

# APPLICATION OF THE PIV METHOD IN THE PRESENCE OF NEGATIVE DATA: AN EMPIRICAL EXAMPLE FROM A REAL-WORLD CASE

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**Abstract:** The presence of negative values in the decision matrix is a rare situation in Multiple Criteria Decision Making (MCDM) methods. In such a case, normalized matrix elements must be between 0 and 1 to use the Proximity Indexed Value (PIV) method. In this study, in which a real-life application is presented, two different solutions are generated for this problem. Firstly, negative decision matrix elements are converted to positive using the Z-score standardization method. Secondly, different normalization techniques are used instead of vector normalization in the algorithm of the PIV method. According to the obtained results, the most appropriate technique to use the PIV method in the presence of negative values in the decision matrix is the min-max normalization technique. The proposed model in this study supports the use the PIV method in the presence of negative values. In addition, this study is the first to test the suitability of different techniques for the PIV method.

**Keywords:** MCDM, PIV Method, Normalization, Standardization, Consistency

## **Negatif Verilerin Varlığı Durumunda PIV Yönteminin Uygulanması: Gerçek Hayat Uygulamasına Dayalı Ampirik Bir Analiz**

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**Özet:** Çok Kriterli Karar Verme (ÇKKV) yöntemlerinde karar matrisinde negatif verilere nadir olarak rastlanılmaktadır. Böyle bir durumda Proximity Indexed Value- Yakınlık Endeksli Değer (PIV) yöntemini uygulamak için normalize edilmiş karar matrisi elemanlarının 0 ile 1 arasında olacak şekilde yeniden düzenlenmesi gerekmektedir. Gerçek hayat uygulamasının ele alındığı bu çalışmada, mevcut problemi ortadan kaldırmak amacıyla iki farklı çözüm yolu sunulmuştur. İlk olarak, negatif karar matrisi elemanları, z-skor standardizasyon yöntemi kullanılarak pozitif hale getirilmiştir. İkinci olarak, PIV yönteminin algoritmasında bulunan vektör normalizasyon tekniği yerine farklı normalizasyon teknikleri kullanılmıştır. Elde edilen sonuçlara göre karar matrisinde negatif verilerin varlığı durumunda PIV yöntemi ile sonuca ulaşmak için en uygun teknik min-max tekniğidir. Bu çalışmada önerilen model, karar matrisinde negatif verilerin bulunması durumunda PIV yönteminin kullanımını desteklemektedir. Ayrıca, bu çalışma farklı tekniklerin PIV yöntemi için uygunluğunu test eden ilk çalışmadır.

**Anahtar Kelimeler:** ÇKKV, PIV Yöntemi, Normalizasyon, Standardizasyon, Tutarlılık

### Research Article

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## 1. INTRODUCTION

Multiple Criteria Decision Making (MCDM) methods provide a suitable framework for decision-makers to choose between multiple alternatives and multiple conflicting criteria. The basic algorithm of MCDM methods is based on criteria, alternative and criteria weights. Although the procedures of the methods differ from each other, there are many factors that affect MCDM results such as criteria weights, data set and the normalization process. The effect of different normalization procedures on MCDM results has been tackled by many studies (Kosareva et al. 2018; Vafaei et al. 2016; Yazdani et al. 2017a; Milani et al. 2005).

Normalized decision matrix elements will be a positive value between 0 and 1 (Yazdani et al., 2017a, p. 60). Negative values in the decision matrix are rarely seen in MCDM methods. Especially in MCDM methods where linear and vector normalization techniques are used, some problems are encountered when there are negative values in the normalized decision matrix. In this case, changing the normalization technique or standardizing the decision matrix and converting it to positive seem to be the two most important ways.

In this study, a real-life application is discussed by measuring the financial performances of 45 companies traded in the Borsa İstanbul (BIST) sustainability index with the Proximity Indexed Value (PIV) method. Firstly, negative decision matrix values are converted to positive using the Z-score standardization method developed by Zhang et al. (2014). As a second way, the PIV method steps were applied using enhanced accuracy and min-max normalization techniques instead of the vector normalization technique in the algorithm of the PIV method. In this study, a four-step process was applied to choose the most appropriate technique for the PIV method in presence of negative values in the decision matrix. In the first stage, Ranking Consistency Index (RCI) approach developed by Chakraborty and Yeh (2009), which takes into account the consistency between ranking results were used. In the second step, the approach suggested by Celen (2014) was considered and the Pearson correlation values of the ranking results obtained by different techniques were calculated. In the third step, the Standard Deviation (STD) of the ranking values was calculated by following the approach suggested by Bland and Altman (1996) and Yeh (2003). In the fourth step, distance measurements (Manhattan, Euclidean, Chebyshev) were calculated by following the approach suggested by Guo (2004) and Hassan et al. (2014). In the last step, the final result was obtained by using the plurality voting method.

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

- In this study, two different ways are proposed to use the PIV method in the presence of negative values in the decision matrix. Through the proposed model, different normalization techniques will be tested for the PIV method and the decision matrix will be standardized.
- This study is the first test of the suitability of different techniques for the PIV method in the presence of negative values in the decision matrix.
- This study guides the decision-makers to use the PIV method and other MCDM methods in the presence of negative values in the decision matrix.

The rest of the paper was organized as follows: In Section 2, the relevant previous literature studies are discussed. In Section 3, the mathematical notation and explanation of the methods used in the study are given. In Section 4, the application part of the study is included. Section 5 describes the proposed approach in this study to select the most suitable technique for the PIV method. Finally, concluding remarks and future research directions are included in Section 6.

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## 2. LITERATURE REVIEW

Many different topics such as health (Stevic et al. 2020), energy (Kumar et al. 2017), manufacturing (Abdel-Basset et al. 2020), banking (Dinçer and Yüksel, 2018), airline (Pineda et al. 2018), construction (Matic et al. 2019), material selection (Mousavi-Nasab and Sotoudeh-Anvari, 2017), financial performance evaluation (Ghadikolaie et al. 2014), vendor selection (Shyur and Shih, 2006), supplier selection (Yazdani et al. 2017b), portfolio optimization (Ehrgott et al. 2004) were handled by using MCDM methods. Studies examining the effect of different normalization methods on MCDM results are given below.

Kosareva et al. (2018) used five different normalization techniques and they ranked the alternatives using the Simple Additive Weighting (SAW) method. It was concluded that none of the five methods are best or worst in all situations. However, the min-max normalization technique is significantly better than others in most cases. The Log method is the worst in some cases, but it is the best compared to other methods. Yazdani et al. (2017a) measured the effects of different normalization techniques for the COPRAS-G model. It was concluded that a different normalization tool would change the ranking results depending on the number of criteria and alternatives. Vafaei et al. (2016) measured the effects of different normalization techniques for the Analytical Hierarchy Process (AHP) method. At the end of the study, it was determined that the logarithmic normalization technique was not suitable for the AHP method. Jahan and Edwards (2015) examined the shortcomings of 18 different normalization techniques and made suggestions for their use in engineering. At the end of the study, it was determined that the differences between normalization techniques have a significant effect on the quality of decision making in material selection in engineering design. Vafaei et al. (2020) tested the suitability of five different normalization techniques for the AHP method. It was concluded that the max-min normalization technique was the most appropriate technique for the AHP, while the sum and vector normalization techniques were the least appropriate techniques. Milani et al. (2005) used the Entropy and the technique for order preference by similarity to ideal solution (TOPSIS) methods for selection the gear material and tested the suitability of five different normalization techniques. It was concluded that using both linear and non-linear norms is more suitable for engineering decisions.

