Necmettin Erbakan Üniversitesi Siyasal Bilgiler Fakültesi Dergisi (NEUSBF Dergisi)
Journal of the Faculty of Political Science (NEUSBF)
DOI: 10.51124/jneusbf.2023.54

Cilt: 5 Sayı: Özel Sayı Yıl: 2023 | Araştırma Makalesi / Research Article | E-ISSN: 2687-5063

Normalization Technique Selection for MCDM Methods: A Flexible and Conjunctural Solution that can Adapt to Changes in Financial Data Types*

Mahmut BAYDAŞ[1] **Tevfik EREN**[2] **Mustafa İYİBİLDİREN**[3]

[1] PhD, Necmettin Erbakan University, Faculty of Applied Sciences, Department of Accounting and Finance Management, Konya, Türkiye, mbaydas@erbakan.edu.tr

[2] PhD, Necmettin Erbakan University, Faculty of Applied Sciences, Department of Accounting and Finance Management, Konya, Türkiye, teren@erbakan.edu.tr

[3] PhD, Necmettin Erbakan University, Faculty of Applied Sciences, Department of Accounting and Finance Management, Konya, Türkiye, miyibildiren@erbakan.edu.tr *(Sorumlu Yazar / Corresponding Author)*

Article Info

Article History

Received: 30/10/2023
Accepted: 30/11/2023
Published: 17/12/2023

Keywords:
MCDM, Normalization Techniques, Financial Performance

Jel Codes:
G30, M21, C44

ABSTRACT

It makes sense to use the MCDM methodology to select and rank alternatives for a multi-criteria problem. As it is known, since it is not possible to use criteria consisting of different units in a common calculation, it is necessary to convert them into a unitless dimension. Many alternative normalization techniques have been proposed in the past for this conversion process. On the other hand, normalization techniques that appear to be accurate fair transformers have the potential to affect the final ranking of any MCDM method, and this is a significant problem. As a matter of fact, these alternative techniques can change the best alternative and overall ranking for an MCDM. Therefore, an unconsciously chosen normalization technique may reduce the quality of the findings. However, it cannot be said that there is a consensus on the choice of normalization methods. This study has shown, from an innovative perspective, how normalization techniques can change an MCDM's relationship with the external environment. In other words, we focus on how the normalization technique affects the relationship of MCDM with an external factor. Thus, we want to achieve a fair assessment by choosing a reference point. According to the findings of the approach tested in different financial data sets, the most successful technique may change periodically. Our recommendation for normalization technique selection for MCDM methods actually offers a flexible conjunctural framework that can be adapted to periodic data changes for financial data types.

ÇKKV Yöntemleri İçin Normalizasyon Tekniği Seçimi: Finansal Veri Türlerindeki Değişikliklere Uyum Sağlayabilecek Esnek ve Konjonktürel Bir Çözüm

Makale Bilgileri

Makale Geçmişi

Geliş: 30/10/2023
Kabul: 30/11/2023
Yayın: 17/12/2023

Anahtar Kelimeler:
ÇKKV, Normalizasyon Teknikleri, Finansal Performans

JEL Kodları:
G30, M21, C44

ÖZ

Çok kriterli bir problem için alternatifleri seçmek ve sıralamak amacıyla ÇKKV metodolojisini kullanmak mantıklıdır. Bilindiği üzere farklı birimlerden oluşan kriterlerin ortak bir hesaplamada kullanılması mümkün olmadığından bunların birimsiz bir boyuta dönüştürülmesi gerekmektedir. Bu dönüştürme işlemi için geçmişte birçok alternatif normalleştirme tekniği önerilmiştir. Öte yandan, doğru ve adil transformatörler gibi görünen normalleştirme teknikleri, herhangi bir ÇKKV yönteminin nihai sıralamasını etkileme potansiyeline sahiptir ve bu önemli bir sorundur. Aslına bakılırsa bu alternatif teknikler, bir ÇKKV için en iyi alternatifi ve genel sıralamayı değiştirebilmektedir. Bu nedenle bilinçsizce seçilen bir normalleştirme tekniği bulguların kalitesini düşürebilir. Ancak normalizasyon yöntemlerinin seçimi konusunda fikir birliğine varıldığı söylenemez. Önceki çalışmalarda normalleştirme yöntemlerinin ÇKKV sonuçlarını etkileyebileceği oybirliğiyle ifade edilmişti. Bu çalışmada yenilikçi bir bakış açısıyla normalleştirme yöntemlerinin sonuçlar üzerindeki etkisi üçüncü bir taraf olan bir dış sabit faktör ile değerlendirilmektedir. Başka bir deyişle normalleştirme tekniğinin ÇKKV'nin dış bir faktörle ilişkisini nasıl etkilediğine odaklanıyoruz. Böylece bir referans noktası seçerek adil bir değerlendirme elde etmek istiyoruz. Farklı finansal veri setlerinde test edilen yaklaşımın bulgularına göre en başarılı teknik dönemsel olarak değişebilmektedir. Bu nedenle veri yapısına bağlı olarak en iyi normalleştirme tekniğinin seçimi statik açıdan değil dinamik açıdan değerlendirilmelidir. ÇKKV yöntemleri için normalleştirme tekniği seçimine yönelik önerimiz aslında finansal veri türleri için dönemsel veri değişikliklerine uyarlanabilecek esnek bir konjonktürel çerçeve sunmaktadır.

Atıf/Citation: Baydaş, M., Eren, T. & İyibildiren, M. (2023). Normalization Technique Selection for MCDM Methods: A Flexible and Conjunctural Solution that can Adapt to Changes in Financial Data Types, *Necmettin Erbakan Üniversitesi Siyasal Bilgiler Fakültesi Dergisi*, *5*(Özel Sayı), 148-164.

* This article is an expanded version of the paper titled "An Innovative Comparison and Evaluation Methodology Approach for Normalization Technique Selection: An MCDM Application with Financial Datasets" presented at SIRCON 2023 held in Tashkent/Uzbekistan on 03-06 October 2023.

INTRODUCTION

MCDM methods are frequently used to solve problems that require the selection of alternatives with multiple criteria, which may also be benefit- and cost-oriented. MCDM methods are used successfully in solving the problem in many application areas with different data types. When the literature is examined, it can be said that MCDM methods are a practical solution to solve problems in many areas (Özdağoğlu, 2013a; Chatterjee and Chakraborty, 2014, Chen, 2019; Satıcı 2021; Mhlanga and Lall 2022; Kızıl, 2019; Sayar et al., 2019; Alkan, 2020). The algorithms of MCDM methods differ from each other in a certain way. We observe that additive, distance-based, pairwise comparison, outranking or multiplication based approaches are frequently used when calculating the final result. The effect of MCDM categories on the results emerges at the point of different rankings or suggesting the best alternative.

There is no clear consensus in the literature yet regarding which MCDM algorithm is more efficient or more suitable. On the other hand, the problem does not end there. The heterogeneous data structure of the criteria in different units in the first decision matrix must be transformed by homogenizing them. If this is not done, it is not possible to apply the principles of addition, multiplication, distance-basedness, and pairwise comparison on which MCDM algorithms are based. On the other hand, outranking methods such as PROMETHEE, FUCA and ELECTRE use a preference function-like hierarchical ranking to transform data as an alternative to normalization. As a result, the need to transform data is mandatory to evaluate the criteria in different units together.

