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Comparison of multi-criteria decision-making methods with the same normalization procedure based on real-life applications

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Abstract

The ranking of a set of objects defined by a single data set may vary due to differences in multi-criteria decision-making (MCDM) procedures. One of these procedural differences is normalization, which is an important step in data analysis and MCDM methods. In terms of demonstrating the impact of the normalization process on the results, this study aims to compare MCDM methods with a linear normalization process. This study works on eight ranking methods (WASPAS, SECA, SAW, OWA, CODAS, MARCOS, PSI, and WPM), and three weighting methods (Entropy, EW, LOPCOW) based on three real-life applications. The study primarily explains the differences in rankings by the MCDM methods. Additionally, it is also important to demonstrate the impact of different weights on the results. The study found that the MCDM rankings obtained with the same normalization process differed, and it also observed that different criterion weights had an impact on the ranking results. This study contributes to the literature as it is the first to compare MCDM methods using linear normalization processes based on real-life applications.

Keywords: MCDM, normalization, linear normalization, decision making, comparative analysis

1. Introduction

Multi-criteria decision-making (MCDM) methods are employed to make optimal decisions by considering multiple criteria. These methods are frequently used when dealing with complex and conflicting objectives. MCDM methods serve various purposes, including selection, ranking, classification, definition, design, evaluation, and elimination of the best or most suitable alternative, aiming to reach a balanced solution in problems with numerous alternatives [1]. The MCDM methodology is one of the most prominent branches of the decision-making process. Within this methodology, the decision matrix comprises criteria (C_j for $j = 1, \ldots, n$), alternatives (A_i for $i = 1, \ldots, n$), and their corresponding weights (w_i),

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which indicate the significance of each criterion [26]. Additionally, by normalizing the value r_{ij}, which is a part of the decision matrix classifying Alternative i according to Criterion j, a dimensionless element is obtained that can be combined to achieve a ranking per alternative [5].

Numerous MCDM methods have been developed since World War II, which vary in terms of the quality and quantity of information, methodology, ease of use, sensitivity tools, and mathematical properties [35]. Despite their differences, the initial step in most MCDM methods involves the normalization process. In a multi-criteria evaluation, this normalization process is carried out to render comparable criteria defined both by quantitative and qualitative factors and having varying measurement units. The choice of appropriate normalization techniques can influence ranking outcomes, underscoring their pivotal role in the final results of decision problems [28].

The values of different quantitative and/or qualitative criteria are aggregated into a single criterion value used in the final ranking of alternatives, and this process is only possible for dimensionless data. Unfortunately, researchers often underestimate the importance of selecting the appropriate data normalization method to solve specific decision-making tasks. However, the normalization techniques significantly impact the outcomes of the decision process and can alter the ranking of alternatives and the final decision [15]. The normalization process scales the criterion values to be approximately of the same magnitude. However, different normalization techniques can yield different solutions, and as a result, deviations from the initially proposed solutions can occur [6]. Normalization techniques are generally categorized into three main categories: i) sum-based (including sum, vector, logarithmic, and enhanced accuracy methods), ii) linear ratio-based (including max, linear, and nonlinear normalization), iii) linear max-min-based (including min-max, Zavadskas and Turkis normalization). As an example, PIV, TOPSIS, and COPRAS methods use sum-based normalization; SAW, PSI, MARCOS, and CODAS methods employ linear normalization methods; while VIKOR, MABAC, CoCoSo, MAIRCA, and ROV methods utilize max-min normalization methods.

In recent years, a multitude of MCDM methods have been developed, and approaches that facilitate compromise between different methods such as iterative compromise ranking analysis (ICRA) [19], have been introduced. With this kind of approach, a compromise is achieved between methods through the iterative evaluation of alternatives' preferences. This study focused on examining the impact of the normalization process on the results rather than compromise between methods. The aim is to compare the outputs obtained with MCDM methods using the same normalization procedure. The WASPAS (weighted aggregated sum product assessment), SECA (simultaneous evaluation of criteria and alternatives), SAW (simple additive weighting), OWA (ordered weighted averaging), CODAS (combinative distance based assessment), MARCOS (measurement of alternatives and ranking according to compromise solution), PSI (performance selection index), and WPM (weighted product model) methods with a linear normalization procedure were compared based on three different case studies. The criteria weights were determined by Entropy, equal weight (EW), and LOPCOW (logarithmic percentage change-driven objective weighting) techniques.

The study's objective has been influential in the selection of methods, with a primary consideration being their feature of having a linear normalization procedure. On the other hand, their ease of application, simplicity in calculation procedures, and suitability for solving real-life problems are other influential factors in the selection process. The most significant reason for the examination of the linear normalization technique is the absence of a previous study comparing the outputs of MCDM methods with this normalization procedure. The central question under investigation in the study is: Are the results obtained with the WASPAS, SECA, SAW, OWA, CODAS, MARCOS, PSI, and WPM methods, which have a linear normalization process, similar?

The originality and advantages of this study can be summarized as follows: MCDM methods with a linear normalization procedure have been compared for the first time in the literature.

The primary starting point is to investigate whether methods with a linear normalization procedure yield similar results but at the same time, MCDM methods have also been compared.

Based on real-life scenarios, three distinct applications with a timeline have been presented. Comparing numerous MCDM methods with different algorithms but similar normalization processes is crucial to determine whether the normalization process is the sole reason for differences in rankings. Using three different objective criteria weighting techniques, the study also aims to reveal the impact of criterion weights on MCDM rankings, thereby moving away from the subjective judgments of decision-makers. Entropy, equal weight (EW), and LOPCOW-based WASPAS, SECA, SAW, OWA, CODAS, MARCOS, PSI, and WPM approaches have been integrated for the first time. The considered case study can be extended and modified for MCDM methods with different normalization procedures. The number of studies examining MCDM methods with the same normalization procedure in the literature is limited, and there is no study comparing linear normalization processes. Therefore, it is believed that this study will contribute to the literature by filling this gap.