Chakraborty and Yeh (2009) tested the suitability of four different normalization techniques for the TOPSIS method. At the end of the study, it was determined that the vector normalization technique is the most suitable for the TOPSIS method. Mathew et al. (2017) tested the suitability of different normalization techniques for the weighted aggregated sum product assessment (WASPAS) method. It was concluded that linear normalization (max-min) proved to be best normalization technique for the WASPAS method. Chakraborty and Yeh (2007) tested the suitability of four different normalization techniques for the SAW method. It was concluded that vector normalization, linear scale transformation and max method are more suitable for the SAW method. Celen (2014) evaluated the effects of the four normalization procedures on the TOPSIS method considering the financial performances of 13 Turkish deposit banks. It was concluded that the vector normalization procedure is the most convenient for the TOPSIS method. Vafaei et al. (2019) selected the better data normalization technique for supplier selecting problem. In the study where six different normalization techniques were used, a four-stage process was followed. Chatterjee and Chakraborty (2014) assessed the effect of different normalization techniques for the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), Grey Relation Analysis (GRA), TOPSIS methods. It was observed that the vector normalization procedure is the most preferred.

### 3. METHODS

In this section, the methods used in the study are emphasized and mathematical notation and explanations are given.

#### 3.1. Normalization Techniques

Normalization techniques can be classified in several ways. Only two of the normalization techniques presented in Table 1 will be used in this study. On the other hand, the max normalization technique (Stopp, 1975), the sum normalization technique (Wang and Luo, 2010), the logarithmic normalization technique (Zavadskas and Turskis, 2008), the Jüttler (1966) and Körth's (1969) normalization techniques, the Lai and Hwang normalization technique (Lai and Hwang, 1994), the peldschus normalisation technique (Peldschus, 1986), the Markovic normalization technique (Markovic, 2010), the linear normalization technique (Milani et al. 2005; Asgharpour, 1998; Farag, 1997; Tzeng and Huang, 2011), the vector normalization technique (Milani et al. 2005) could not be used since they lead to negative values in the normalized decision matrix. The normalization techniques used in this study are presented in Table 1.

**Table 1.** Normalization Techniques

Normalization method	Source	Benefit criteria	Cost criteria
Enhanced accuracy technique	Zeng et al. (2013)	$n_{ij} = 1 - \frac{r_j^{\max} - r_{ij}}{\sum_{i=1}^m (r_j^{\max} - r_{ij})}$	$n_{ij} = 1 - \frac{r_{ij} - r_j^{\min}}{\sum_{i=1}^m (r_{ij} - r_j^{\min})}$
Linear max min normalization technique	Weitendorf (1976)	$n_{ij} = \frac{r_{ij} - r_j^{\min}}{r_j^{\max} - r_j^{\min}}$	$n_{ij} = \frac{r_j^{\max} - r_{ij}}{r_j^{\max} - r_j^{\min}}$

#### 3.2. Z-Score (Standard Score) Standardization Method

In the evaluation process, decision matrix elements need to be standardized to compare criteria with different dimensions and units. On the other hand, the existence of negative value in the decision matrix is not frequently encountered in MCDM problems. In such a case, since the negative values cannot be included in the normalized matrix, the decision matrix elements must be converted to positive.

In this study, the Z-score standardization method which was introduced by Zhang et al. (2014) was used to turn negative data into positive. The steps of the Z-score standardization method are as follows (Zhang et al., 2014, p. 3).

**Step 1:** Decision matrix elements are transformed using equation (1).

$$x_{ij} = \frac{X_{ij} - \bar{X}_i}{S_i} \tag{1}$$

$X_{ij}$  is the standardized data of the  $i$ th index in the  $j$ th region

$X_{ij}$  is the original data

$\bar{X}_i$  and  $S_i$  are the mean value and standard deviation of the  $i$ th index.

**Step 2:** The negative elements of the decision matrix are converted to positive using equation (2).

$$x'_{ij} = x_{ij} + A \quad A > |\min x_{ij}| \tag{2}$$

$x'_{ij}$  represents the standard value after transformation,  $x'_{ij} > 0$

#### 3.3. PIV Method

The PIV method was developed by Mufazzal and Muzakkir (2018). This method considers the proximity of alternatives to the best possible value. The steps of the PIV method are as follows (Mufazzal and Muzakkir, 2018, pp. 430-431):

**Step 1:** Construction of decision matrix

In the first step, the decision matrix is created by determining the alternatives  $A_i = (i = 1, 2, 3, \dots, m)$  and criteria  $C_j = (j = 1, 2, 3, \dots, n)$ .

**Step 2:** Normalization of decision matrix

Decision matrix elements are normalized using equation (3).

$$r_i = \frac{x_i}{\sqrt{\sum_{i=1}^m x_i^2}} \quad (3)$$

$r_i$  is the actual decision value of the  $i$ th alternative.

**Step 3:** Determination of weighted normalized decision matrix

Each element in the normalized decision matrix is multiplied by the criterion weights using equation (4).

$$v_{ij} = w_j * r_i \quad (4)$$

where  $w_j$  is the weight of the  $j$ th criterion.

**Step 4:** Evaluation of Weighted Proximity Index (WPI)

WPI is calculated to find the closeness of each alternative to the best solution available.

$$u_i = v_{max} - v_i \text{ for benefit criteria} \quad (5)$$

$$u_i = v_i - v_{min} \text{ for cost criteria} \quad (6)$$

**Step 5:** Determination of overall proximity value

The total proximity value is calculated using equation (7).

$$d_i = \sum_{j=1}^n u_j \quad (7)$$

**Step 6:** Ranking of alternatives

The alternative with the lowest  $d_j$  value represents the minimum deviation from the best solution and ranks first.

#### 4. APPLICATION

The main purpose of this study is to decide whether the standardization of the decision matrix or changing the normalization technique is the right way to apply the PIV method in the presence of negative values in the decision matrix. In this study, the financial performances of 45 companies traded in the BİST sustainability index in 2019 were measured using the PIV method. The data was collected on June 2021 and was retrieved from the companies' financial reports. The alternatives and the criteria used in the study are presented in Appendix 1 and Table 2, respectively. The financial ratios determined by a comprehensive literature review were selected from among the ratios that provide information about the company's ability to pay its debts, the effective use of assets and resources, and profitability.