On the other hand, there is an important risk and problem, which is that normalization techniques have different calculation procedures. These procedures mean that even when tested in a fixed MCDM method, very different sequences or alternative solutions are produced. There is almost a consensus in the literature that normalization techniques (or methods) directly affect the results (Pavlicic, 2001, Milani et al., 2005; Chakraborty and Yeh, 2009; Çelen 2014, Mathew, Sahu and Upadhyay, 2017; Jafaryeganeh, Ventura, and Guedes Soares 2020; Polska et al. 2021). These results clearly demonstrated the effect of normalization. Some authors, who see this as a problem, have thus entered into an intensive study on which normalization method to choose (Lakshmi and Venkatesan, 2014; Aytekin, 2021; Ersoy, 2022; Vafaei, Ribeiro and Camarinha-Matos, 2022; Jafaryeganeh, Ventura and Soares, 2020). The findings in the literature are quite controversial in terms of whether the answer sought regarding the choice of normalization is correct or appropriate. Although some normalization techniques are rejected and some are highlighted, depending on the data structure or tools such as statistical analysis, SD and Entropy, it can be said that an objective criterion required for a background normalization selection is not solid and generalizable.

In this study, we propose to evaluate the problem from a different perspective and approach. Some previous studies (Baydaş et al. 2023; Baydaş and Pamucar 2022; Yaakob et al. 2018) have suggested that real-life rankings or a relationship with a third party can be used as an evaluation criterion in the evaluation of MCDM methods and have successfully tested them. These studies used financial data and therefore reported that a particular method came to the fore. On the other hand, Baydaş and Eren (2021), although not the focus of the study, partially touched on the subject and clearly showed that the min-max normalization technique for the SAW method explains stock returns better than the max normalization technique. Based on this approach, comprehensive testing can be performed by using more normalization techniques and including a larger number of problem scenarios.

The aim of this study is to reveal how normalization techniques affect the results of the CODAS method and the level of relationship of these results with real life in 10 different scenarios. In other words, in this study, unlike the literature, we focus on how normalization techniques change the relationship of an MCDM method with external factors. Thus, we act based on the fact that a normalization technique can be more successful than other normalization techniques based on an objective criterion. Investigating the reasons why some types of normalization capture the relationship between two variables better is an issue that needs to be emphasized. We consider that the results of this study, in which we use the measurement of companies' financial performance with multiple criteria as a problem and stock returns as a third independent party, will make a significant contribution to the literature. Moreover, in addition to classical normalization methods, we proposed and successfully implemented a preference function based on an alternative ranking that is not widely used in the MCDM literature. There is generally little sensitivity/ awareness in choosing the normalization technique, and MCDM calculations are made with an almost random normalization technique and it is suggested that the result produced is the best result. In this study, an awareness is created that the choice of normalization is quite critical. Moreover, as an objective evaluation criterion, the relationship with a third party has been proposed as a comparison framework.

In this study, firstly, a general literature on normalization techniques will be discussed. The focus of the literature is on the effects of normalization techniques on MCDM results and examining the reasons for choosing a technique. Then, the methodology and application of MCDM and normalization methods will be discussed. Finally, the insightful approaches of the study will be exhibited with discussion and results.

1. LITERATURE REVIEW

Criteria, which play a very critical role in MCDM methods, generally have different types of measurement units and numerical dimensions. Data normalization techniques, which are the first step of MCDM methods, come into play here and their purpose is to enable comparison of alternatives. For this, heterogeneous (in different units and ranges) criterion data series must be converted into homogeneous (with the same unitless and range) data. Because in order to perform mathematical operations (for example, adding or obtaining a common result score), the criteria must have a common unit (Biswas and Pamucar, 2021; Vafaei et al., 2022; Aytekin, 2021).

Of course, various normalization techniques have different calculation procedures and approaches. This is a phenomenon that often differentiates the ranking results of MCDM methods. However, this will cause confusion for an MCDM user. In this regard, it is important to be aware that the various normalization techniques preferred change or affect the final results of an MCDM. Thus, choosing an appropriate normalization technique is critical. Moreover, the lack of an objective consensus on which normalization technique to choose makes things difficult. Similarly, although some criteria for this selection have been proposed in past studies, the truth is that these cannot be fully verified (Ersoy, 2022; Vafaei et al., 2018; Aytekin, 2021).

There are various studies in the literature about the effects of different normalization techniques on MCDM methods and how to choose a technique. Therefore, we roughly divide the literature into two: The impact of normalization on MCDM results and the frameworks related to the selection of an appropriate normalization suggested by the authors.

1.1. Effect of Normalization on MCDM Results

It can easily be said that normalization has different effects on MCDM results. As a matter of fact, research confirms this. In this section, where we examine the reasons for this, different findings stand out depending on different data structures. Pavlicic (2001) investigated the effects of simple, linear, and vector normalization techniques on the results of MCDM methods (SAW, TOPSIS, and ELECTRE). The study concluded that distortions in data resulting from the use of normalization types may affect the final selections. Milani et al. (2005) found that for the TOPSIS method, linear normalization could not significantly affect the order of alternatives, but the non-linear normalization technique could cause some deviations. Baghla and Bansal (2014) used the VIKOR method and found that different normalization techniques were effective in ranking. They concluded that different normalization techniques are effective on the MCDM method. Jafaryeganeh et al. (2020) investigated the suitability of different normalization techniques for ELECTRE, SAW, and TOPSIS methods. It was stated that the linear ratio-based and linear maximum-minimum normalization techniques selected in the study were consistent in all MCDM methods, but there were minor differences in the ranking of the alternatives, and a similar alternative ranking was also observed in the sum-based vector technique.

Polska et al. (2021), in their study, it was recommended to use Vector, Sum or Max techniques because the Max-Min normalization technique showed low consistency. According to the results obtained from 10 different data sets in his study, Özdağoğlu (2013b) suggested that vector normalization could be used for the COPRAS method instead of the common technique in the literature, based on correlation findings. Chatterjee and Chakraborty (2014) investigated the effect of normalization on TOPSIS, PROMETHEE, and GRA methods. Accordingly, it has been observed that the most preferred of the four methods adopted for normalizing criterion values in decision matrices is the vector normalization process. In their study, Lakshmi and Venkatesan (2014) applied different normalization techniques to find the most appropriate normalization for the TOPSIS Method. It is concluded that linear sum-based normalization provides less computational time and complexity. In the study of Özdağoğlu (2014), it was examined whether the order of preference changed by applying different normalization methods for the MOORA method. Within the scope of this study, 10 different data sets containing 10 alternatives and 5 evaluation criteria were created. Accordingly, linear normalization (3) and non-monotonic normalization methods are not recommended for the MOORA method. On the other hand, it was stated that any of the vector normalization, linear normalization (1), linear Normalization (2) and linear normalization (4) methods can be easily used in the decision-making process with the MOORA method.

Jahan and Edwards (2015) showed in their study that although many normalization methods may appear to differ little from each other, these small differences can have significant consequences on the quality of decision-making when choosing materials. In their study, Palczewskia and Sałabun (2019) used five different normalization methods to investigate the normalization effects in the PROMETHEE II method, and the situation without normalization was also examined. Accordingly, normalization has an impact on the final ranking. Więckowski and Sałabun (2020) show that the presentation of input data has an impact on the final ranking obtained. Zolfani et al., (2020) reveal in their study that normalization methods are sensitive to normalization methodologies. Biswas and Pamucar (2021) aimed to present an extended CODAS framework using the logarithmic normalization scheme. As a result of the study, the result obtained from this extended version of the CODAS method was consistent with the results obtained using other MCDM approaches.

According to the study of Satıcı (2021), he proposed sum and vector normalization techniques as an alternative to the traditional technique in the original WASPAS method. Moreover, the Max-Min technique gave relatively the worst results. Mhlanga and Lall (2022) showed that when different normalization techniques were applied to the VIKOR method, different ranking lists were produced and normalization was effective in the final ranking list.

We can clearly say that the literature agrees on the effect of normalization on MCDM rankings.