The remainder of the study is followed by: Section 2 explains the normalization techniques and reviews the related literature. Section 3 presents the methods used and provides a review of the literature on MCDM methods. Section 4 implements the described methods. Section 5 examines the discussion and theoretical implications of the paper. The conclusion Section 6 highlights some important findings.

2. Normalization techniques and literature review

Normalization is a scaling process used to render criteria comparable by eliminating the influence of the optimization aspect (benefit or cost), unit of measure, and range of variation. Through normalization, data is transformed into a specific norm or standard [23]. Normalization technique primarily equalizes attributes (criteria) with different units of measurement to the same scale within the range of 0 to 1 [5].

Normalization techniques are extensively presented by [2]. The classification of these techniques makes it easier to identify similarities and differences, standardize concepts in the field, and examine the growing number of techniques. On the other hand, the choice of a normalization technique depends on the nature of the problem and the assumptions of the MCDM methods [23]. The normalization process is one of the main factors distinguishing MCDM methods from each other. In MCDM methods, the first step after creating the decision matrix is the normalization process which significantly impacts ranking results. Numerous studies focus on selecting an appropriate normalization technique and examining its effect on rankings. For instance, Zavadskas and Turskis [35] assessed the suitability of four different normalization techniques for the analytical hierarchy process (AHP). Aytekin [23] compared various normalization techniques using 14 sets representing different decision problem scenarios. Mhlanga and Lall [8] investigated the effects of different normalization techniques on the AHP-VIKOR hybrid model.

Sarraf and McGuire [10] examined the impact of normalization techniques on the results obtained by the TOPSIS and fuzzy TOPSIS methods, while Trung [20] aimed to determine the most suitable normalization technique for the CODAS method by employing six different normalization techniques. Budiman and Hairah [5] compared vector and linear normalization techniques using the VIKOR method while addressing a real-life problem. The results showed variations in the outcomes obtained with vector and linear normalization techniques. Ersoy [21] aimed to demonstrate the impact of normalization techniques on MCDM results and selected the most appropriate one using five techniques (vector, max, sum, minmax, peldschus) for Biswas and Saha's method. Kosareva et al. [15] analyzed the effect of five commonly used normalization methods (Vector, max, sum, log, minmax) on the accuracy of alternative selection using the SAW method. Do and Nguyen [32] tested 12 different normalization techniques to expand the application range of the PSI method. Four of the twelve techniques were found suitable when combined with the PSI method.

Chatterjee and Chakraborty [6] examined various normalization procedures (vector, Weitendorf's linear normalization, Jüttler's-Körth's normalization, non-linear normalization) for the PROMETHEE, GRA, and TOPSIS methods while addressing the flexible manufacturing system selection problem. They concluded that vector normalization is the most preferred procedure. Mhlanga and Lall [8] investigated the effects of normalization on an AHP-VIKOR hybrid method in the selection of Web services. In the study that used max, max-min, sum, vector, and enhanced accuracy normalization techniques, the rankings obtained with different normalization techniques differed.

The studies mentioned above provide examples of comparisons between MCDM methods using different algorithms and the selection of the most appropriate normalization technique for MCDM methods. However, only one study has been found in the literature that compares MCDM methods using the same normalization process. Dung et al. [22] compared the MABAC, COCOSO, MAIRCA, VIKOR, and ROV methods, all employing a max-min normalization process. They used four different weighting techniques: EW, ROC, RS, and Entropy. The study found variations in the rankings obtained by these five methods, highlighting the significance of criterion weights in determining the results.

3. Methods

In this section, we explain some MCDM methods, including Entropy, EW, and LOPCOW weighting techniques, as well as the ranking methods WASPAS, SECA, SAW, OWA, CODAS, MARCOS, PSI, and WPM. The study procedure is presented in the following chart (Figure 1). Various weight determination methods are utilized in the literature for criterion weight determination. In this study, we employed the following weight determination methods: the Entropy method, an established and widely used technique; the LOPCOW method, a relatively new addition to the literature; and the equal weight method, based on a simple calculation. The Entropy method, used to gauge system uncertainty, is influenced by the extent of dispersion, with greater dispersion having a more pronounced impact on the results [31]. The LOPCOW method, which involves logarithm, mean, and standard deviation calculations, is commonly preferred for effectively measuring criteria data with minimal variability. The equal weight method assigns equal weights to alternatives and is based on a straightforward calculation.

The correlation coefficients calculated to express the similarity between two different rankings were used to represent the similarity of the compared rankings measurably. The weighted Spearman's correlation coefficient is used in this study like the literature [11, 19]. While there are numerous MCDM methods in the literature, this study focuses exclusively on methods employing the same normalization procedure, namely linear normalization. The WASPAS method, a combination of weighted sum and weighted product methods, is featured. The SECA method, another method using linear normalization, is advantageous as it does not require expert opinion and simultaneously determines the criteria weights and the ranking of alternatives. Similarly, the SAW, OWA, CODAS, MARCOS, PSI, AND WPM methods also employ linear normalization. Notably, all these methods have distinct mathematical backgrounds, but they share the same normalization process and are applied in different areas of study.