**Table 2.** Criteria

Rank	Code	Financial Ratios and Disclosures	Opt.
<b>Liquidity ratios</b>			
1	CR	Current ratio = Current Assets / Current Liabilities	max
2	QR	Quick ratio = (Current Assets - Inventories) / Current Liabilities	max
<b>Leverage ratios</b>			
3	DTE	Debt-to-Equity Ratio = Total Liabilities / Total Shareholders' Equity	min
4	LR	Leverage Ratio = Total Liabilities / Total assets	min
<b>Profitability ratios</b>			
5	ROE	Return on Equity = Net Income (annual) / Shareholders' Equity	max
6	ROA	Return on Assets = Net Income (annual) / Total assets	max
<b>Efficiency Ratios</b>			
7	WCT	Working capital turnover ratio = Net sales / Current Assets	max
8	ATR	Asset Turnover Rate = Net Sales / Total Assets	max

#### 4.1. Weighting of Criteria

Criterion weights are an important threshold in MCDM problems and have an impact on the results. In this study, the equal weighting technique developed by Jahan et al. (2012) was used to determine the criterion weights. The results obtained are presented in Table 3.

$$w_j = \frac{1}{n} \quad (8)$$

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

**Table 3.** Criteria Weights

CR	QR	DTE	LR	ROE	ROA	WCTR	ATR
0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125

#### 4.2. Standardization of the Decision Matrix Using Z-Score (Standard Score)

##### Standardization Method

Firstly, the decision matrix was created. The decision matrix with alternatives (firms) in rows and criteria (financial ratios) in columns is presented in Table 4.

**Table 4.** Decision Matrix

Alternatives	Criteria							
	CR	QR	DTE	LR	ROE	ROA	WCTR	ATR
AKENR	0.52	0.52	6.15	0.86	-0.77	-0.11	3.38	0.12
AKSA	1.05	0.73	1.73	0.63	0.18	0.07	1.67	0.87
AKSEN	0.91	0.82	1.23	0.55	0.09	0.04	2.08	0.66
ANACM	1.46	1.15	1.57	0.61	0.19	0.07	1.50	0.59
AEFES	1.33	1.09	0.90	0.47	0.04	0.02	1.84	0.51
ANELE	1.37	1.20	1.77	0.64	0.01	0.003	1.34	0.73
ARCLK	1.58	1.19	2.54	0.72	0.10	0.03	1.44	0.96
ASELS	1.80	1.23	0.89	0.47	0.25	0.13	0.93	0.51
AYGAZ	1.06	0.89	1.00	0.50	0.11	0.06	6.43	2.06
BRISA	0.95	0.68	4.89	0.83	0.13	0.02	1.60	0.67
CCOLA	1.55	1.30	1.17	0.54	0.13	0.06	2.24	0.77
CIMSA	0.78	0.65	1.54	0.61	0.01	0.003	1.64	0.46
DOHOL	2.47	2.25	0.47	0.32	0.08	0.05	1.90	1.18
DOAS	0.81	0.51	2.72	0.73	0.06	0.02	3.93	2.12
ENJSA	0.79	0.77	2.42	0.71	0.15	0.04	3.36	0.83
ENKAI	3.00	2.73	0.25	0.20	0.10	0.08	0.62	0.22
EREGL	2.55	1.57	0.49	0.33	0.11	0.07	1.14	0.59
PROTO	1.17	0.96	2.52	0.72	0.42	0.12	3.86	2.39
GLYHO	0.86	0.80	3.65	0.78	-0.09	-0.02	1.03	0.20
SAHOL	0.74	0.73	5.11	0.84	0.06	0.01	0.09	0.50
ISDMR	3.32	1.96	0.34	0.25	0.13	0.10	1.68	0.76
KERVT	2.47	1.80	1.82	0.65	0.14	0.05	1.63	0.92
KCHOL	1.39	1.10	2.05	0.67	0.09	0.03	1.86	1.01
KORDS	1.18	0.71	1.54	0.61	0.12	0.05	1.67	0.72
LOGO	1.55	1.55	0.97	0.49	0.22	0.11	1.12	0.54
MGROS	0.70	0.35	43.79	0.98	-1.52	-0.03	4.39	1.60
OTKAR	1.87	1.13	3.20	0.76	0.55	0.13	1.25	0.91
PETKIM	1.86	1.68	2.05	0.67	0.17	0.05	1.22	0.79
POLHO	1.32	1.24	0.59	0.37	0.05	0.03	1.64	0.44
SODA	2.66	2.30	0.50	0.33	0.19	0.13	1.03	0.48
TATGD	2.84	1.61	0.83	0.45	0.12	0.06	1.46	1.11
TAVHL	1.20	1.19	1.93	0.66	0.06	0.02	0.66	0.19
TKFEN	1.39	1.17	1.30	0.57	0.26	0.11	1.58	1.15
TOASO	1.14	1.02	1.96	0.66	0.34	0.12	2.71	1.48
TRKCM	1.81	1.44	1.19	0.54	0.11	0.05	0.96	0.45
TCELL	1.53	1.51	1.53	0.60	0.18	0.07	1.24	0.52
TUPRS	0.99	0.66	3.23	0.76	0.04	0.01	3.21	1.61
THYAO	0.80	0.75	2.60	0.72	0.11	0.03	2.65	0.51
TTKOM	0.88	0.86	3.23	0.76	0.25	0.06	1.96	0.59
TTRAK	1.77	1.19	2.82	0.74	0.15	0.04	1.97	1.31
SISE	2.10	1.64	1.03	0.51	0.10	0.05	1.05	0.47
ULKER	1.28	1.20	1.59	0.61	0.18	0.07	0.89	0.61
VESBE	1.06	0.84	1.76	0.64	0.31	0.11	2.20	1.40
VESTL	0.66	0.46	4.15	0.81	0.09	0.02	1.79	0.88
ZOREN	0.51	0.50	10.39	0.91	-0.08	-0.01	1.96	0.45

**Step 1:** Decision matrix with negative values is transformed using equation (1) and the results are presented in Table 5.