1.2. Evaluation Frameworks for Normalization Technique Selection

Different recommendations have been made with different criteria regarding which normalization technique to use for an MCDM method. However, it can be said that the accuracy of the criteria on which these recommendations are based is not sufficiently based and is not satisfactory. As a result of the simulation study conducted by Chakraborty and Yeh (2009), it was claimed that it is appropriate to use the vector normalization method for TOPSIS. Çelen (2014) argued that the vector normalization technique used with the TOPSIS method gives the most consistent results. On the contrary, Lakshmi and Venkatesan (2014) concluded that the most appropriate normalization technique for the TOPSIS method is linear sum-based normalization. In addition, while the PROMETHEE II method was less affected by different normalization procedures, TOPSIS emerged as the most sensitive MCDM method. Vafaei, Ribeiro, and Camarinha-Matos (2015) argued that the worst normalization technique for the TOPSIS method is max-min, and the best ones are vector, linear, and logarithmic normalization techniques. According to another study by Vafaei, Ribeiro, and Camarinha-Matos (2016), the most suitable normalization type for the AHP-based MCDM method is linear sum and linear maximum techniques. Mathew et al. (2017), it was concluded that the Max-Min technique is the best normalization technique for the WASPAS method. Vafaei et al., (2018) concluded that the most suitable normalization techniques for the SAW method are linear sum, vector, and maximum, respectively, while maximum-min, logarithmic and blurring techniques are not suitable. Kosareva et al., (2018) investigated how various data normalization methods affect the accuracy of MCDM. The alternatives were ranked by applying the SAW method, and the Monte Carlo procedure was applied for data matrices of different sizes and two optimization directions. In conclusion; None of the five normalization methods was identified as the best or worst in all cases. But in most cases, the Min-max method turns out to be significantly better than others. In the study of Chen (2019), VN is recommended as a result of the analysis of normalization on the entropy-based TOPSIS method. As a result of the study conducted by Vafaei et al., (2020) to recommend the most suitable normalization technique for the AHP method, it was concluded that the best technique is max-min and the max normalization technique is the second.

We see Aytekin's (2021) effort to propose a more objective and consistent criterion for selecting a suitable normalization technique for MCDM methods. By presenting a comparison of normalization techniques for different criterion structures, the study aims to reveal the positive and negative features of these techniques and to guide decision-makers or researchers in the selection of techniques. According to the research, if the normalization technique is not chosen according to the 'data structure', the validity of the results can be questioned, and the result of our study confirms this. In addition, the author stated that for the selection of normalization techniques, the nature of the decision matrix, the preferences of the decision maker, and the characteristics of the MCDM method to be used in the solution should be taken into account. Moreover, the decision problem should be taken into account in the selection of the normalization technique. According to the study by Ersoy (2022), Max normalization was found to be the most consistent procedure in the MCDM method proposed by Biswas and Saha, and Peldschus was found to be the least consistent procedure. Yang et al., (2021) As a result of the study, it was first stated that the entropy-based and coefficient of variation-based performance scores in TOPSIS can be used to evaluate the performance of the normalization method, therefore it would be logical to select the most suitable material using the normalization method with the highest value. Vafaei et al. (2022) evaluated different normalization techniques with the SAW method using the metrics included in the evaluation framework, and the most appropriate technique was selected for the case study obtained from the literature. This research evaluated six normalization techniques selected for the case study using the SAW method to recommend the best technique. The results obtained show that the best technique for the relevant case study is Max-Min normalization.

1.3. Referencing Real-Life Rankings (Stock Returns) for Normalization Method Selection

The recent studies that refer to the relationship between stock return (SR) and financial performance (FP) for MCDM selection are interesting. In a study, a significant relationship was found between SR and TOPSIS-based FP results (Yaakob et al., 2018). In another study, periodically strong, stable and significant relationships between FP rankings and SR for TOPSIS, WSA and PROMETHEE methods were used for MCDM selection (Baydaş & Elma, 2021). Among the many methods examined, PROMETHEE and FUCA were found to be the most efficient in terms of the results it produced in FP analysis. (Baydaş et al. 2022; Baydaş, 2022) In short, the existence of a sustainable and significant relationship between FP and SR gave very consistent results for MCDM selection. Therefore, if we approach the subject with the same parallel logic, it may be possible to choose the most appropriate normalization method. In fact, Baydaş and Eren (2021) partially applied this approach for two normalization types. But for more normalization methods, this problem has not been comprehensively addressed. It should be noted that SR is not an investment recommendation in this study. Looking at it from a different approach, SR has been considered as an solution to a methodological problem related to normalization, derived from patterns from real-life data.

2. RESEARCH METHODOLOGY

In this study, the MCDM type (CODAS) was kept constant in order to determine the relationship between different normalization types and real-life sequences. We want to take advantage of the meaningful relationships between companies' CODAS-based FP alternatives obtained with different normalization types and their SR return. Thus, the success of a normalization type for a particular problem can be determined. In this section, performance criteria, weighting technique and CODAS method will be explained briefly. The related financial statement data sets of Borsa Istanbul (BIST) Sustainability index companies examined in the study were drawn from the FINNET financial analysis program.

Table 1. *Normalization and MCDM Methods, Performance Criteria and Weighting Technique used in this Study*

Normalization Method	Weighting Method	MCDM Methods	Performance Criteria
Max, Sum, Vector Mın-Max, No Normalization, Rank Based Score	CRITIC Method	CODAS	Altman-Z, EPS, MVA Spread, Market-to-Book, ROE, ROA

In this study, in which the CRITIC weighting method was preferred, the strength of the relationships between CODAS rankings modified with different normalization types was determined by Spearman correlation analysis. Thus, efficient methods that produce high correlation will be suggested to those concerned. The diagram showing the methodology applied in this study is shown in Figure 1.