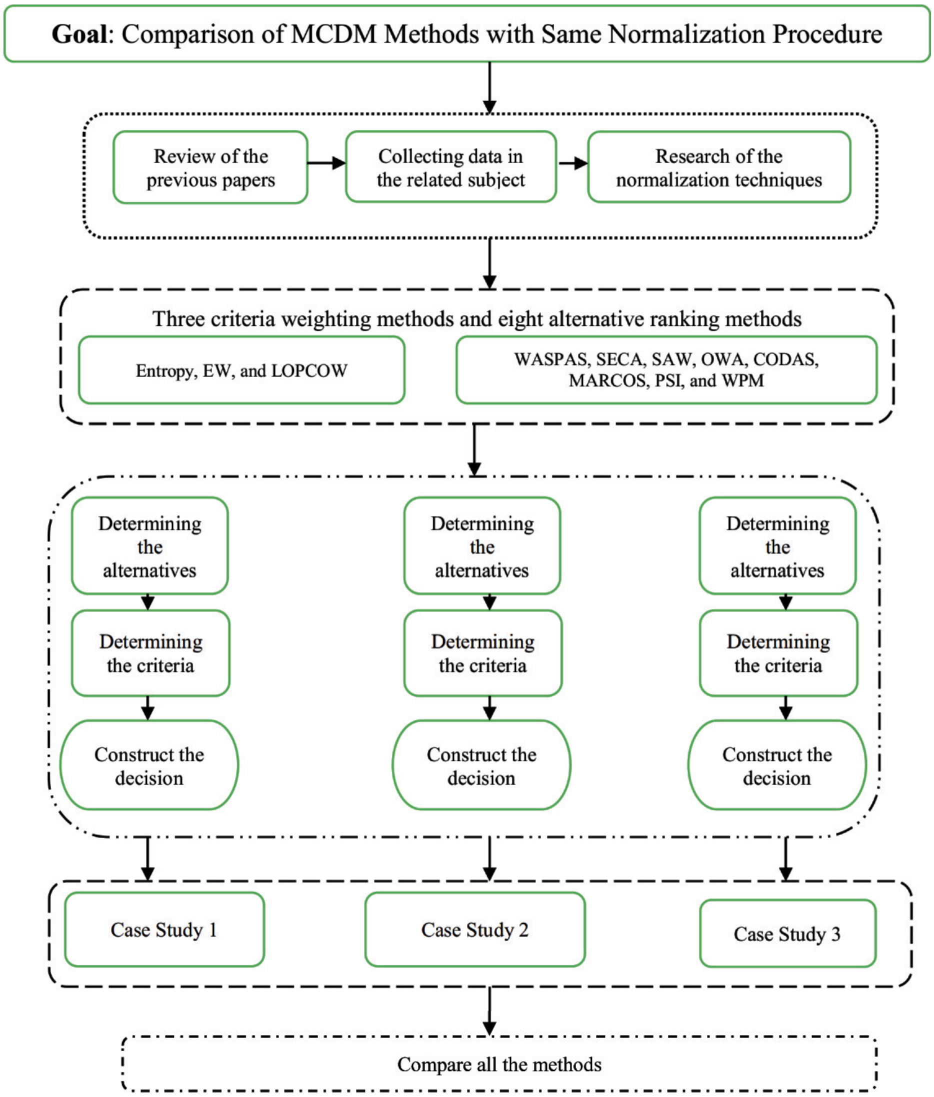

Figure 1. The flowchart of the paper.

4. Applications

MCDM rankings obtained using the same dataset can vary due to differences in algorithms. One of the most significant factors contributing to these variations is the normalization process. This study delves into three distinct case studies to compare MCDM methods with identical normalization processes.

The selection of case studies in which the simple random sampling technique was used was influenced by the fact that they were easily applicable and real-life problems, as well as the fact that they were published in journals with high quality standards to provide reliable results. Specifically, the study compares the following methods, all of which employ linear normalization processes: WASPAS, SECA, SAW, OWA, CODAS, MARCOS, PSI, and WPM. Criteria weights were determined using the Entropy, EW, and LOPCOW techniques. To provide a more appropriate measure and potentially provide a more detailed understanding, the weighted Spearman's correlation coefficient and weighted similarity are used to compare rankings.

4.1. Case study 1

An example from Chodha et al. [29] is examined, involving eight alternatives (Robot 1–8) and five criteria: mechanical weight (RC-1), repeatability (RC-2), payload (RC-3), maximum reach (RC-4), and average power consumption (RC-5) (Table 1).

Table 1. Decision matrix (Example 1) [29]

Alternative	RC-1	RC-2	RC-3	RC-4	RC-5
	min	max	max	max	min
Robot 1	145	0.02	12	1441	1
Robot 2	27	0.018	7	911	0.5
Robot 3	170	0.05	4	1500	0.6
Robot 4	272	0.04	20	1650	3.4
Robot 5	250	0.02	25	2409	2
Robot 6	230	0.05	10	1925	5.6
Robot 7	501	0.15	6	4368	2.5
Robot 8	215	0.08	8	1801	5.05

First of all, the decision matrix is presented in Table 1, the steps of LOPCOW, EW, and Entropy techniques are applied, and the criterion weights are presented in Table 2.

Table 2. Criterion weights (Example 1)

Method	RC-1	RC-2	RC-3	RC-4	RC-5
LOPCOW	0.195	0.050	0.079	0.534	0.142
Entropy	0.172	0.269	0.173	0.109	0.277
EW	0.200	0.200	0.200	0.200	0.200

The findings from the LOPCOW and Entropy methods indicate that there could be differences in the rankings of the alternatives due to significant variations in the criteria weights. All the ranking results obtained are presented in Table 3 and Figure 2.

MCDM rankings obtained with the same normalization process differ from each other, as shown in Table 3 and Figure 2. Similarly, rankings obtained using the three different weighting techniques also differ. While the rankings obtained based on Entropy and EW were closer to each other, the rankings obtained based on the LOPCOW technique showed differences. In Table 4, WSC represents weighted Spearman correlations results, and WS represents weighted similarity results.

When the weighted Spearman correlations and weighted similarity of the findings of different weighting methods (EW, LOPCOW, and ENTROPY) are examined in Table 4, considering all methods, it can be said that there is complete similarity for the SECA and PSI rankings, and high-level correlations are obtained for the others. This means that the difference in criterion weights doesn't change the results for SECA and PSI methods.

