4, N_5, N_6, N_7, N_8 produced different rankings

$T_{12345678}$ Total number of times N_1, N_2, N_3, N_4, N_5, N_6, N_7, N_8 produced the same ranking
$T_{1234567}$ Total number of times N_1, N_2, N_3, N_4, N_5, N_6, N_7 produced the same ranking
T_{123456} Total number of times N_1, N_2, N_3, N_4, N_5, N_6 produced the same ranking
T_{12345} Total number of times N_1, N_2, N_3, N_4, N_5 produced the same ranking
T_{1234} Total number of times N_1, N_2, N_3, N_4 produced the same ranking
T_{123} Total number of times N_1, N_2, N_3 produced the same ranking
T_{12} Total number of times N_1, N_2 produced the same ranking

RCI values were calculated for all normalization techniques and the results obtained are presented in Table 13.

Table 13. *RCI values and Ranking*

	RCI	Rank
N1	296.58	2
N2	290.42	4
N3	257.99	6
N4	279.00	5
N5	298.72	1
N6	298.72	1
N6a	290.7	3
N6b	298.72	1

In Table 13, it can be seen that max-min normalization (N5), linear normalization (N6) and linear normalization (N6b) are the most suitable procedures for ROV method. The Enhanced accuracy method (N3) is the least suitable.

Step 2: Determining Spearman correlation [37]; Pearson correlation [14] andmean value (ks)

In this step, Spearman correlation ([37])and Pearson correlation [14] was calculated using the ranking results in Table 12.

The following formula (10) was used when calculating the Spearman correlation

$$qs = 1 - 6\frac{\sum_{i=1}^{m} \mathrm{Di2}}{m(\mathrm{m2}-1)} \tag{10}$$

D_i is the difference between ranks ri and ri ′
m is the number of alternatives
qs value lies between –1 and +1 where +1 indicates strong match and -1 indicates weak relationship. This inference also applies to Pearson correlation approach.

The following formula (11) was used when calculating the Pearson correlation

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{(N-1)\sigma_x \sigma_y} \tag{11}$$

$\bar{x}$ and $\bar{y}$ indicate the mean weight
N is the number of alternatives

Spearman correlation and Pearson correlation results are presented in Tables (14) and (15), respectively.

Table 14. *Spearman correlation results and mean Ks values*

	N1	N2	N3	N4	N5	N6	N6a	N6b	Mean ks	rank
N1		0.915	0.879	0.867	0.988	0.988	0.939	0.988	0.938	1
N2	0.915		0.818	0.952	0.891	0.891	0.988	0.891	0.907	4
N3	0.879	0.818		0.721	0.927	0.927	0.782	0.927	0.854	5
N4	0.867	0.952	0.721		0.818	0.818	0.964	0.818	0.851	6
N5	0.988	0.891	0.927	0.818		1	0.903	1	0.932	2
N6	0.988	0.891	0.927	0.818	1		0.903	1	0.932	2
N6a	0.939	0.988	0.782	0.964	0.903	0.903		0.903	0.912	3
N6b	0.988	0.891	0.927	0.818	1	1	0.903		0.932	2

Table 15. *Pearson correlation results and mean Ks values*

	N1	N2	N3	N4	N5	N6	N6a	N6b	Mean ks	rank
N1		0.986	0.979	0.948	0.996	0.997	0.995	0.997	0.985	1
N2	0.986		0.958	0.961	0.979	0.980	0.996	0.980	0.977	3
N3	0.979	0.958		0.898	0.993	0.991	0.970	0.991	0.969	4
N4	0.948	0.961	0.898		0.932	0.935	0.968	0.935	0.940	5
N5	0.996	0.979	0.993	0.932		1	0.989	1	0.984	2
N6	0.997	0.980	0.991	0.935	1		0.990	1	0.985	1
N6a	0.995	0.996	0.970	0.968	0.989	0.990		0.990	0.985	1
N6b	0.997	0.980	0.991	0.935	1	1	0.990		0.985	1

Step 3: Calculation of Standard deviation (STD) from [38]; [40]

STD is a measure of the spread of the data set from the mean. A low STD indicates that the data is close to the average value, while a high STD indicates that the data is far from the average. However, a small STD value is not always appropriate, and its interpretation varies according to the case study and characteristics [35]. The STD formula is expressed as:

$$STD = \sqrt{\frac{\sum_{i=1}^{p}(x_i - \bar{x})^2}{q-1}}. \tag{12}$$

The STD results obtained from 8 normalization methods are presented in Table 16.

Table 16. *STD results for the normalization methods*

	STD	Rank
N1	0.0512	5
N2	0.0206	6
N3	0.0111	7
N4	0.0880	1
N5	0.0739	2
N6	0.0707	3
N6a	0.0695	4
N6b	0.0707	3

Step 4: Calculation of Minkowski distances from [41]; [42]

In the last step, Minkowski distance measurements are used to determine the most appropriate normalization technique for the ROV method. Accordingly, Manhattan, Euclidean and Chebyshev measures, which are among the most common Minkowski distances, are preferred in this study. The formulas of the methods are as shown in Equations (13), (14) and (15), respectively

$$\text{Manhattan}\,(\rho=1): d(x,y)=\sum_{i=1}^{n}\left|(x_i-y_i)\right| \tag{13}$$

$$\text{Euclidean}\,(\rho=2): d(x,y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2} \tag{14}$$

$$\text{Chebyshev}\,(\rho=\infty): d(x,y)=\max_i(\left|x_i-y_i\right|). \tag{15}$$