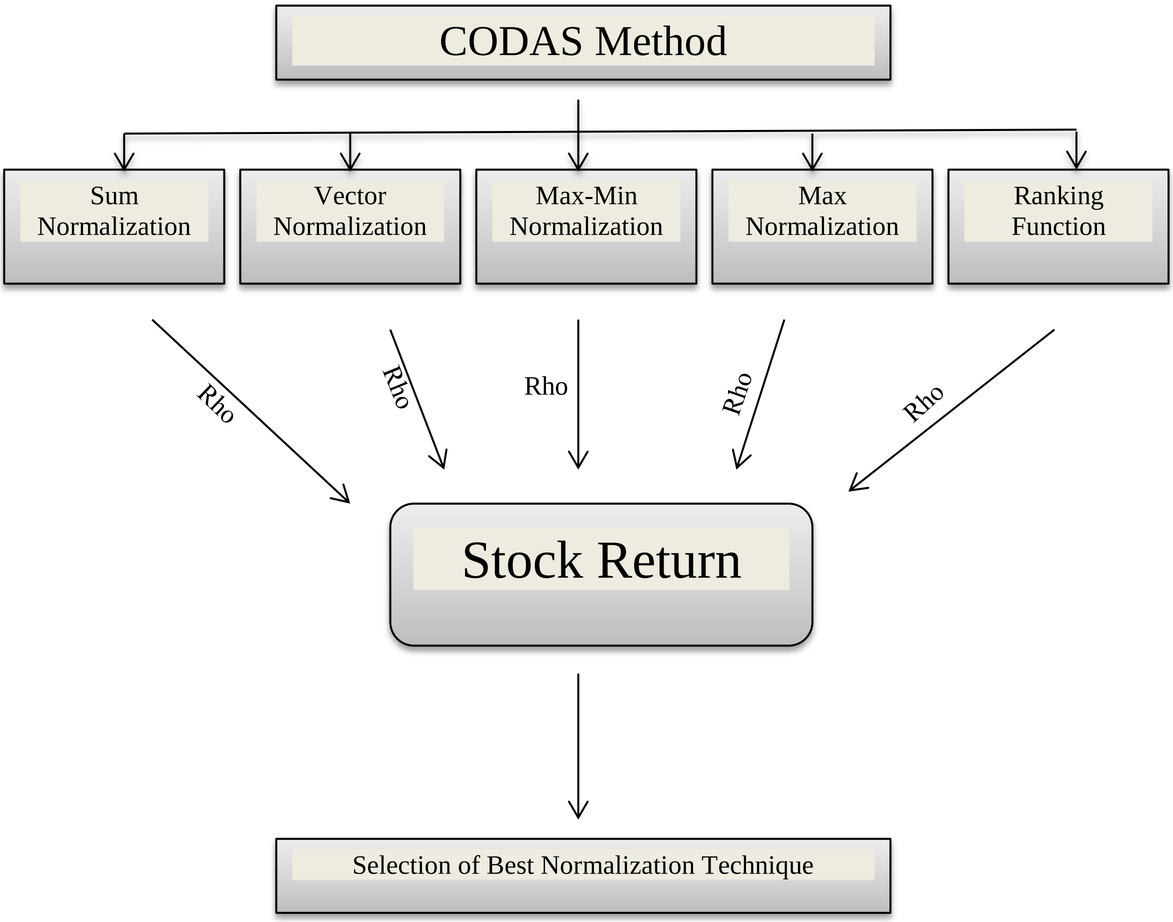

Figure 1. *The Flow Chart of the Methodology Used in this Research*

2.1. Performance Criteria

In this study, six performance criteria were selected to measure the financial performances of 42 companies in the BIST sustainability index with the CODAS method, whose normalization techniques were changed many times. These are market value-added spread, Altman-Z score, market-to-book ratio, return on equity, return on assets and earnings per share. All of these 6 criteria are based on the change (delta ratio) between the two periods, that is, the growth. Table 2 summarizes the criteria (financial ratios and SR) in this study.

Table 2. *Formulas of the Financial Criteria Used in this Study*

Decision Criteria	Formulas	References
MVA Spread	Market Value Added / Invested Capital	Stewart (2013)
EPS	Net Income Available to Shareholders / Number of Shares Outstanding	Yalcin et al. (2012)
Market to Book	Market Capitalization / Net Book Value	Stewart (2013)
ROE	Net Income / Stockholders' Equity	Brigham and Houstan (2019)
ROA	Net Income / Total Assets	Brigham and Houstan (2019)
ALTMAN-Z	1.2 (Working Capital / Total Assets) + 1.4 (Retained Earnings / Total Assets) + 3.3 (EBIT / Total Assets) + 0.6 (Market Value of Equity / Book Value of Total Liabilities) + 1.0 (Sales / Total Assets) (Applies to companies registered in the stock market)	Baydaş et al. (2023)
External Benchmarking		
Share Return (SR)	(Closing Share Price – Initial Share Price) / Initial Share Price	Baydaş et al. (2023)

2.2. Normalization Methods

Below, the normalization and alternative techniques used in this study are shown with their formulas.

Table 3. *Demonstration of Different Normalization Methods and Calculations*

Method	Calculations
Sum Normalization	$F_{ij} = \frac{f_{ij}}{\sum_{k=1}^{m} f_{kj}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}$
Vector Normalization	$F_{ij} = \frac{f_{ij}}{\sqrt{\sum_{k=1}^{m} f_{kj}^{2}}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}$
Max-Min Normalization	$F_{ij} = \frac{f_{ij} - min_{i\in m} f_{ij}}{max_{i\in m} f_{ij} - min_{i\in m} f_{ij}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}\ for\ benefit\ objectives$ $F_{ij} = \frac{max_{i\in m} f_{ij} - f_{ij}}{max_{i\in m} f_{ij} - min_{i\in m} f_{ij}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}\ for\ cost\ objectives$
Max Normalization	$F_{ij} = \frac{f_{ij}}{max_{i\in m} f_{ij}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}\ for\ benefit\ objectives$ $F_{ij} = \frac{min_{i\in m} f_{ij}}{f_{ij}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}\ for\ cost\ objectives$
Ranking based preference function	For each of the criteria, the best value is assigned the 1st rank, and the worst value is assigned the m.rank. A weighted preference function for each best solution i is calculated as: $F_{ij} = r_{ij} \times w_j$ where r_{ij} is the rank of solution i for criteria j. Note: This method is recommended as an alternative to the normalization method. This method is used instead of normalization techniques in the FUCA method. This approach is similar to the preference function in outranking MCDM schools.

Source: Wang et al. (2020)

2.3. MCDM Method: Combinative Distance-based Assessment (CODAS)

The CODAS method has been used in many studies in many different fields (Biswas and Pamucar, 2021). While in TOPSIS, closeness to the positive and negative ideal solution simultaneously affects the results, for CODAS, the negative ideal solution is prioritized. It has been suggested in some studies that this method may be more successful if an appropriate normalization technique is selected (Baydaş et al., 2022). Therefore, it is critical to choose an appropriate technique for the CODAS method. In this study, in order to compare different normalization methods, all calculation steps in the CODAS algorithm, except the normalization technique, are static, that is, the same. Then, the FUCA method (since it is generally a more successful MCDM method in previous financial performance studies (Baydaş, 2022; Baydaş and Pamucar, 2022) will be compared with the modified CODAS derivatives. It will be seen that the CODAS method can be a successful method when an appropriate normalization technique is selected.

In CODAS, one of the most popular methods of recent times, the overall performance of an alternative is measured by its distance from the negative ideal point (Ghorabaee et al., 2016; Biswas and Pamucar (2021). In this method, the relative superiority of each alternative to the other is defined by two criteria. The main criterion is the Euclidean distance of the considered alternatives from the negative ideal. The other criterion is the distance of the Taxicab distance from the negative ideal. Here, Taxicab distance is preferred When Euclidean distance cannot be used. Thus, since the CODAS method is calculated according to the distance from the negative ideal, the alternative with the largest distance is preferred.

In this study, τ=0.02 was preferred as the threshold parameter required to decide the degree of closeness of Euclidean distances. The calculation stages of the CODAS method are shown below.

Step 1. The first decision matrix is normalized with the maximum normalization type. (Ghorabaee et al., 2016; Wang vd. (2020)

$$F_{ij} = \frac{f_{ij}}{max_{i\epsilon m} f_{ij}} \quad i \in \{1,2,\dots,m\};\ j \in \{1,2,\dots,n\} \quad for\ benefit\ objectives \quad (1)$$

$$F_{ij} = \frac{min_{i\epsilon m} f_{ij}}{f_{ij}} \quad i \in \{1,2,\dots,m\};\ j \in \{1,2,\dots,n\} \quad for\ cost\ objectives \quad (2)$$

Step 2. A weighted normalized decision matrix is created by multiplying each column by the weight coefficient obtained previously. wj:

$$v_{ij} = F_{ij} \times w_j \quad i \in \{1,2,\dots,m\};\ j \in \{1,2,\dots,n\} \quad (3)$$

Step 3. The negative ideal solution, which is the worst value of each criterion, which is the smallest value in the relevant column of the decision matrix, is determined.

$$A^- = \{(Min_i(v_{ij})|i \ \in\ 1,2,\dots,m\}$$
$$= \{v_1^-, v_2^-, v_3^-, \dots, v_j^-, \dots, v_n^-\} \quad (4)$$

Step 4. Euclidean and Taxi distance between each criterion value and negative value is calculated:

$$E_i = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \quad i = 1,2,3,\dots,m \quad (5)$$

$$T_i = \sum_{j=1}^{n} |v_{ij} - v_j^-| \quad i = 1,2,3,\dots,m \tag{6}$$

Step 5. The relevant evaluation matrix is created as follows:

$$h_{ik} = (E_i - E_k) + \psi(E_i - E_k) \times (T_i - T_k) \quad i,k \in \{1,2,\dots,m\} \tag{7}$$

Here, $\psi(x) = 1$ if $|x| \geq \tau$ and $= 0$ if $|x| < \tau$. Recall $\tau = 0.02$ is the threshold parameter to decide the degree of closeness of Euclidean distances.