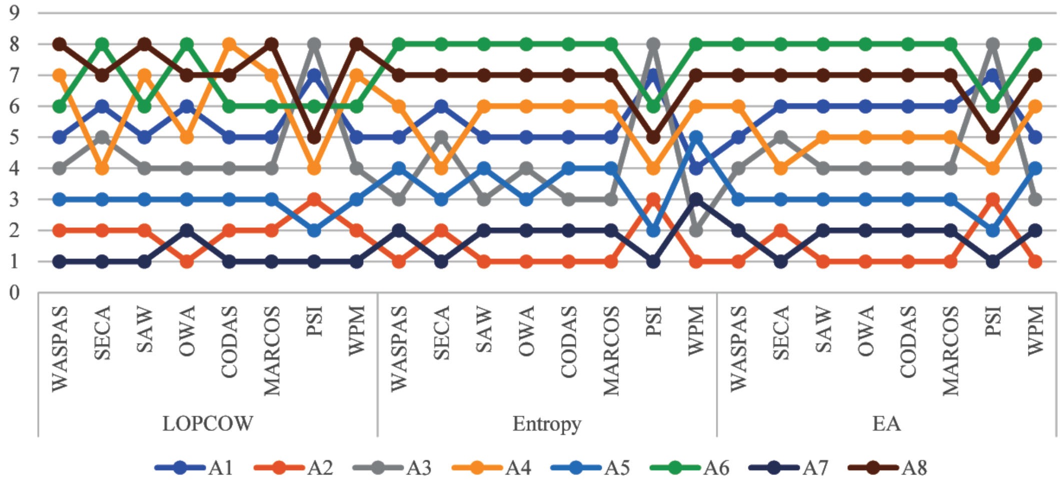

Figure 2. Comparative results of the methods for Case Study1

Table 3. Comparative results (Example 1)

	LOPCOW								Entropy								EA							
	a	b	c	d	e	f	g	h	a	b	c	d	e	f	g	h	a	b	c	d	e	f	g	h
A1	5	6	5	6	5	5	7	5	5	6	5	5	5	5	7	4	5	6	6	6	6	6	7	5
A2	2	2	2	1	2	2	3	2	1	2	1	1	1	1	3	1	1	2	1	1	1	1	3	1
A3	4	5	4	4	4	4	8	4	3	5	3	4	3	3	8	2	4	5	4	4	4	4	8	3
A4	7	4	7	5	8	7	4	7	6	4	6	6	6	6	4	6	6	4	5	5	5	5	4	6
A5	3	3	3	3	3	3	2	3	4	3	4	3	4	4	2	5	3	3	3	3	3	3	2	4
A6	6	8	6	8	6	6	6	6	8	8	8	8	8	8	6	8	8	8	8	8	8	8	6	8
A7	1	1	1	2	1	1	1	1	2	1	2	2	2	2	1	3	2	1	2	2	2	2	1	2
A8	8	7	8	7	7	8	5	8	7	7	7	7	7	7	5	7	7	7	7	7	7	7	5	7

a – WASPAS, b – SECA, c – SAW, d – OWA, e – CODAS, f – MARCOS, g – PSI, h – WPM.

Table 4. Weighted spearman correlations (Example 1)

Method	WASPAS	SECA	SAW	OWA	CODAS	MARCOS	PSI	WPM
EW-LOPCOW-WSC	0.929	1.000	0.894	1.000	0.870	0.894	1.000	0.899
EW-LOPCOW-WS	0.881	1.000	0.866	1.000	0.859	0.866	1.000	0.841
EW-ENTROPY-WSC	0.971	1.000	0.952	0.981	0.952	0.952	1.000	0.942
EW-ENTROPY-WS	0.959	1.000	0.948	0.989	0.948	0.948	1.000	0.910
LOPCOW-ENTROPY-WSC	0.899	1.000	0.899	0.981	0.889	0.899	1.000	0.746
LOPCOW-ENTROPY-WS	0.838	1.000	0.838	0.989	0.839	0.838	1.000	0.718

4.2. Case Study 2

This example pertains to the renewable energy source problem in India [12], involving six renewable energy sources (RE1-RE6) and six criteria: efficiency (EF), average units produced (UP), capital cost (CC), CO_2 emissions (E), land requirement (LR), and operations and maintenance cost (O-M) (see Table 5). EF and UP criteria are maximum but others are minimum.

Table 5. Decision matrix (Example 2) [12]

Criterion	EF	UP	CC	E	LR	O-M
RE1	8.5	8.3	25	372	0.975	3
RE2	12.5	1.66	5.5	45	6.5	1
RE3	45	1.93	5.675	8	50	9
RE4	85	3.9	15.75	48	1.75	5
RE5	80	0.2	5.25	1500	4000	7

The decision matrices are presented in Table 5 and the criterion weights are provided in Table 6. It is evident that there is no similarity between the criterion weights; on the contrary, significantly different criterion weights are observed.

Table 6. Criterion weights (Example 2)

Method	EF	UP	CC	E	LR	O and M
LOPCOW	0.1074	0.0904	0.1949	0.2262	0.2336	0.1475
Entropy	0.0797	0.1095	0.0631	0.2559	0.4398	0.0519
EW	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667

All the results are presented in Table 7 and Figure 3. Different rankings are obtained due to the various methods, influenced by the criterion weights.

Table 7. Comparative results (Example 2)

	LOPCOW								Entropy								EA							
	a	b	c	d	e	f	g	h	a	b	c	d	e	f	g	h	a	b	c	d	e	f	g	h
A1	4	4	3	3	2	3	3	4	1	4	1	4	5	1	3	2	4	4	3	3	2	3	3	4
A2	2	3	2	4	3	2	1	2	4	3	4	3	1	4	1	3	2	3	4	4	4	4	1	2
A3	3	2	1	2	1	1	2	3	3	2	3	2	2	3	2	4	3	2	1	1	1	1	2	3
A4	1	1	4	1	4	4	4	1	2	1	2	1	4	2	4	1	1	1	2	2	3	2	4	1
A5	5	4	5	5	5	5	5	5	5	4	5	5	3	5	5	5	5	4	5	5	5	5	5	5

a – WASPAS, b – SECA, c – SAW, d – OWA, e – CODAS, f – MARCOS, g – PSI, h – WPM.