**Table 5.** Z-Score Standardization

Alternatives	CR	QR	DTE	LR	ROE	ROA	WCTR	ATR
AKENR	-0.764	-1.206	0.472	1.396	-2.824	-3.323	1.287	-1.357
AKSA	0.202	-0.802	-0.212	0.073	0.323	0.427	-0.207	0.075
AKSEN	-0.793	-0.629	-0.289	-0.387	0.025	-0.198	0.151	-0.326
ANACM	0.187	0.006	-0.236	-0.042	0.356	0.427	-0.355	-0.460
AEFES	-0.058	-0.110	-0.340	-0.847	-0.141	-0.615	-0.058	-0.613
ANELE	-0.303	0.102	-0.206	0.131	-0.250	-0.969	-0.495	-0.193
ARCLK	-0.317	0.083	-0.086	0.591	0.058	-0.406	-0.408	0.246
ASELS	1.067	0.160	-0.342	-0.847	0.554	1.677	-0.853	-0.613
AYGAZ	0.159	-0.495	-0.325	-0.675	0.091	0.219	3.951	2.346
BRISA	-0.865	-0.899	0.277	1.223	0.157	-0.615	-0.268	-0.307
CCOLA	1.110	0.294	-0.298	-0.445	0.157	0.219	0.291	-0.116
CIMSA	-2.436	-0.956	-0.241	-0.042	-0.240	-0.969	-0.233	-0.708
DOHOL	2.393	2.122	-0.407	-1.710	-0.009	0.010	-0.006	0.666
DOAS	0.029	-1.226	-0.059	0.648	-0.075	-0.615	1.767	2.461
ENJSA	-3.185	-0.725	-0.105	0.533	0.223	-0.198	1.269	-0.002
ENKAI	0.649	3.046	-0.441	-2.400	0.058	0.635	-1.124	-1.166
EREGL	1.989	0.814	-0.404	-1.652	0.091	0.427	-0.670	-0.460
FROTO	0.447	-0.360	-0.089	0.591	1.118	1.469	1.706	2.976
GLYHO	0.173	-0.668	0.085	0.936	-0.572	-1.448	-0.766	-1.204
SAHOL	-3.719	-0.802	0.311	1.281	-0.075	-0.823	-1.587	-1.491
ISDMR	1.225	1.564	-0.427	-2.112	0.157	1.052	-0.198	-0.135
KERVT	1.557	1.256	-0.198	0.188	0.190	0.010	-0.242	0.170
KCHOL	0.303	-0.090	-0.162	0.303	0.025	-0.406	-0.041	0.342
KORDS	-0.533	-0.841	-0.241	-0.042	0.124	0.010	-0.207	-0.212
LOGO	1.225	0.775	-0.329	-0.732	0.455	1.260	-0.687	-0.555
MGROS	-1.686	-1.534	6.298	2.086	<b>-5.308*</b>	-1.656	2.169	1.468
OTKAR	0.014	-0.033	0.016	0.821	1.548	1.677	-0.574	0.151
PETKIM	0.778	1.026	-0.162	0.303	0.289	0.010	-0.600	-0.078
POLHO	-1.931	0.179	-0.388	-1.422	-0.108	-0.406	-0.233	-0.746
SODA	-0.259	2.219	-0.402	-1.652	0.356	1.677	-0.766	-0.670
TATGD	2.364	0.891	-0.351	-0.962	0.124	0.219	-0.390	0.533
TAVHL	-0.274	0.083	-0.181	0.246	-0.075	-0.615	-1.089	-1.223
TKFEN	0.360	0.044	-0.278	-0.272	0.588	1.260	-0.285	0.609
TOASO	-0.966	-0.244	-0.176	0.246	0.853	1.469	0.702	1.239
TRKCM	0.404	0.564	-0.295	-0.445	0.091	0.010	-0.827	-0.727
TCELL	0.778	0.698	-0.243	-0.099	0.323	0.427	-0.582	-0.593
TUPRS	0.274	-0.937	0.020	0.821	-0.141	-0.823	1.138	1.487
THYAO	-0.115	-0.764	-0.077	0.591	0.091	-0.406	0.649	-0.613
TTKOM	-1.283	-0.552	0.020	0.821	0.554	0.219	0.047	-0.460
TTRAK	-0.476	0.083	-0.043	0.706	0.223	-0.198	0.055	0.914
SISE	1.182	0.949	-0.320	-0.617	0.058	0.010	-0.748	-0.689
ULKER	0.317	0.102	-0.233	-0.042	0.323	0.427	-0.888	-0.422
VESBE	0.577	-0.591	-0.207	0.131	0.753	1.260	0.256	1.086
VESTL	0.216	-1.322	0.163	1.108	0.025	-0.615	-0.102	0.094
ZOREN	0.735	-1.245	1.129	1.683	-0.539	-1.240	0.047	-0.727

\*The A value in Equation (1.2) has been taken as 5.3874803

**Step 2:** Negative values in the decision matrix are converted to positive using equation (2). The results are presented in Table 6.

**Table 6.** Positive Decision Matrix

Alternatives	CR	QR	DTE	LR	ROE	ROA	WCTR	ATR
AKENR	4.624	4.181	5.860	6.783	2.563	2.065	6.674	4.031
AKSA	5.589	4.585	5.176	5.461	5.710	5.815	5.181	5.462
AKSEN	4.595	4.758	5.098	5.001	5.412	5.190	5.539	5.061
ANACM	5.575	5.393	5.151	5.346	5.743	5.815	5.032	4.928
AEFES	5.330	5.278	5.047	4.540	5.246	4.773	5.329	4.775
ANELE	5.085	5.489	5.182	5.518	5.137	4.419	4.893	5.195
ARCLK	5.070	5.470	5.301	5.978	5.445	4.981	4.980	5.634
ASELS	6.454	5.547	5.046	4.540	5.942	7.065	4.534	4.775
AYGAZ	5.546	4.893	5.063	4.713	5.478	5.606	9.338	7.734
BRISA	4.523	4.489	5.665	6.611	5.544	4.773	5.120	5.080
CCOLA	6.497	5.682	5.089	4.943	5.544	5.606	5.679	5.271
CIMSA	2.952	4.431	5.146	5.346	5.147	4.419	5.155	4.680
DOHOL	7.780	7.510	4.981	3.678	5.379	5.398	5.382	6.054
DOAS	5.416	4.162	5.329	6.036	5.313	4.773	7.155	7.848
ENJSA	2.202	4.662	5.283	5.921	5.611	5.190	6.657	5.386
ENKAI	6.036	8.433	4.947	2.988	5.445	6.023	4.264	4.221
EREGL	7.377	6.201	4.984	3.735	5.478	5.815	4.718	4.928
FROTO	5.834	5.028	5.298	5.978	6.505	6.856	7.094	8.363
GLYHO	5.560	4.720	5.473	6.323	4.816	3.940	4.622	4.183
SAHOL	1.669	4.585	5.699	6.668	5.313	4.565	3.801	3.897
ISDMR	6.613	6.952	4.961	3.275	5.544	6.440	5.189	5.252
KERVT	6.944	6.644	5.190	5.576	5.578	5.398	5.146	5.558
KCHOL	5.690	5.297	5.225	5.691	5.412	4.981	5.347	5.729
KORDS	4.854	4.547	5.146	5.346	5.511	5.398	5.181	5.176
LOGO	6.613	6.163	5.058	4.655	5.843	6.648	4.700	4.832
MGROS	3.701	3.854	11.685	7.473	0.079	3.731	7.556	6.856
OTKAR	5.402	5.355	5.403	6.208	6.936	7.065	4.814	5.538
PETKIM	6.166	6.413	5.225	5.691	5.677	5.398	4.788	5.309
POLHO	3.456	5.566	4.999	3.965	5.279	4.981	5.155	4.641
SODA	5.128	7.606	4.985	3.735	5.743	7.065	4.622	4.718
TATGD	7.751	6.278	5.036	4.425	5.511	5.606	4.997	5.920
TAVHL	5.114	5.470	5.207	5.633	5.313	4.773	4.299	4.164
TKFEN	5.748	5.432	5.109	5.115	5.975	6.648	5.102	5.997
TOASO	4.422	5.143	5.211	5.633	6.240	6.856	6.089	6.626
TRKCM	5.791	5.951	5.092	4.943	5.478	5.398	4.561	4.660
TCELL	6.166	6.086	5.145	5.288	5.710	5.815	4.805	4.794
TUPRS	5.661	4.450	5.408	6.208	5.246	4.565	6.526	6.875
THYAO	5.272	4.624	5.310	5.978	5.478	4.981	6.037	4.775
TTKOM	4.105	4.835	5.408	6.208	5.942	5.606	5.434	4.928
TTRAK	4.912	5.470	5.344	6.093	5.611	5.190	5.443	6.302
SISE	6.569	6.336	5.067	4.770	5.445	5.398	4.639	4.699
ULKER	5.705	5.489	5.154	5.346	5.710	5.815	4.499	4.966
VESBE	5.964	4.797	5.180	5.518	6.141	6.648	5.644	6.474
VESTL	5.604	4.066	5.550	6.496	5.412	4.773	5.286	5.481
ZOREN	6.123	4.143	6.516	7.071	4.849	4.148	5.434	4.660