Step 6. Evaluation score of each solution is calculated.

$$H_i = \sum_{k=1}^{m} h_{ik} \quad i = 1,2,3,\dots,m \tag{8}$$

The non-dominant solution with the largest H_i value is the proposed optimal solution.

3. APPLICATION

In this study, 42 non-financial companies traded in the BIST Sustainability index were analyzed on a quarterly (3-month) basis between the years 2019-2021. Separate financial performance measurements were made for the modified CODAS method with four different normalization types over 10 different decision matrices consisting of 6 financial ratios representing the risk, profitability efficiency, and value production performance of the companies. CRITIC was used for each period as the weighting method. Then, in order to compare the effect of normalization methods, the relationship between MCDM rankings and stock return rankings was calculated with Spearman correlation. The stages of the approach used in this study can be summarized as follows:

Step 2. Decision matrices creation: First of all, financial performance measures consisting of 6 ratios were created as the first decision matrix for CODAS. Then, the weight coefficients were calculated by applying the CRITIC weighting method. Four different normalization types and one preference function were applied to the decision matrix separately for each quarter.

Step 2. Calculation of MCDM results: Modified CODAS results are obtained for 42 firms over 10 quarters from 2019-2021. Methods are calculated in Excel.

Step 3. Step 3. Determining and evaluating the relationship between the CODAS results and the ranking results of the stock returns: The ranking of the stock returns obtained every quarter is compared according to the Spearman correlation relationship between the ranking result obtained with the CODAS method obtained every quarter. The comparison is based on the same quarters for the two variables. The performance of companies is volatile and it is a well-known fact that financial data is volatile (in terms of skewness and kurtosis). Therefore, in order to avoid hasty and absolute judgments, we are not content with only one-period data. That's why we evaluated data for 10 different quarters in total to see the big picture as much as possible. Thus, we evaluate that the normalization integrated CODAS method, which periodically gives the highest correlation result to the decision-makers, is more successful. We want to emphasize that the capability and capacity of each normalization method may vary depending on the data type in the initial decision matrix.

Since an MCDM-based Financial performance model may be oriented toward stock returns, its relationship with it is important (Baydaş & Elma, 2021; Yaakob et al. 2018). By keeping an MCDM method constant and changing the normalization type, its relationship to stock return can be used to evaluate normalization types. (Baydaş and Eren, 2021) Thus, in this context, the relationship produced with SR becomes a criterion for the hierarchical comparison of normalization types among themselves.

3.1. Findings and Results

In this study, the correlation values of the modified different CODAS method results added by various normalization techniques with real-life stock returns are taken into account as an objective comparison criterion. In other words, this study focuses on the determination of the most appropriate normalization method for decision-makers by taking the ability of normalization techniques to produce different Spearman correlation coefficients as the CODAS algorithm is kept constant.

In this study, many decision matrices are used to measure the financial performance of companies. Since 10 different matrices take up a lot of space, the first decision matrix (2021/09) is shown to the reader in Table-4 to be an example and gives an idea. Six benefit-oriented performance criteria consisting of ALTMAN-Z score, ROE, ROA, MVA spread, MV/BV (Baydaş and Pamucar, 2022), and Earnings Per Share (EPS) ratios, which are based on risk, profit, and value creation, respectively, were used for company. The values calculated according to the CRITIC weighting technique for each quarter are shown in Table-5. If we look at the 10-quarter analysis, it is observed that the weight coefficients constantly change to a certain extent. But on average, it can be said that the Altman-Z score and ROE have the highest coefficients. For each company examined in Table-6, the CODAS scores modified according to the normalization produced by the four different normalizations and one preference function examined in the study are given from the best company to the worst company for the 2021/09 quarter selected as an example.

Table 4. *Decision Matrix (2021/09) used for the CODAS Method*

	ALTMAN Z SKOR	**ROE**	**ROA**	**MVA spread**	**MV/BV**	**EPS**
AEFES	0.35	0.03	0.02	0.14	0.24	1.84
AGHOL	0.36	0.03	0.02	0.17	0.47	5.12
AKCNS	0.67	0.02	0.01	0.42	0.41	0.19
AKSA	1.25	0.11	0.04	2.18	2.14	1.06
ANELE	0.07	-0.04	0.001	0.25	0.25	-0.01
ARCLK	0.56	0.04	0.01	1.01	1.15	1.06
ASELS	1.07	0.03	0.02	1.05	1.02	0.27
AYGAZ	1.01	0.11	0.04	1.15	1.11	1.07
BIMAS	0.82	0.09	0.03	-0.22	-0.42	1.47
BIZIM	0.95	0.09	0.01	0.47	0.36	0.26
BRISA	0.5	0.07	0.02	1.51	1.22	0.56
CCOLA	0.64	0.08	0.04	0.64	0.64	3.9
CIMSA	0.85	0.01	0.01	0.74	0.82	0.41
DOAS	1.79	0.08	0.06	1.3	1.3	1.69
DOHOL	0.38	0.02	0.01	0.06	0.05	0.05
ENJSA	0.48	0.06	0.02	0.53	0.45	0.45
ENKAI	1.11	0.02	0.01	0.48	0.48	0.2
FROTO	0.5	0.12	0.02	2.1	2.18	5.39
KARSN	0.16	0.05	0.02	-0.23	-0.26	0.03
KERVT	0.19	0.03	0.01	0.04	0.04	0.07
KORDS	0.63	0.04	0.02	0.85	0.95	0.85
KRDMD	1.03	0.09	0.05	1.19	1.11	0.62
LOGO	0.99	0.06	0.03	0.72	0.74	0.48
MAVI	0.75	0.14	0.04	0.07	0.04	3.28
NETAS	0.05	-0.1	-0.02	0.09	0.11	-0.71

OTKAR	0.76	0.06	0.02	0.86	1	5
PETKM	1.11	0.11	0.07	0.89	0.77	0.67
PNSUT	0.28	0.001	-0.01	0.08	0.07	-0.13
POLHO	0.39	0.03	0.01	0.13	0.14	0.06
SAHOL	0.07	0.06	0.01	0.24	0.25	2.67
TATGD	-0.5	0.03	-0.01	0.42	0.57	0.22
TAVHL	0.25	0.06	0.01	0.64	0.45	1.81
TCELL	0.43	0.06	0.02	0.32	0.28	0.65
THYAO	0.31	0.11	0.03	0.65	0.31	4.56
TKFEN	0.43	0.06	0.02	0.4	0.4	1.28
TOASO	1.55	0.06	0.02	4.92	4.85	1.16
TTKOM	0.57	0.1	0.04	1.04	0.65	0.59
TTRAK	1.59	0.08	0.05	1.18	1.07	4.16
TUPRS	0.7	0.06	0.01	1.72	1.57	4.03
ULKER	0.001	0.1	0.001	-0.82	1.09	0.001
VESBE	0.87	0.08	0.02	1.19	1.19	-3.66
ZOREN	0.17	-0.01	0.001	1.79	0.06	-0.01

Table 5. *Results of CRITIC method, the weighting method used in this study, for the criteria of CODAS Methods*

											Mean
ALTMAN Z SKOR	0.164075	0.171872	0.211171	0.187696	0.177118	0.146865	0.169666	0.139125	0.143907	0.160656	0.167215
ROE	0.138436	0.148225	0.11885	0.10548	0.12317	0.142335	0.182147	0.131143	0.138982	0.165941	0.139471
ROA	0.137517	0.186645	0.13248	0.172471	0.212661	0.126924	0.19425	0.155951	0.150666	0.166714	0.163628
MVA spread	0.204183	0.163447	0.178642	0.138056	0.160056	0.171888	0.163658	0.223494	0.191725	0.137172	0.173232
PD/DD	0.196967	0.166118	0.198083	0.222111	0.181359	0.214015	0.17316	0.22159	0.205116	0.139323	0.191784
Profit per Share	0.158822	0.163693	0.160774	0.174186	0.145637	0.197972	0.117119	0.128698	0.169603	0.230193	0.16467