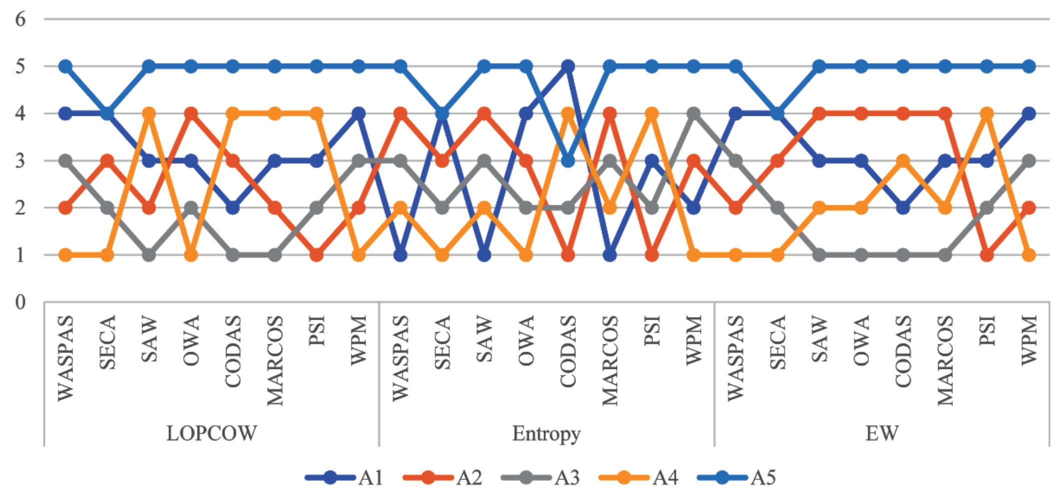

Figure 3. Comparative results of the methods for Case Study 2

As can be seen in Table 7 and Figure 3, the rankings obtained with MCDM methods with the same normalization processes and different weighting techniques differed significantly from each other, especially for the rankings obtained by Entropy-based MCDM methods. This is consistent with other studies in the literature where different rankings were obtained by MCDM methods with the same normalization process [18, 22, 24], and where different weights led to different rankings [9, 33].

Table 8. Weighted correlations and weighted similarity (Example 2)

Method	WASPAS	SECA	SAW	OWA	CODAS	MARCOS	PSI	WPM
EW-LOPCOW-WSC	1.000	1.000	0.600	0.850	0.917	0.600	1.000	1.000
EW-LOPCOW-WS	1.000	1.000	0.792	0.792	0.917	0.792	1.000	1.000
EW-ENTROPY-WSC	0.200	1.000	0.467	0.767	-0.150	0.467	1.000	0.700
EW-ENTROPY-WS	0.646	1.000	0.625	0.708	0.484	0.625	1.000	0.813
LOPCOW-ENTROPY-WSC	0.200	1.000	0.067	0.917	0.150	0.067	1.000	0.700
LOPCOW-ENTROPY-WS	0.646	1.000	0.417	0.917	0.484	0.417	1.000	0.813

Taking all methods into account and examining the weighted Spearman correlations and weighted similarity of findings related to different weighting methods (EW, LOPCOW, and ENTROPY), it can be said that there is a complete similarity in the ranking results of SECA and PSI, similar to Case Study 1, while for others, correlations at low-medium-high levels are obtained (Table 8).

4.3. Case Study 3

In this case study, the renewable energy source selection problem is considered for electricity generation in Taiwan from Lee and Chang [3]. There are five alternatives such as solar energy (Solar PV) (A1), wind (Wind) (A2), hydro (Hydro) (A3), biomass (Biomass) (A4), and geothermal (Geothermal) (A5), and 10 criteria including such as investment cost (C1), operation and maintenance cost (O-M cost) (C2), electricity cost (C3), efficiency (C4), capacity factor (C5), technical maturity (C6), greenhouse gas emission (GHG emission) (C7), land use (C8), job creation (C9), and social acceptance (C10) (Table 9). The criteria weights are presented in Table 10, and all the results are presented in Table 11 and Figure 4.

Table 9. Decision matrix (Example 3) [3]

Criteria	Alternatives				
	Solar PV (A1)	Wind (A2)	Hydro (A3)	Biomass (A4)	Geothermal (A5)
Investment cost (C1)	4550	3005	2040	3370	3920
O-M cost (C2)	30	60.86	14.85	99.4	112.6
Electric cost (C3)	6.74	2.4	1.7	3.25	4.93
Efficiency (C4)	20	35	90	25.3	11.4
Capacity factor (C5)	15	27	25	54	71.7
Technical maturity (C6)	5	4	5	3	2
GHG emission (C7)	85	26	26	45	50
Land use (C8)	150	200	500	222	100
Job creation (C9)	0.87	0.17	0.27	0.21	0.25
Social acceptance (C10)	4.76	4.51	4.19	3.78	4.11

Table 10. Criterion weights (Example 3)

Method	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
LOPCOW	0.0996	0.0996	0.1371	0.0256	0.0694	0.1119	0.1498	0.1918	0.0074	0.1078
Entropy	0.0259	0.1539	0.0888	0.1991	0.1149	0.0396	0.0803	0.1227	0.1724	0.0025
EW	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Table 11. Comparative results (Example 3)

	LOPCOW								Entropy								EA							
	a	b	c	d	e	f	g	h	a	b	c	d	e	f	g	h	a	b	c	d	e	f	g	h
A1	5	4	4	3	4	4	3	5	2	4	2	3	2	2	3	2	3	4	3	3	2	3	3	3
A2	2	2	2	2	2	2	2	2	3	2	3	2	4	3	2	3	2	2	2	2	3	2	2	2
A3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A4	4	5	5	5	5	5	5	4	5	5	5	5	5	5	5	4	4	5	5	5	5	5	5	4
A5	3	3	3	4	3	3	4	3	4	3	4	4	3	4	4	5	5	3	4	4	4	4	4	5

a – WASPAS, b – SECA, c – SAW, d – OWA, e – CODAS, f – MARCOS, g – PSI, h – WPM.