**4.3. Evaluation of Firms' Performance using the PIV Method**

In this section, the positive decision matrix in Table 6 will be used to apply the PIV method. In the first step, the elements in in Table 6 are normalized using equation (3). In the second step, the weighted normalized matrix was obtained by multiplying the normalized criteria values and the criteria weights in Table 3. Then, considering the benefit-oriented (CR, QR, ROE, ROA, WCTR, ATR) and cost-oriented criteria (DTE, LR), the deviation of each alternative from the best value was measured using equation (5) and the sum of elements in each row was calculated using equation (6). The results are presented in Table 7.

**Table 7.** Ranking Results Obtained by the PIV Method

Firms	$\Sigma$	Rank	Firms	$\Sigma$	Rank	Firms	$\Sigma$	Rank
AKENR	0.097	43	ENKAI	0.046	6	TATGD	0.046	5
AKSA	0.062	24	EREGL	0.048	8	TAVHL	0.074	38
AKSEN	0.066	29	FROTO	0.039	3	TKFEN	0.052	12
ANACM	0.061	21	GLYHO	0.081	41	TOASO	0.052	13
AEFES	0.064	28	SAHOL	0.097	44	TRKCM	0.062	22
ANELE	0.070	34	ISDMR	0.042	4	TCELL	0.058	19
ARCLK	0.067	30	KERVT	0.053	14	TUPRS	0.062	23
ASELS	0.052	11	KCHOL	0.063	26	THYAO	0.068	33
AYGAZ	0.038	1	KORDS	0.067	31	TTKOM	0.070	35
BRISA	0.077	39	LOGO	0.051	9	TTRAK	0.063	27
CCOLA	0.054	15	MGROS	0.113	45	SISE	0.057	18
CIMSA	0.080	40	OTKAR	0.056	16	ULKER	0.062	25
DOHOL	0.038	2	PETKIM	0.058	20	VESBE	0.051	10
DOAS	0.057	17	POLHO	0.067	32	VESTL	0.073	36
ENJSA	0.073	37	SODA	0.047	7	ZOREN	0.082	42

**4.4. Application of Different Normalization Methods**

At this stage enhanced accuracy and linear max-min normalization techniques were used instead of the vector normalization technique in the PIV methods' algorithm. Table 8 presents an example of normalization calculation using the AKENR's benefit criteria (CR) and AKENR's cost criteria (DTE).

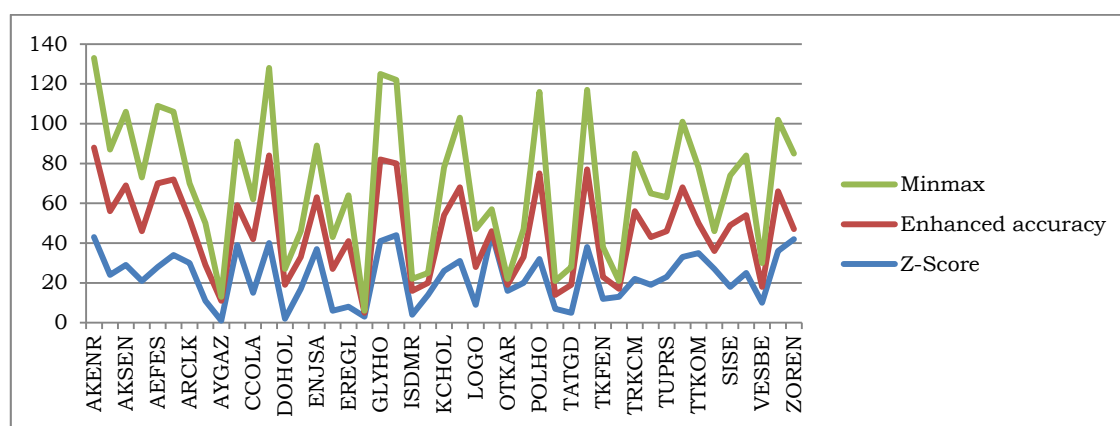
**Table 8.** Normalization Sample

Normalization technique	Condition of use	Formula	Process	Value
Enhanced accuracy technique	Benefit criteria	$n_{ij} = 1 - \frac{r_j^{\max} - r_{ij}}{\sum_{i=1}^m (r_j^{\max} - r_{ij})}$	$1 - \frac{3.32 - 0.52}{\sum_{i=1}^m (3.32 - 0.52) + (3.32 - 1.05) + \dots + (3.32 - 0.51)}$	0.967
	Cost criteria	$n_{ij} = 1 - \frac{r_{ij} - r_j^{\min}}{\sum_{i=1}^m (r_{ij} - r_j^{\min})}$	$1 - \frac{6.15 - 0.25}{\sum_{i=1}^m (6.15 - 0.25) + (1.73 - 0.25) + \dots + (10.39 - 0.25)}$	0.954
Linear max min normalization technique	Benefit criteria	$n_{ij} = \frac{r_j^{\max} - r_{ij}}{r_j^{\max} - r_j^{\min}}$	$\frac{0.52 - 0.51}{3.32 - 0.51}$	0.004
	Cost criteria	$n_{ij} = \frac{r_j^{\max} - r_{ij}}{r_j^{\max} - r_j^{\min}}$	$\frac{43.79 - 6.15}{43.79 - 0.25}$	0.864

The normalization process shown in Table 8 has been applied to all criteria. The ranking results obtained are given in Table 9.