Table 6. *Final Score Results Produced by the CODAS Methods for the year 2021/09*

	MAX	**SUM**	**VECTOR**	**MIN MAX**	**WR**	**NO NORM**
AEFES	-3.13332	-0.00566	-0.05532	-0.12062	34.80839	0.72554
AGHOL	8.439817	0.086182	0.264488	0.525233	0.361204	65.67913
AKCNS	-8.46595	-0.04689	-0.19215	-0.52324	68.1616	-25.7188
AKSA	12.98206	0.041042	0.219477	0.733427	-131.878	21.24704
ANELE	-18.0162	-0.07339	-0.33942	-1.44685	148.5875	-36.7749
ARCLK	-3.05137	-0.01419	-0.06919	-0.22912	-16.4687	-0.83224
ASELS	-2.63632	-0.02389	-0.0763	-0.09179	-5.165	-12.2995
AYGAZ	9.097239	0.01951	0.12488	0.452974	-116.569	4.039911
BIMAS	2.581504	0.003698	0.031907	0.166125	-12.6875	-8.59368
BIZIM	-0.98401	-0.0248	-0.06533	-0.04188	16.26965	-21.401
BRISA	-0.8368	-0.01086	-0.02989	-0.06394	-35.6485	-6.14506
CCOLA	12.06572	0.070602	0.256622	0.684425	-80.498	48.56081
CIMSA	-6.71415	-0.03588	-0.14801	-0.39033	39.01975	-15.0673
DOAS	15.32087	0.050888	0.268066	1.198905	-138.29	24.78474

DOHOL	-11.2321	-0.05772	-0.24287	-0.81375	117.646	-35.4363
ENJSA	-3.90937	-0.02969	-0.11059	-0.2555	26.33237	-20.4677
ENKAI	-5.80612	-0.0387	-0.14267	-0.27827	34.29779	-20.8491
FROTO	20.5472	0.127224	0.520296	1.622448	-136.838	95.99092
KARSN	-9.12069	-0.05092	-0.20044	-0.55092	109.8495	-40.4469
KERVT	-11.3069	-0.05713	-0.24121	-0.82728	127.5321	-36.4726
KORDS	-2.63761	-0.01766	-0.07276	-0.12638	-17.2184	-6.62161
KRDMD	7.589363	0.012367	0.104079	0.378633	-95.8972	-3.69971
LOGO	0.539957	-0.01484	-0.02993	0.065564	-32.6013	-12.9913
MAVI	13.74465	0.063629	0.265882	0.887755	-45.7791	30.58058
NETAS	-26.9395	-0.10228	-0.62241	-2.12962	174.5574	-52.7812
OTKAR	12.91933	0.094053	0.317837	0.854644	-77.5487	73.76966
PETKM	12.08524	0.02812	0.192304	0.850081	-104.446	-6.12554
PNSUT	-16.1064	-0.07252	-0.31895	-1.30225	157.2275	-39.4952
POLHO	-10.1619	-0.05452	-0.22544	-0.72014	88.67453	-34.0877
SAHOL	-0.70392	0.01732	0.025036	0.031892	43.65797	15.39941
TATGD	-14.6965	-0.05665	-0.25664	-1.13829	102.2258	-32.3701
TAVHL	-1.88728	-0.00155	-0.03246	-0.09073	11.8124	3.977983
TCELL	-3.88135	-0.02771	-0.10796	-0.25563	16.82742	-19.5525
THYAO	13.29611	0.08646	0.308347	0.851575	-58.2882	56.97144
TKFEN	-1.97617	-0.0117	-0.05507	-0.0926	-10.4803	-6.15668
TOASO	16.14346	0.107113	0.534815	1.482443	-111.219	69.37727
TTKOM	3.874009	-0.00117	0.035228	0.172336	-61.8331	-12.2725
TTRAK	19.95598	0.096223	0.4391	1.696151	-142.212	67.20202
TUPRS	10.45909	0.07413	0.251437	0.504398	-77.2302	64.38992
ULKER	-6.2946	-0.03962	-0.13951	-0.3957	90.39833	-36.8972
VESBE	-7.62959	-0.05734	-0.15268	-0.27646	-16.369	-73.3711
ZOREN	-13.5134	-0.05127	-0.23262	-0.99771	116.9175	-25.7689

The most critical part of this study is Spearman's Rho coefficient results, which express the relationship between FP results and SR results. Accordingly, the RHO coefficient produced by the derivatives of the modified CODAS method based on 4 different normalizations and one preference function is shown in Table-7 According to the results of the 10-quarter analysis, it can be said that there is no sustainable, absolute, or dominant normalization derivative covering all periods in this study. However, while this is the general case, the same analyzes show that a particular normalization method is dominantly more successful for one-period results. The reason for this interesting situation can be explained by the fact that financial data has a highly volatile structure.

The findings of this study showed that four different normalizations and one preference function can be recommended to financial decision-makers in terms of their Rho generation capacity on a periodic basis.

Table 7. *Rho coefficients generated by the effect of normalization techniques showing the relationship between Spearman's SR and CODAS based FP Scores*

	2019/06	2019/09	2019/12	2020/03	2020/06	2020/09	2020/12	2021/03	2021/06	2021/09	MEAN
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	
MAX	0.687	0.508	0.553	0.404	0.216	0.821	0.459	0.172	0.843	0.655	0.531
SUM	0.639	0.794	0.541	0.393	0.157	0.776	0.641	0.624	0.297	0.688	0.555
VECTOR	0.741	0.637	0.561	0.573	0.223	0.808	0.587	0.381	0.733	0.647	0.589
MIN-MAX	0.654	0.252	0.594	0.55	0.252	0.711	0.446	0.38	0.683	0.634	0.515
NO NORM.	0.596	0.441	0.571	0.374	0.581	0.599	0.745	0.301	0.663	0.723	0.559
Weightage Rank	0.627	0.264	0.506	0.494	0.39	0.71	0.516	0.554	0.679	0.671	0.541

Although it is very difficult to have a general opinion in the big picture, based on the average Spearman correlation results, it is a fact that Vector normalization is the best normalization technique. In other words, the normalization technique varies depending on the period and data structure. Then, the choice of normalization depends on conditions and time, which we can consider as a conjectural choice.

As can be seen in Table 8 below, financial data has a highly variable structure depending on time and other conditions. This may give an idea about why the success of normalization techniques is affected by the data.

Table 8. *The skewness and kurtosis values of the first decision matrix data*

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
skewness	0.657988	0.412319	0.687978	-1.03375	1.518515	0.244023	1.160675	0.376206	-0.34923	0.946811
kurtosis	12.38173	1.369583	2.274258	2.639377	6.013946	3.199313	3.792909	4.869925	5.372797	4.3009

Below, the seasonal CODAS-SR statistical relationship results created with the effect of normalization techniques are shown.