Table 17. *Minkowski distances measurement results for the normalization methods*

	Manhattan	**Rank**	**Euclidean**	**Rank**	**Chebishev**	**Rank**
N1	2.355	6	1.203	6	0.189	5
N2	0.978	7	0.498	7	0.074	6
N3	0.510	8	0.263	8	0.043	7
N4	3.785	1	2.006	1	0.295	1
N5	3.386	2	1.746	2	0.280	2
N6	3.238	4	1.666	4	0.267	3
N6a	2.404	5	1.628	5	0.251	4
N6b	3.239	3	1.666	3	0.267	3

In Table 17, it can be seen that Manhattan and Euclidean have the same ranking. On the other hand, while the Chebyshev ranking results differ greatly from those of Manhattan and Euclidean, the first three rows did not change. All the results obtained at the end of the 4-step process used in this study are given in Table 18.

Table 18. *Normalization methods values on the basis of measurement*

	RCI	**Mean Ks (Spearman)**	**Mean Ks (Pearson)**	**STD**	**Manhattan**	**Euclidean**	**Chebishev**
N1	296.58	0.938	0.985	0.0512	2.3553	1.203465	0.189
N2	290.42	0.907	0.977	0.0206	0.9775	0.497745	0.074
N3	257.99	0.854	0.969	0.0111	0.51	0.263478	0.043
N4	279.00	0.851	0.940	0.0880	3.7854	2.006377	0.295
N5	298.72	0.932	0.984	0.0739	3.3863	1.745852	0.280
N6	298.72	0.932	0.985	0.0707	3.2381	1.666082	0.267
N6a	290.7	0.912	0.985	0.0695	2.4043	1.627964	0.251
N6b	298.72	0.932	0.985	0.0707	3.2385	1.66624	0.267

As mentioned above, the larger the values obtained at the end of the measurements in Table 18, the better. In Table 18, it is shown that the ranking results varies greatly according to the methods used. In this situation, it is still quite difficult to determine which method best suits the ROV method. Therefore, the plurality voting from social choice method [44] recommended by [5] is used at this stage. Thus, the alternative with the highest number of first ranks is chosen. The plurality voting method results used to reach the final decision are given in Table 19.

Table 19.*Normalization methodsrankings on the basis of measurement and pluralityvoting results*

	RCI	**Mean Ks (Spearman)**	**Mean Ks (Pearson)**	**STD**	**Manhattan**	**Euclidean**	**Chebishev**	**Plurality Voting**
N1	2	1	1	5	6	6	5	2
N2	4	4	3	6	7	7	6	0
N3	6	5	4	7	8	8	7	0
N4	5	6	5	1	1	1	1	4
N5	1	2	2	2	2	2	2	1
N6	1	2	1	3	4	4	3	2

N6a	3	3	1	4	5	5	4	1
N6b	1	2	1	3	3	3	3	2

Based on the results of Table 19, the most suitable normalization technique for the ROV method is non-linear normalization (N4). This technique is followed by vector normalization (N1), linear normalization (N6) and linear normalization (N6b) techniques. Two techniques not recommended for the ROV method are linear normalization sum based method (N2) and enhanced accuracy method (N3).

4. CONCLUSION AND RECOMMENDATIONS

This study is aimed at testing the suitability of eight different normalization techniques for the ROV method. In this direction, a real life practice was set out, and the financial performances of the companies that ranked top 10 in the FORTUNE 500 list of 2020 were evaluated using MCDM methods on the basis of seven ratios. While the entropy method was used to determine the weight of the criteria, the ROV method was used to rank the alternatives.

A 4-step process was followed to test the suitability of the selected normalization techniques for the ROV method. In the first stage, the RCI method, which measures consistency by taking into consideration the similarities and differences in the ranking of alternatives, was used. In the second stage, using the Spearman and Pearson correlation approaches, the relationships between ranking results were revealed. In the third stage, STD was calculated. In the fourth stage, Minkowski distance measurements (Manhattan, Euclidean, Chebishev) were used. In the last stage, plurality voting method was used to obtain a logical and consistent single result from the results obtained with five different measures.

According to the results obtained at the end of the study, non-linear normalization (N4) is the most suitable technique for ROV method. Two techniques not recommended for the ROV method are linear normalization sum based method (N2) and enhanced accuracy method (N3).

It can be stated that the 4-step process used in this study is more comprehensive compared to other studies. [14] tested the suitability of the four different normalization techniques for the TOPSIS method by calculating the Pearson correlation, and it was determined that the vector normalization technique was suitable for the TOPSIS method. [43] tested the suitability of 6 different normalization techniques for TOPSIS method by calculating the RCI, Pearson and Spearman correlation and it was determined that the vector normalization technique was suitable for the TOPSIS method. [5] tested the suitability of five different normalization techniques for the AHP method by taking into account Minkowski distances, Standard Deviation, Mean Ks values, and Ranking Consistency Index (RCI). In the last stage, they used the plurality voting method. [35] used RCI metric, Spearman correlation, Standard Deviation, and Minkowski distances metrics. In this study, the suitability of 8 normalization techniques for the ROV method was tested using RCI metric, Pearson and Spearman correlation, mean value, Standard deviation, Minkowski distances and Plurality Voting method.

In future studies, the suitability of different normalization techniques for the ROV method could be tested using different data sets. Also, criteria weights could be determined by objective methods, such as CRITIC and Standard Deviation, or by subjective methods, such as AHP and Delphi, and the results obtained can be compared.

CONFLICTS OF INTEREST

No conflict of interest was declared by the author.

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