**Table 9.** Final Ranking Results Obtained with Three Different Techniques

	Z-Score	Enhanced accuracy	Min-max
	Rank	Rank	Rank
AKENR	43	45	45
AKSA	24	32	31
AKSEN	29	40	37
ANACM	21	25	27
AEFES	28	42	39
ANELE	34	38	34
ARCLK	30	22	18
ASELS	11	18	21
AYGAZ	1	10	2
BRISA	39	20	32
CCOLA	15	27	20
CIMSA	40	44	44
DOHOL	2	17	8
DOAS	17	16	13
ENJSA	37	26	26
ENKAI	6	21	16
EREGL	8	33	23
PROTO	3	2	1
GLYHO	41	41	43
SAHOL	44	36	42
ISDMR	4	12	6
KERTV	14	6	5
KCHOL	26	28	24
KORDS	31	37	35
LOGO	9	19	19
MGRS	45	1	11
OTKAR	16	3	3
PETKIM	20	13	14
POLHO	32	43	41
SODA	7	7	7
TATGD	5	14	9
TAVHL	38	39	40
TKFEN	12	11	15
TOASO	13	4	4
TRKCM	22	34	29
TCELL	19	24	22
TUPRS	23	23	17
THYAO	33	35	33
TTKOM	35	15	28
TTRAK	27	9	10
SISE	18	31	25
ULKER	25	29	30
VESBE	10	8	12
VESTL	36	30	36
ZOREN	42	5	38



**Figure 1.** Ranking Results

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It is very difficult to decide which technique is the most suitable for the PIV method by using the data in Table 9 and Figure 1 enhanced accuracy and linear max-min normalization techniques were used instead of the vector normalization technique in the PIV methods' algorithm.

### 5. A PROPOSED APPROACH FOR SELECTING THE BEST SUITABLE TECHNIQUE FOR THE PIV METHOD

Determining the best technique for MCDM methods is not an easy process. The rankings obtained are also different due to the differences in the algorithms of the methods. There are various approaches developed in the literature to select the most appropriate technique for MCDM methods.

Celen (2014) suggested the Pearson correlation approach to choose the best normalization techniques. Chakraborty and Yeh (2009) developed a RCI approach that takes into account consistency between the ranking results. Vafaei et al. (2018) used Spearman's rank correlation (used by Wang and Luo, 2010) in addition to approaches of Celen's (2014) and Chakraborty and Yeh's (2009).

In this study, a four-stage model was proposed. In the first stage, the consistency between the ranking results was examined using the RCI approach (Chakraborty and Yeh, 2009). In the second stage, the relationship between the ranking results obtained with different techniques was examined using the Pearson correlation technique (Celen, 2014). In the third stage, new rankings were obtained using the STD approach from (Bland and Altman, 1996; Yeh, 2003). In the fourth step, Minkowski distances (Guo, 2004; Hassan et al. 2014) were calculated to determine the most appropriate technique for the PIV method.

**Step A:** Determining the RCI from Chakraborty and Yeh (2009).

Ranking consistency is used to show how well a normalization procedure produces similar rankings with other procedures. The higher the RCI, the better the procedure is (Chakraborty and Yeh, 2009, p.1817). In this study, the consistency weight (CW) was used as follows:

- 1) If a technique is consistent with all other two techniques, then  $CW = 2/2 = 1$
- 2) If a technique is consistent with one of the two techniques, then  $CW = 1/2$
- 3) If a technique is not consistent with any other five techniques, then  $CW = 0/2 = 0$ .

The ranking consistency index of Z-Score is calculated as;

$$RCI(\text{Vector}) = [(T_{123} * (CW=1)) + (T_{12} * (CW=1/2)) + (T_{13} * (CW=1/2)) + TD_{123} * (CW=0)] / TS$$

The ranking consistency index of **Enhanced accuracy** is calculated as;

$$RCI(\text{Vector}) = [(T_{123} * (CW=1)) + (T_{21} * (CW=1/2)) + (T_{23} * (CW=1/2)) + TD_{123} * (CW=0)] / TS$$

The ranking consistency index of **min-max** is calculated as;

$$RCI(\text{Vector}) = [(T_{123} * (CW=1)) + (T_{31} * (CW=1/2)) + (T_{32} * (CW=1/2)) + TD_{123} * (CW=0)] / TS$$

where

$RCI(X)$  RCI for normalization procedure ( $X = N_1, N_2, \dots, N_3$ )

$TS$  = Total number of times the simulation was run (in this study  $TS = 1$ )

$TD_{123}$  = Total number of times  $N_1, N_2, N_3$  produced different rankings

$T_{123}$  = 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 are presented in Table 10.

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**Table 10.** RCI Values and Ranking

	<b>RCI</b>	<b>Rank</b>
Z-Score	4.5	3
Enhanced accuracy	6.0	2
Min-max	6.5	1

From Table 10, the min-max normalization technique is the most suitable for the PIV method. This technique was followed by Z-score and enhanced accuracy techniques, respectively.

**Step B:** Determining the Pearson correlation from Celen (2014).

In this step, Pearson correlation coefficient was calculated using the ranking values in Table 9. The results obtained are presented in Table 11. The following formula (9) was used for calculating the Pearson correlation.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{(N-1)\sigma_x\sigma_y} \quad (9)$$

$\bar{x}$  and  $\bar{y}$  indicate the arithmetic mean

N is the number of alternatives.

**Table 11.** Pearson Correlation Results and Mean Ks Values

	<b>Z-Score</b>	<b>Enhanced accuracy</b>	<b>Min-max</b>	<b>Mean ks</b>	<b>Rank</b>
Z-Score	-	-0.100	0.687	0.294	2
Enhanced accuracy	-0.100	-	0.594	0.247	3
Min-max	0.687	0.594	-	0.641	1

According to the results in Table 11, the min-max normalization technique was determined to be the most suitable for the PIV method, while the enhanced accuracy normalization technique was determined to be the most inappropriate technique.

**Step C:** Calculation of STD from (Bland and Altman, 1996; Yeh, 2003).

The standard deviation was calculated using the data in Table 9 and the results obtained are presented in Table 12.

The STD formula is expressed as:

$$STD = \sqrt{\frac{\sum_{i=1}^p (x_i - \bar{x})^2}{q-1}} \quad (10)$$

**Table 12.** STD Results for the Different Techniques

	<b>STD</b>	<b>Rank</b>
Z-Score	0.016	2
Enhanced accuracy	0.006	3
Min-max	0.069	1

According to the results in Table 12, the min-max normalization technique was determined to be the most suitable for the PIV method, while the enhanced accuracy normalization technique was determined to be the least appropriate technique.