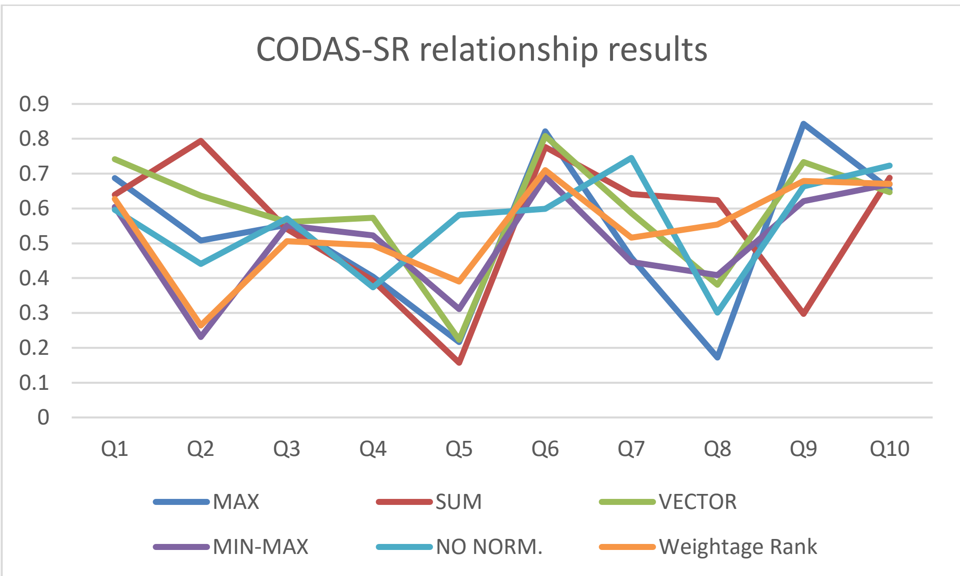

Figure 2. *Different CODAS-SR relationship (spearman correlation) results created with the effect of normalization techniques are shown. (weighted rank: rank based)*

Below, the mean CODAS-SR statistical relationship results created with the effect of normalization techniques are shown.

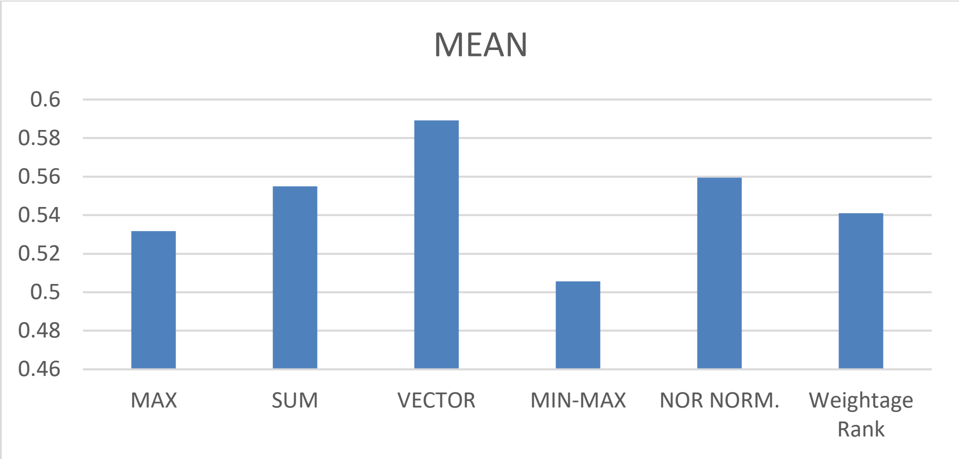

Figure 3. *Different CODAS-HG relationship (mean spearman correlation) results created with the effect of normalization techniques are shown*

This study reveals how normalization techniques affect the results of the CODAS-MCDM method and how these results relate to real life in 10 different scenarios. In this study, unlike previous literature, it was revealed that a normalization technique with an objective criterion can be more successful than other normalization techniques. It is an issue that needs to be emphasized in further research to examine in depth the reasons why some types of normalization capture the relationship between two variables better.

CONCLUSION

The aim of this study, conducted with 10 different data sets, is to see the effect of normalization techniques on the CRITIC weighting integrated CODAS MCDM method. The study, conducted on 42 companies and 6 ratios registered in the BIST Sustainability Index, covers the period 2019-2021. According to the results of the study, as in other studies, normalization techniques clearly change the results. Unlike other studies, according to this study, normalization techniques can also change the relationship with a third party. While some methods produce very high correlations with stock returns, others do not even provide a significant relationship. This shows how misleading the results can be if the normalization technique is chosen incorrectly. According to this study, which we conducted by taking advantage of the relationship between financial performance and stock returns, Vector normalization is more successful on average. Although this is the case on average, a different normalization technique has been more successful in almost every period. This shows how much the normalization technique is affected by the data. Therefore, according to the findings, the selection of the best normalization technique based on the periodic data structure should be evaluated dynamically, not statically. So a good choice should be made conjuncturally. Each normalization technique has different capabilities, capacities, advantages and disadvantages.

It can be said that the CODAS algorithm is also effective in the results. This study, in which we solved the problem with reference to stock returns in the selection of normalization techniques, is the first comprehensive and innovative study in the literature. In this study, which was conducted based on the assumption that the normalization technique can destroy relationships or preserve an existing relationship, Vector normalization stands out as the best technique on average, while the Min-Max method is the technique that produces the worst relationship. Another finding of this study is the suggestion to question the Min-Max technique, which is often used in artificial intelligence and machine learning algorithms. Finally, these results, findings and past studies have shown that when the normalization technique and MCDM methods are compatible, more realistic and accurate results are obtained. For example, the classic normalization technique for TOPSIS is Vector. But this may change depending on the data. Additionally, as an alternative to classical normalization techniques, rank-based converter can also be used. Although the scope of this study is quite large, these findings and conclusions have limitations. We recommend that this study, conducted with CRITIC, CODAS and financial data, be compared with other methods and data. The normalization technique is also very sensitive to the number of alternatives and criteria. Therefore, another limitation in this study is the use of 6 criteria and 42 alternatives.

This study recommends choosing a normalization technique suitable for financial data according to period conditions. However, if the strengths and weaknesses of normalization techniques are discovered with the help of the perspective in this study, a robust normalization method can be invented.

Also, we recommend that future researchers include converters that are not commonly used in MCDM, such as Z-Score, Logarithmic, and Decimal, in their analyses.

REFERENCES

Alkan, T., & Durduran, S. S. (2020). Konut seçimi sürecinin AHP temelli TOPSIS yöntemi ile analizi. Necmettin Erbakan Üniversitesi Fen ve Mühendislik Bilimleri Dergisi, 2(2), 12-21.

Aytekin, A. (2021). Comparative Analysis of Normalizatıon Techniques in the Context of MCDM Problems. Decision Making: Applications in Management and Engineering, 4(2), 1-25.

Baghla, S., and Bansal, S. (2014). Effect of normalization techniques in VIKOR method for network selection in heterogeneous networks. in 2014 IEEE International Conference on Computational Intelligence and Computing Research (Coimbatore: IEEE), 1–6.

Baydaş, M., & Elma, O. E. (2021). An objectıve criteria proposal for the comparison of MCDM and weighting methods in financial performance measurement: An application in Borsa Istanbul. Decision Making: Applications in Management and Engineering, 4(2), 257-279.

Baydaş, M., Eren, T., Stević, Ž., Starčević, V., & Parlakkaya, R. (2023). Proposal for an objective binary benchmarking framework that validates each other for comparing MCDM methods through data analytics. PeerJ Computer Science, 9, e1350.

Baydaş, M., & Pamučar, D. (2022). Determining objective characteristics of MCDM methods under uncertainty: an exploration study with financial data. Mathematics, 10(7), 1115.

Baydaş, M., & Tevfik, Eren. (2021). Finansal performans ölçümünde ÇKKV yöntem seçimi problemine objektif bir yaklaşım: Borsa İstanbul'da bir uygulama. Eskişehir Osmangazi Üniversitesi İktisadi ve İdari Bilimler Dergisi, 16(3), 664-687.

Biswas, S., & Pamucar, D. (2021). Combinative Distance based Assessment (CODAS) Framework using Logarithmic Normalization for Multi-Criteria Decision Making. Serbian Journal of Management, 16(2), 321-340.

Brigham, E. F., & Houston, J. F. (2019). Fundamentals of financial management 15th.

Chakraborty, S., and Yeh, C.-H. (2009). "A simulation comparison of normalization procedures for TOPSIS," in 2009 International Conference on Computers & Industrial Engineering (IEEE). University of Technology of Troyes.

Chatterjee, P., & Chakraborty, S. (2014). Investigating the Effect of Normalization Norms in Flexible Manufacturing Sytem Selection Using Multi-Criteria Decision-Making Methods. Journal of Engineering Science and Technology Review, 7(3), 141-150.