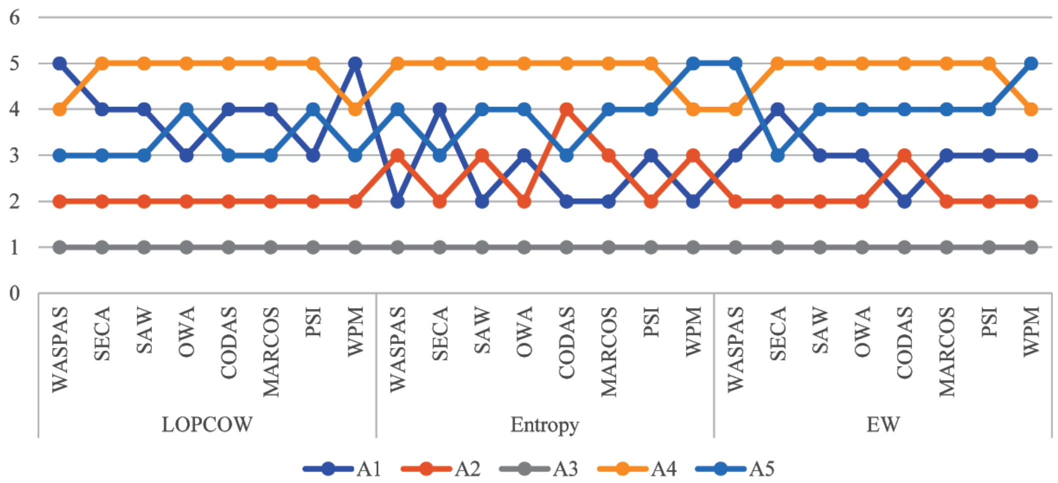

Figure 4. Comparative results of the methods for Case Study 3

The rankings derived from MCDM methods with the same normalization process display significant disparities (Table 11 and Figure 4). The solitary consistent outcome discerned across eight methods and three weighting techniques is the first-place ranking of alternative A3. In a comprehensive assessment, it becomes evident that rankings based on the same dataset have experienced variations contingent on the specific MCDM methods featuring identical normalization processes and weighting techniques.

Table 12. Weighted correlations and weighted similarity (Example 3)

Method	WASPAS	SECA	SAW	OWA	CODAS	MARCOS	PSI	WPM
EW-LOPCOW-WSC	0.733	1.000	0.917	1.000	0.700	0.917	1.000	0.733
EW-LOPCOW-WS	0.859	1.000	0.917	1.000	0.750	0.917	1.000	0.859
EW-ENTROPY-WSC	0.833	1.000	0.883	1.000	0.917	0.883	1.000	0.883
EW-ENTROPY-WS	0.826	1.000	0.854	1.000	0.917	0.854	1.000	0.417
LOPCOW-ENTROPY-WSC	0.500	1.000	0.700	1.000	0.600	0.700	1.000	0.433
LOPCOW-ENTROPY-WS	0.810	1.000	0.813	1.000	0.792	0.813	1.000	0.331

When the weighted Spearman correlations and weighted similarity of the findings of different weighting methods (EW, LOPCOW, and ENTROPY) are examined (Table 12), there is complete similarity for the SECA, OWA, and PSI ranking results, and moderate-high-level correlations are obtained for the others.

5. Discussion and theoretical implications

In this study, various MCDM methods utilizing the same normalization processes, including WASPAS, SECA, SAW, OWA, CODAS, MARCOS, PSI, and WPM, were compared. Three different case studies were examined, and the criterion weights were determined using the LOPCOW, Entropy, and EW methods. The literature contains examples where MCDM methods with the same normalization process yield different rankings [4, 18, 22, 24], as well as instances where varying weights result in distinct rankings [9, 33].

In this study, MCDM ranking methods with a linear normalization procedure were preferred to fill the gap in the literature. When selecting weighting methods, objective methods such as Entropy, EW, and LOPCOW were chosen to exclude the subjective judgments of decision-makers. The Entropy, EW, and LOPCOW methods ensure the objective determination of criteria weights, eliminating the subjective viewpoints, experiences, knowledge, and perceptions of the decision-makers regarding the decision-making problem. The simplicity of these methods and their ease of application, as well as their suitability for real-life problems, are other significant factors influencing their selection. In this study, the aim is to achieve more reliable results by incorporating the outcomes of three objective weighting methods into the process, as opposed to relying on a single target weighting method.

The WASPAS method, which is a unique combination of the well-known weighted sum model (WSM) and weighted product model, provides results that are 1.3 times more reliable than WPM and 1.6 times more reliable than WSM [27]. However, a disadvantage of the WASPAS method is that if the matrix becomes too large, it may require more time for the solution. This issue can be overcome by using software that implements the steps of the WASPAS method [36]. On the other hand, the SECA method [13] is advantageous for the simultaneous programming of performance scores. The advantage of SAW is that it is not difficult to compute. However, it often overestimates the suitability of the analysis results [7]. While the CODAS method [30] is an effective method, the inconsistency arises from not measuring the criteria's weights and each criterion adding direct Euclidean distances and Hamming distances, which does not align with the actual situation [14]. The MARCOS method is important for defining reference points, determining relationships between references, and defining the degree of benefit of alternatives. On the other hand, it has a disadvantage due to its use of a single normalization technique [25]. The main advantage of the PSI model [16] is the direct ranking without the need to define any criteria weights. Thus, there is no requirement for another MCDM tool to determine relative weights [17]. WPM is advantageous due to its simplicity in the evaluation process and its applicability without the need for software. However, it can generally be applied to decision problems with similar types of criteria [34].

Even when using the same dataset, the ranking results change when employing methods with the same normalization process but different weights. This emphasizes the significance of the weight determination phase in solving a decision problem. Decision-making involves not only ranking alternatives but also determining the appropriate weights for the criteria required to evaluate these alternatives. As the study's findings are derived from case studies, it is anticipated that similar results may be observed in other research. The reproducibility of scientific findings will provide guidance for future researchers, decision-makers, and scholars.