**Step D:** Calculating Minkowski Distances (Guo, 2004; Hassan et al. 2014)

In the last step, Minkowski distance measurements were used to determine the most suitable technique for the PIV method. Accordingly, the most used measurements such as Manhattan, Euclidean and Chebyshev were preferred in this study. The formulas of the methods are as shown in equations (11), (12) and (13) respectively.

$$\text{Manhattan } (p = 1): d(x, y) = \sum_{i=1}^n |x_i - y_i| \quad (11)$$

$$\text{Euclidean } (p = 2): d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (12)$$

$$\text{Chebyshev } (p = \infty): d(x, y) = \max_i |x_i - y_i| \quad (13)$$

**Table 13.** Minkowski Distances Measurement Results for the Normalization Methods

	<b>Manhattan</b>	<b>Rank</b>	<b>Euclidean</b>	<b>Rank</b>	<b>Chebichev</b>	<b>Rank</b>
Z-Score	16.992	2	3.933	2	0.075	2
Enhanced accuracy	4.676	3	1.022	3	0.039	3
Min-max	78.214	1	17.599	1	0.342	1

In this study, a four-step process was followed to determine the most suitable technique for the PIV method in the presence of negative values in the decision matrix. Except for RCI, ranking results obtained with Pearson correlation, STD, and Minkowski measurements were determined to be the same. According to Table 13, min-max is the most suitable technique for the PIV method. However, the plural voting method suggested by Vafaei et al. (2020) is used at this stage to reach a definite conclusion. Thus, the alternative with the highest number of first ranks is chosen. The results of plurality voting method are given in Table 14.

**Table 14.** The Final Ranking Results

	<b>RCI</b>	<b>Mean Ks (Pearson)</b>	<b>STD</b>	<b>Manhattan</b>	<b>Euclidean</b>	<b>Chebichev</b>	<b>Plurality Voting</b>
Z-Score	3	2	2	2	2	2	0
Enhanced accuracy	2	3	3	3	3	3	0
Minmax	1	1	1	1	1	1	6

According to the results in Table 14, the most suitable technique for the PIV method is the min-max normalization technique. The Z-Score standardization technique and enhanced accuracy normalization technique were identified as the least appropriate techniques for the PIV method.

## 6. CONCLUSION

In MCDM methods, negative and zero value data are generally not found in the decision matrix. In such a case, it is necessary to convert the negative decision matrix data to positive because the values in the normalized decision matrix must be between 0 and 1.

The PIV method cannot be used when there are negative values in the decision matrix. It is necessary to change the normalization method or standardize the decision matrix elements to obtain the final result with the PIV method. In this study, in which the financial performance of companies listed in the BİST sustainability index are evaluated, two different solutions have been proposed to the negative data problem in the PIV method and the most effective approach has been tried to be determined. Firstly, the decision matrix with negative data value was converted to positive using the Z-Score standardization method developed by Zhang et al. (2014), and the steps of the PIV method were applied. Then, the PIV method steps were repeated using the enhanced accuracy and min-max normalization techniques instead of the vector normalization technique included in the algorithm of the PIV method.

This study sought to answer the following research questions:

- In the presence of observations with negative values in the decision matrix, would it be more appropriate to standardize the decision matrix or change the normalization technique to use MCDM methods?
- If the second way is to be followed, which normalization technique is most suitable for the PIV method?

In this study, a four-step process was applied to find answers to the above questions and RCI values developed by Chakraborty and Yeh (2009) were calculated. In the second stage, the Pearson correlation values of the ranking results obtained by different techniques were calculated by following the approach suggested by Celen (2014). In the third step, the STD of the ranking values

was calculated (Bland and Altman, 1996; Yeh, 2003). In the fourth step, Manhattan, Euclidean, Chebyshev distance measures, (Guo, 2004; Hassan et al. 2014) were calculated. In the last stage, the plurality voting method (d'Angelo et al. 1998) proposed by Vafaei et al. (2020) was used to obtain a final result. Accordingly, the most suitable technique for the PIV method is the min-max normalization technique. The Z-score standardization technique and enhanced accuracy normalization techniques were determined unsuitable for the PIV method. As a result, the min-max normalization technique is the best solution to use for the PIV method in the presence of negative data values.

This study is helpful for researchers who want to use the PIV method in presence of negative values in the decision matrix and motivates them for future studies. In addition, this study guides researchers to use other MCDM techniques when there are negative values in the decision matrix. In future studies, the proposed model can be tested for different MCDM methods and the number of normalization techniques can be increased.

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## APPENDIX

### Appendix 1. Alternatives

Rank	Company's name	Rank	Company's name	Rank	Company's name
1	AKENERJİ ELEKTRİK ÜRETİM A.Ş. (AKENR)	16	ENKA İNŞAAT VE SANAYİ A.Ş. (ENKAİ)	31	TAT GIDA SANAYİ A.Ş. (TATGD)
2	AKSA AKRİLİK KİMYA SANAYİİ A.Ş. (AKSA)	17	EREĞLİ DEMİR VE ÇELİK FABRİKALARI T.A.Ş. (EREGL)	32	TAV HAVALİMANLARI HOLDİNG A.Ş. (TAVHL)
3	AKSA ENERJİ ÜRETİM A.Ş. (AKSEN)	18	FORD OTOMOTİV SANAYİ A.Ş. (FROTO)	33	TEKFEN HOLDİNG A.Ş. (TKFEN)
4	ANADOLU CAM SANAYİİ A.Ş. (ANACM)	19	GLOBAL YATIRIM HOLDİNG A.Ş. (GYLHO)	34	TOFAŞ TÜRK OTOMOBİL FABRİKASI A.Ş. (TOASO)
5	ANADOLU EFES BİRACILIK VE MALT SANAYİİ A.Ş. (AEFES)	20	HACI ÖMER SABANCI HOLDİNG A.Ş. (SAHOL)	35	TRAKYA CAM SANAYİİ A.Ş. (TRKCM)
6	ANEL ELEKTRİK PROJE TAAHHÜT VE TİCARET A.Ş. (ANELE)	21	İSKENDERUN DEMİR VE ÇELİK A.Ş. (ISDMR)	36	TURKCELL İLETİŞİM HİZMETLERİ A.Ş. (TCELL)
7	ARÇELİK A.Ş. (ARCLK)	22	KEREVİTAŞ GIDA SANAYİ VE TİCARET A.Ş. (KERVIT)	37	TÜPRAŞ-TÜRKİYE PETROL RAFİNERİLERİ A.Ş. (TUPRS)
8	ASELSAN ELEKTRONİK SANAYİ VE TİCARET A.Ş. (ASELS)	23	KOÇ HOLDİNG A.Ş. (KCHOL)	38	TÜRK HAVA YOLLARI A.O. (THYAO)
9	AYGAZ A.Ş. (AYGAZ)	24	KORDSA TEKNİK TEKSTİL A.Ş. (KORDS)	39	TÜRK TELEKOMÜNİKASYON A.Ş. (TTKOM)
10	BRİSA BRIDGESTONE SABANCI LASTİK SANAYİ VE TİCARET A.Ş. (BRISA)	25	LOGO YAZILIM SANAYİ VE TİCARET A.Ş. (LOGO)	40	TÜRK TRAKTÖR VE ZİRAAT MAKİNELERİ A.Ş. (TTRAK)
11	COCA-COLA İÇECEK A.Ş. (CCOLA)	26	MİGROS TİCARET A.Ş. (MIGROS)	41	TÜRKİYE ŞİŞE VE CAM FABRİKALARI A.Ş. (SISE)
12	ÇİMSA ÇİMENTO SANAYİ VE TİCARET A.Ş. (CİMSA)	27	OTOKAR OTOMOTİV VE SAVUNMA SANAYİ A.Ş. (OTKAR)	42	ÜLKER BİSKÜVİ SANAYİ A.Ş. (ULKER)
13	DOĞAN ŞİRKETLER GRUBU HOLDİNG A.Ş. (DOHOL)	28	PETKİM PETROKİMYA HOLDİNG A.Ş. (PETKİM)	43	VESTEL BEYAZ EŞYA SANAYİ VE TİCARET A.Ş. (VESBE)
14	DOĞUŞ OTOMOTİV SERVİS VE TİCARET A.Ş. (DOAS)	29	POLİSAN HOLDİNG A.Ş. (POLHO)	44	VESTEL ELEKTRONİK SANAYİ VE TİCARET A.Ş. (VESTL)
15	ENERJİSA ENERJİ A.Ş. (ENJSA)	30	SODA SANAYİİ A.Ş. (SODA)	45	ZORLU ENERJİ ELEKTRİK ÜRETİM A.Ş. (ZOREN)