Chen, P. (2019). Effects of Normalization on the Entropy-Based TOPSIS Method. Expert Systems With Applications, 136, 33-41.

Çelen, A. (2014). Comparative analysis of normalization procedures in TOPSIS method: with an application to Turkish deposit banking market. Informatica 25, 185–208. doi: 10.15388/Informatica.2014.10

Ersoy, N. (2022). The Influence of Statistical Normalization Techniques on Performance Ranking Results: The Application of MCDM Method Proposed by Biswas and Saha. International Journal of Business Analytics (IJBAN), 9(5), 1-21.

Ghorabaee, K. M., Zavadskas, E. K., Turskis, Z., & Antucheviciene, J. (2016). A new combinative distance-based assessment (CODAS) method for multi-criteria decision-making. Economic Computation & Economic Cybernetics Studies & Research, 50(3).

Jafaryeganeh, H., Ventura, M., & Soares, C. (2020). Effect of Normalization Techniques in Multi-criteria Decision Making Methods for the Design of Ship Internal Layout from A Pareto Optimal Set. Structural and Multidisciplinary Optimization, 62(3), 1849-1863.

Jahan, A., & Edwards, K. (2015). A State-of-the-Art Survey on the Influence of Normalization Techniques in Ranking: Improving the Materials Selection Process in Engineering Design. Materials and Design, 65, 335-342.

Kızıl, E. (2019). Borsada İşlem Gören Şirketlerin Finansal Performansları İle Borsa Performansları Arasındaki İlişki: BİST Taş, Toprak Endeksindeki Çimento Firmaları Üzerine Bir Uygulama. Necmettin Erbakan Üniversitesi Siyasal Bilgiler Fakültesi Dergisi, 1(1), 51-67.

Kosareva, N., Aleksandras, K., & Zavadskas, E. (2018). Statistical Analysis of MCDM Data Normalization Methods Using Monte Carlo Approach. The Case of Ternary Estimates Matrix. Economic Computation and Economic Cybernetics Studies and Research / Academy of Economic Studies, 52, 159-175.

Lakshmi, T., & Venkatesan, V. (2014). A Comparison of Various Normalization in Techniques for Order Performance by Similarity to Ideal Solution (TOPSIS). International Journal of Computing Algorithm, 03(03), 255-259.

Mathew, M., Sahu, S., and Upadhyay, A. K. (2017). Effect of normalization techniques in robot selection using weighted aggregated sum product assessment. Int. J. Innov. Res. Adv. Stud 4, 59–63. Available online at: https://www.ijiras.com/2017/Vol_4-Issue_2/paper_12.pdf

Mhlanga, S., & Lall, M. (2022). Influence of Normalization Techniques on Multi-criteria Decision-making Method. Journal of Physics: Conference Series, 2224, 1-13.

Milani, A. S., Shanian, A., Madoliat, R., and Nemes, J. A. (2005). The effect of normalization norms in multiple attribute decision making models: a case study in gear material selection. Struct. Multidiscipl. Optimiz. 29, 312–318. doi: 10.1007/s00158-004-0473-1

Özdağoğlu, A. (2013a). Farklı Normalizasyon Tekniklerinin TOPSIS'te Karar Verme Sürecine Etkisi. Ege Academic Review, 13(2), 245-257.

Özdağoğlu, A. (2013b). Çok Ölçütlü Karar Verme Modellerinde Normalizasyon Tekniklerinin Sonuçlara Etkisi: COPRAS Örneği. Eskişehir Osmangazi Üniversitesi İİBF Dergisi, 8(2), 229-252.

Özdağoğlu, A. (2014). Normalizasyon Yöntemlerinin Çok Ölçütlü Karar Verme Sürecine Etkisi - MOORA Yöntemi İncelemesi. Ege Academic Review, 14(2), 283-294.

Palczewski, K., and Sałabun, W. (2019). Influence of various normalization methods in PROMETHEE II: an empirical study on the selection of the airport location. Proc. Comput. Sci. 159, 2051–2060. doi: 10.1016/j.procs.2019.09.378

Pavlicic, D. (2001). Normalization affects the results of MADM methods, Yugoslav Journal of Operations Research, 11(2): 251–265.

Polska, O., Kudermetov, R., Alsayaydeh, J. A. J., & Shkarupylo, V. (2021). QoS-aware Web-services ranking: normalization techniques comparative analysis for LSP method. ARPN Journal of Engineering and Applied Sciences, 16(2), 248-254.

Satıcı, S. (2021). Farklı Normalizasyon Tekniklerinin Çok Kriterli Karar Verme Yöntemlerine Etkisi: WASPAS Örneği. The Journal of Business, Economic and Management Research(2), 350-361.

Sayar, M. A., SELVİ, H. Z., & BUĞDAYCI, İ. (2019). Suruç Çadırkent Alanının Analitik Hiyerarşi Yöntemiyle Belirlenmesi. Necmettin Erbakan Üniversitesi Fen ve Mühendislik Bilimleri Dergisi, 1(1), 20-31.

Stewart, B. (2013). Best-practice EVA: the definitive guide to measuring and maximizing shareholder value. John Wiley & Sons.

Vafaei, N., Ribeiro, R. A., and Camarinha-Matos, L. M. (2015). Importance of data normalization in decision making: case study with TOPSIS method. İn ICDSST 2015 Proceedings–The 1st International Conference on Decision Support Systems Technologies, An EWG-DSS Conference (Belgrade).

Vafaei, N., Ribeiro, R. A., and Camarinha-Matos, L. M. (2016). Normalization techniques for multi-criteria decision making: analytical hierarchy process case study. in Doctoral Conference on Computing, Electrical and Industrial Systems (Costa de Caparica).

Vafaei, N., Ribeiro, R. A., and Camarinha-Matos, L. M. (2018). Selection of normalization technique for weighted average multi-criteria decision making. İn Doctoral Conference on Computing, Electrical and Industrial Systems (Costa de Caparica).

Vafaei, N., Ribeiro, R. A., and Camarinha-Matos, L. M. (2020). Selecting normalization techniques for the analytical hierarchy process. in Doctoral Conference on Computing, Electrical and Industrial Systems (Costa de Caparica).

Vafaei, N., Ribeiro, R., & Camarinha-Matos, L. (2022). Assessing Normalization Techniques for Simple Additive Weighting Method. Procedia Computer Science, 199, 1229-1236.

Wang, Z., Parhi, S. S., Rangaiah, G. P., & Jana, A. K. (2020). Analysis of weighting and selection methods for pareto-optimal solutions of multiobjective optimization in chemical engineering applications. Industrial & Engineering Chemistry Research, 59(33), 14850-14867.

Więckowski, J., & Sałabun, W. (2020). How the Normalization of the Decision Matrix Influences the Results in the VIKOR Method? Procedia Computer Science, 176, 2222-2231.

Yaakob, A., Gegov, A., & Rahman, S. F. A. (2018). Fuzzy networks with rule base aggregation for selection of alternatives. Fuzzy Sets and Systems, 341, 123-144.

Yalcin, N., Bayrakdaroglu, A., & Kahraman, C. (2012). Application of fuzzy multi-criteria decision making methods for financial performance evaluation of Turkish manufacturing industries. Expert systems with applications, 39(1), 350-364.

Yang, W. C., Chon, S. H., Choe, C. M., & Yang, J. Y. (2021). Materials selection method using TOPSIS with some popular normalization methods. Engineering Research Express, 3(1), 015020.

Zolfani, S., Yazdani, M., Pamucar, D., & Zarate, P. (2020). A VIKOR And TOPSIS Focused Reanalysis of the MADM Methods Based on Logaııthmic Normalization. Facta Universitatis Series: Mechanical Engineeringis, 18(3), 341-355.