6. Conclusions

The primary objective of this paper is to determine whether the MCDM outputs obtained with the same normalization procedure change. In this context, three real-life case studies were examined, employing eight ranking methods (WASPAS, SECA, SAW, OWA, CODAS, MARCOS, PSI, and WPM) and three objective criterion weighting methods (LOPCOW, Entropy, and EW) to conduct a comprehensive analysis. As seen in the results presented in Tables 3, 7, 11, the rankings obtained using eight MCDM methods with linear normalization procedures generally differ. Another notable finding is that different weights also have an impact on the results.

The relationships between rankings are comprehensively examined by the Spearman–Rho correlation analysis of the three examples (Table 13). This study found total correlations for the eight methods and examined the lowest correlations between the methods.

Table 13. Correlations in the methods

	LOPCOW total	Entropy total	EW total	LOPCOW minimum	Entropy minimum	EW minimum
Case study-1	54.10	53.33	56.90	0.50	0.12	0.40
Case study-2	37.08	24.92	41.33	0.10	-0.70	0.20
Case study-3	58.40	55.00	58.20	0.70	0.50	0.70

When the correlations between the eight MCDM methods were examined in the context of case study 1, the total correlations were 54.095 by the LOPCOW method. The smallest correlation was observed between PSI and CODAS ($r = 0.500$). According to the Entropy method, the total correlations were 53.333, and the smallest correlation was observed between PSI and WPM ($r = 0.119$). As for the EW method, the total correlations amounted to 56.905, and the smallest correlation was again found between PSI and WPM ($r = 0.405$). For case study 2, the smallest correlation by the LOPCOW method was between PSI and OWA ($r = 0.100$). In the case of the Entropy method, the smallest correlations were found between CODAS and WASPAS ($r = -0.700$), CODAS and SAW ($r = -0.700$), and CODAS and MARCOS ($r = -0.700$). In the EW method, the smallest correlations were between CODAS and WASPAS ($r = 0.200$) and CODAS and WPM (0.200). In case study 3, the smallest correlations were found between the SECA, PSI, and CODAS methods and the other methods. Similar values were observed in the other two case studies. In summary, the total correlations between the methods, when considering the LOPCOW and EW weights, were higher than those in the Entropy method. Conversely, the smallest correlation values were higher in the rankings based on LOPCOW and EW weights but lower in the Entropy method. Based on these findings, it is more reasonable to utilize the weights determined by the LOPCOW or EW methods rather than relying on rankings derived from the Entropy method.

Moreover, this study examined the relationships between the methods using weighted Spearman's correlation and weighted similarity. Changing the criterion weights for SECA and PSI was not significant and would not affect the findings by the weighted Spearman's correlation and Weighted similarity results. A similar situation applies to the OWA method in Case 3 as well. The rankings generated by methods employing the same normalization process differed when the results from three distinct case studies were examined. SECA and PSI methods stood out due to their unique approach, where criteria weights are calculated using each method's proprietary algorithms. Consequently, variations in rankings produced by the SECA and PSI methods may be attributed to the distinct algorithmic approaches of these methods. In the case of the CODAS method, despite employing the same normalization process, it diverged from the others because it provides solutions based on different distance metrics. Additionally, the study revealed that the weights determined using Entropy, EW, and LOPCOW techniques had varying impacts on the results, aligning with findings in the existing literature. The study's results can be summarized as follows: Rankings derived from MCDM methods sharing the same normalization process can exhibit disparities. Weights obtained through Entropy, EW, and LOPCOW techniques exert differing influences on the results.

Due to the limited availability of research comparing MCDM methods with similar normalization processes, this study aims to fill this gap in the literature. The results of this study are considered significant in encouraging researchers to explore the use of other normalization techniques. The contributions of this study can be outlined as follows: Three real-life applications involving different scenarios were analyzed. A systematic decision-making framework for evaluating MCDM outputs with similar normalization processes was proposed. The study integrated 11 methods for the first time, including eight ranking methods and three weighting methods. Using the Entropy, EW, and LOPCOW methods, optimal criterion weights were obtained, eliminating the subjective judgments of decision-makers. The discussed case studies can be extended to other normalization techniques as well.

In this study, MCDM methods were compared using objective criterion weights and a linear normalization procedure, based on three different case studies. The study is limited to the model and the three case studies used, and the results obtained are generally applicable within this scope. In future studies, it may be beneficial to compare MCDM methods using different normalization techniques and to also include other objective or subjective methods. Methods that combine various normalization techniques, such as DNMA, can be included in the analysis. In similar studies, it may be recommended to evaluate the PSI, SECA, and CODAS methods separately or not to use them together with the other methods, as they can influence the results.

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References

[1] Aytekin, A. Measurement of effectiveness, diversity and performance of leading companies in Turkey. *Anadolu Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi 21*, 4 (2020), 19–35.

[2] Aytekin, A. Comparative analysis of normalization techniques in the context of MCDM problems. *Decision Making: Applications in Management and Engineering 4*, 2 (2021), 1-25.

[3] Brauers, W. K., and Zavadskas, E. K. The MOORA method and its application to privatization in a transition economy. *Control and Cybernetics 35*, 2 (2006), 445–469.

[4] Brauers, W. K. M., and Zavadskas, E. K. Project management by MULTIMOORA as an instrument for transition economies. *Technological and Economic Development of Economy 16*, 1 (2010), 5–24.

[5] Budiman, E., and Hairah, U. Comparison of linear and vector data normalization techniques in decision making for learning quota assistance. *Journal of Information Technology and Its Utilization 4*, 1 (2021), 23–28.

[6] Chatterjee, P., and Chakraborty, S. Investigating the effect of normalization norms in flexible manufacturing system selection using multi-criteria decision-making methods. *Journal of Engineering Science & Technology Review 7*, 3 (2014), 141–150.

[7] Churchman, C. W., and Ackoff, R. L. An approximate measure of value. *Journal of the Operations Research Society of America 2*, 2 (1954), 172–187.

[8] Gardziejczyk, W., and Zabicki, P. Normalization and variant assessment methods in selection of road alignment variants–case study. *Journal of Civil Engineering and Management 23*, 4 (2017), 510–523.