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## GENİŞLETİLMİŞ ÖZET

### Amaç

Karar matrisinde negatif değerlerin varlığına Çok Kriterli Karar Verme (ÇKKV) yöntemlerinde nadir olarak rastlanır. Böyle bir durumda ise karar matrisinde yer alan negatif değerler pekçok ÇKKV yönteminde normalize matriste negatif değerlere yol açmaktadır ve işleme devam edilememektedir. Proximity Indexed Value (PIV) yöntemi de işleme devam edilemeyen yöntemler arasında yer almaktadır. Bu çalışmanın amacı, karar matrisinde negatif verilerin varlığı durumunda PIV yöntemini uygulayabilmek için en iyi çözüm yolunu sunmaktır.

### Yöntem

Negatif verilerin varlığı durumunda PIV yöntemini kullanabilmek amacıyla iki farklı çözüm yolu sunulmuştur. İlk olarak, negatif karar matrisi elemanları, Z-skor standartlaştırma yöntemi kullanılarak pozitif hale getirilmiştir. İkinci yol olarak, PIV yönteminin algoritmasında bulunan vektör normalizasyon tekniği yerine Gelişmiş doğruluk (Enhanced accuracy) ve min-max normalizasyon teknikleri kullanılmıştır. En iyi çözüm yolunu seçmek amacıyla ise dört aşamalı bir yaklaşım önerilmiştir. İlk aşamada, Tutarlılık İndeksi (Ranking Consistency Index (RCI)) kullanılmış ve sıralama tutarlılığı hesaplanmıştır. İkinci aşamada, Pearson korelasyon katsayısı hesaplanmıştır. Üçüncü aşamada, standart sapma (STD) yaklaşımı ele alınmıştır. Dördüncü aşamada, Minkowski uzaklık ölçülerinden Manhattan, Euclidean, Chebyshev ölçüleri hesaplanmıştır. Son aşamada ise çoğul oy sistemi (Plural voting) yöntemi kullanılarak en iyi yaklaşım belirlenmiştir.

### Bulgular

Elde edilen sonuçlara göre karar matrisinde negatif verilerin varlığı durumunda PIV yöntemini kullanabilmek için en iyi yol normalizasyon yöntemini değiştirmek ve min-max normalizasyon tekniğini kullanmaktır. Z-skor standartlaştırma tekniği ve Gelişmiş doğruluk (Enhanced accuracy) normalizasyon tekniği, min-max normalizasyon tekniğine kıyasla daha az etkin yöntemler olarak tespit edilmiştir.

### Sonuç

ÇKKV yöntemlerinde, karar matrisinde genellikle negatif ve sıfır değerli veriler bulunmaz. Böyle bir durumda normalize edilmiş karar matrisindeki değerlerin 0 ile 1 arasında olması gerektiğinden negatif karar matrisi verilerini pozitif çevirmek gerekir.

Karar matrisinde negatif değerler olduğunda PIV yöntemi kullanılamaz. PIV yöntemi ile nihai sonucu elde etmek için normalizasyon yöntemini değiştirmek veya karar matrisi elemanlarını standardize etmek gerekir. Borsa İstanbul (BİST) sürdürülebilirlik endeksinde yer alan şirketlerin finansal performanslarının değerlendirildiği bu çalışmada, PIV yöntemindeki olumsuz veri sorununa iki farklı çözüm önerilmiş ve en etkin yaklaşım belirlenmeye çalışılmıştır. İlk olarak, negatif verilere sahip olan karar matrisi, Z-Skor standartlaştırma yöntemi kullanılarak pozitif dönüşürülmüştür. Daha sonra, PIV yönteminin algoritmasında yer alan vektör normalizasyon tekniği yerine gelişmiş doğruluk (Enhanced accuracy) ve min-max normalizasyon teknikleri kullanılarak PIV yöntemi adımları tekrarlanmıştır.

Bu çalışmada aşağıdaki araştırma sorularına yanıt aranmıştır:

- Karar matrisinde negatif gözlem değerlerinin varlığında ÇKKV yöntemlerini kullanabilmek için karar matrisini standartlaştırmak mı yoksa normalleştirme tekniğini değiştirmek mi daha uygun olur?

- İkinci yol izlenecek ise PIV yöntemi için en uygun normalizasyon tekniği hangisidir?

Bu çalışmada yukarıdaki sorulara cevap bulmak için dört aşamalı bir süreç uygulanmıştır. İlk aşamada RCI değerleri hesaplanmıştır. İkinci aşamada, farklı tekniklerle elde edilen sıralama sonuçlarının Pearson korelasyon değerleri hesaplanmıştır. Üçüncü aşamada, sıralama değerlerinin STD'si hesaplanmıştır. Dördüncü aşamada, Manhattan, Euclidean, Chebyshev uzaklık ölçüleri hesaplanmıştır. Son aşamada, çoğul oylama yöntemi nihai bir sonuç elde etmek için kullanılmıştır. Buna göre PIV yöntemi için en uygun teknik min-max normalizasyon tekniği olarak tespit edilmiştir. Z-skor standartlaştırma ve gelişmiş doğruluk (Enhanced accuracy) normalizasyon tekniklerinin PIV yöntemi için uygun olmadığı belirlenmiştir. Sonuç olarak, normalizasyon tekniği değişimine giderek min-max normalizasyon tekniğini kullanmak, negatif verilerin varlığında PIV yöntemini kullanmak için en iyi çözümdür.

Bu çalışma, karar matrisinde negatif değerlerin varlığında PIV yöntemini kullanmak isteyen araştırmacılara yardımcı olmakta ve onları gelecek çalışmalar için motive etmektedir. Ayrıca bu çalışma, karar matrisinde negatif değer olduğunda araştırmacılara diğer ÇKKV tekniklerini kullanmaları konusunda rehberlik etmektedir.