[9] Hwang, C.-L., Yoon, K. Methods for multiple attribute decision making. In *Multiple Attribute Decision Making: Methods and Applications. A State-of-the-Art Survey* (Berlin, 1981), C.-L. Hwang and K. Yoon, Eds., vol. 186 of *Lecture Notes in Economics and Mathematical Systems*, Springer, 58–191.

[10] Jahan, A., and Edwards, K. L. A state-of-the-art survey on the influence of normalization techniques in ranking: Improving the materials selection process in engineering design. *Materials & Design (1980-2015) 65* (2015), 335–342.

[11] Julong, D. Introduction to grey system theory. *The Journal of Grey System 1*, 1 (1989), 1–24.

[12] Keeney, R. L., and Raiffa, H. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. Cambridge University Press, 1993.

[13] Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E. K., Turskis, Z., and Antucheviciene, J. Simultaneous evaluation of criteria and alternatives (SECA) for multi-criteria decision-making. *Informatica 29*, 2 (2018), 265–280.

[14] Keshavarz Ghorabaee, M., Zavadskas, E. K., Turskis, Z., and Antucheviciene, J. A new combinative distance-based assessment (CODAS) method for multi-criteria decision-making. *Economic Computation & Economic Cybernetics Studies & Research 50*, 3 (2016), 25–44 .

[15] Kosareva, N., Krylovas, A., and Zavadskas, E. K. 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 52*, 4 (2018), 159–175.

[16] Maniya, K., and Bhatt, M. G. A selection of material using a novel type decision-making method: Preference selection index method. *Materials & Design 31*, 4 (2010), 1785–1789.

[17] Miller, D. W., and Starr, M. K. *Executive Decisions and Operations Research*. Prentice-Hall, Inc., 1969.

[18] Mufazzal, S., and Muzakkir, S. M. A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals. *Computers & Industrial Engineering 119* (2018), 427–438.

[19] Mulliner, E., Malys, N., and Maliene, V. Comparative analysis of MCDM methods for the assessment of sustainable housing affordability. *Omega 59* (2016), 146–156.

[20] Opricovic, S., and Tzeng, G.-H. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research 156*, 2 (2004), 445–455.

[21] Pamučar, D., and Ćirović, G. The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). *Expert Systems with Applications 42*, 6 (2015), 3016–3028.

[22] Pamučar, D., Vasin, L., and Lukovac, L. Selection of railway level crossings for investing in security equipment using hybrid DEMATEL-MARICA model. In *Proceedings of the XVI International Scientific-Expert Conference on Railway, RAILCON'14, October, 09-10 2014, Niś, Serbia* (2014), University of Niś, pp. 89–92.

[23] Paradowski, B., Kizielewicz, B., Shekhovtsov, A., and Sałabun, W. The Iterative Compromise Ranking Analysis (ICRA)-the new approach to make reliable decisions. In *Special Sessions in the Advances in Information Systems and Technologies Track of the Conference on Computer Science and Intelligence Systems* (Cham, 2022), E. Ziemba, W. Chmielarz and J. Wątróbski, Eds., vol. 471 of *Lecture Notes in Business Information Processing*, Springer, pp. 151–170.

[24] Parkan, C. Operational competitiveness ratings of production units. *Managerial and Decision Economics 15*, 3 (1994), 201–221.

[25] Stević, Ž., Pamučar, D., Puška, A., and Chatterjee, P. Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS). *Computers & Industrial Engineering 140* (2020), 106231.

[26] Triantaphyllou, E., and Sánchez, A. A sensitivity analysis approach for some deterministic multi-criteria decision-making methods. *Decision Sciences 28*, 1 (1997), 151–194.

[27] Ulutaş, A., Stanujkic, D., Karabasevic, D., Popovic, G., Zavadskas, E. K., Smarandache, F., and Brauers, W. K. M. Developing of a novel integrated MCDM MULTIMOOSRAL approach for supplier selection. *Informatica 32*, 1 (2021), 145–161.

[28] Vafaei, N., Ribeiro, R. A., and Camarinha-Matos, L. M. Selecting normalization techniques for the analytical hierarchy process. In *Technological Innovation for Life Improvement: 11th IFIP WG 5.5/SOCOLNET Advanced Doctoral Conference on Computing, Electrical and Industrial Systems, DoCEIS 2020, Costa de Caparica, Portugal, July 1–3, 2020, Proceedings 11* L. M. Camarinha-Matos, N. Farhadi, F. Lopes and H. Pereira (2020), vol. 577 of *IFIP Advances in Information and Communication Technology*, Springer, pp. 43–52.

[29] Voogd, H. Multicriteria evaluation with mixed qualitative and quantitative data. *Environment and Planning B: Planning and Design 9*, 2 (1982), 221–236.

[30] Yager, R. R. On ordered weighted averaging aggregation operators in multicriteria decisionmaking. *IEEE Transactions on Systems, Man, and Cybernetics 18*, 1 (1988), 183–190.

[31] Yakowitz, D. S., Lane, L. J., and Szidarovszky, F. Multi-attribute decision making: dominance with respect to an importance order of the attributes. *Applied Mathematics and Computation 54*, 2-3 (1993), 167–181.

[32] Yazdani, M., Zarate, P., Zavadskas, E. K., and Turskis, Z. A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Management Decision 57*, 9 (2019), 2501–2519.

[33] Zavadskas, E. K., and Kaklauskas, A. *Multicriteria evaluation of buildings*. Technika, 1996 (in Lithuanian).

[34] Zavadskas, E. K., and Turskis, Z. A new additive ratio assessment (ARAS) method in multicriteria decision-making. *Technological and Economic Development of Economy 16*, 2 (2010), 159–172.

[35] Zavadskas, E. K., and Turskis, Z. Multiple criteria decision making (MCDM) methods in economics: an overview. *Technological and Economic Development of Economy 17*, 2 (2011), 397–427.

[36] Zavadskas, E. K., Turskis, Z., Antucheviciene, J., and Zakarevicius, A. Optimization of weighted aggregated sum product assessment. *Elektronika ir Elektrotechnika 122*, 6 (2012), 3–6.