New Multi-Criteria Approach to Sustainable Development Assessment

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Abstract. Multi-Criteria Decision Analysis (MCDA) methods are commonly used to evaluate alternatives based on various criteria within different fields. However, most traditional MCDA approaches assess alternatives at a single point in time, which limits their ability to evaluate performance across multiple periods. To address this limitation, this research introduces the Data vARIability Assessment - Measurement of Alternatives and Ranking according to COmpromise Solution (DARIA-MARCOS) method for temporal multi-criteria assessment. This new approach is applied to evaluate the achievement of Sustainable Development Goal 7 (SDG 7) targets by selected European countries from 2017 to 2022, focusing specifically on renewable energy sources (RES). Building on its successful use in assessing SDG 11, this investigation demonstrates the potential of the DARIA-MARCOS method for sustainability evaluations over multiple timeframes. The findings illustrate the method's effectiveness in tracking progress over time, making it a valuable tool for policymakers and researchers involved in sustainable energy planning. The results showed that Norway showed the best performance in all the years evaluated, which gave it the leading position in the DARIA-MARCOS ranking.

Keywords: DARIA-MARCOS · Multi-criteria decision analysis · Temporal assessment · SDG 7.

1 Introduction

Multi-criteria decision analysis (MCDA) methods are commonly employed to address evaluation problems that involve multiple criteria across various fields [9, 21]. These methods are applied in a wide scope of areas such as sustainability [3], waste management [19], productivity [15], risk assessment [14], the selection of renewable energy sources [16], share of renewable energy sources (RES) in sustainable energy mix management assessment [24], healthcare evaluation [23], and the assessment of policy implementation [2], among others [10]. The popularity of MCDA methods can be attributed to their ability to simultaneously consider multiple, often conflicting evaluation criteria, the variety of available methods,

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and their ease of application [8, 16]. Despite their numerous advantages, Multi-Criteria Decision Analysis (MCDA) methods have certain limitations that must be addressed in specific situations. One such limitation is that these methods typically evaluate alternatives at only one point in time [12]. When the goal is to assess alternatives based on performances achieved over multiple periods of time, decision-makers need to take additional steps [26]. These may include aggregating results from successive periods, using techniques like weighted averages or weighted sums [11], or employing multi-criteria methods specifically designed for temporal assessments [20]. Currently, there are few methods available for multi-criteria assessment over multiple periods, and the existing approaches come with their limitations [6, 7, 20].

The author of this article proposes a multi-criteria method, known as Data vARIability Assessment - Measurement of Alternatives and Ranking according to COmpromise Solution (DARIA-MARCOS), to evaluate the achievement of Sustainable Development Goal 7 (SDG 7) targets by selected European countries. This evaluation is based on their performance over six years, from 2017 to 2022. The DARIA-MARCOS method was initially developed and successfully applied by the author to assess the achievement of Sustainable Development Goal 11 (SDG 11) targets across multiple periods [4]. The successful application of this method in evaluating sustainability issues has prompted the author to explore its potential in other domains. Therefore, they present the idea of utilizing it to analyze sustainability in the context of affordable and clean energy, with a specific focus on RES.

The remainder of this paper is organized as follows. Section 2 presents a literature review. In section 3, the fundamentals and mathematical formulas of the proposed method are provided, DARIA-MARCOS, and describe the dataset used in this research. Section 5 discusses the research results. Finally, section 6 draws conclusions and outlines directions for future work.

2 Literature review

Incorporating a long-term perspective into sustainable decision-making necessitates the development of extensions to multi-criteria decision analysis (MCDA) that enable the evaluation of multiple periods. A multi-criteria approach using the TOPSIS method has been proposed to identify the best options for sustainable forest management, considering economic benefits, environmental impacts, and the preferences of decision-makers [7]. Another multi-criteria method that considers multiple periods is MUPOM (MUlti-criteria multi-Period Outranking Method) [6]. MUPOM is an outranking method that consists of four steps: multi-criteria aggregation, temporal aggregation, exploitation, and follow-up. This method was applied in a case study aimed at selecting the best compromise option for sustainable forest management, considering environmental impacts, economic benefits, and the preferences of the decision-maker. Additionally, the literature describes another multi-criteria method that incorporates multiple periods, known as PROMETHEE-MP. This method generalizes PROMETHEE to

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account for uncertainty and involves a double aggregation process, which includes both multi-criteria aggregation and temporal aggregation, followed by an exploitation phase [20]. The proposed method was demonstrated through a practical example of sustainable forest management assessment. A multi-period approach based on PROMETHEE was utilized to evaluate a case study from the German energy sector focused on the transition to renewable energy, considering periods of uncertainty [26]. In a different research paper, the classic MCDA paradigm, based on AHP, TOPSIS, and COMET methods, was expanded to incorporate aspects of temporal evaluation. Various temporal aggregation strategies were also introduced for supplier selection evaluation [11]. In the following research paper, a temporal extension of PROMETHEE II was developed and applied for evaluating the sustainable consumption of alternative fuels across multiple periods [22].

The examples discussed demonstrate that temporal extensions of Multi-Criteria Decision Analysis (MCDA) are gradually evolving. However, these developed approaches tend to be computationally complex and involve multiple steps, complicating their application. Most existing methods rely on aggregating results from individual periods considered, but this does not always accurately represent the intended strategies. This complexity has spurred the development of multi-criteria approaches that utilize MCDA methods incorporating performance variability measures over time. An example of such an approach is the DARIA-TOPSIS method created by the author. This method is illustrated in the context of assessing sustainable cities and societies, using data on the implementation of Sustainable Development Goal (SDG) 11 targets [25]. The successful application of the previous method led the author to develop a temporal MCDA approach using another multi-criteria method, MARCOS, to assess the achievement of the SDG 7 targets related to affordable and clean energy sustainability.

3 Methodology

3.1 The DARIA-MARCOS Method

This section describes the fundamentals and principles of the proposed multi-criteria temporal method named DARIA-MARCOS. Software for this method was implemented in Python and it is provided in an open GitHub repository at link `https://github.com/energyinpython/DARIA-MARCOS-for-temporal-sustainability-assessment`, along with the DARIA class with five methods for variability measurement. Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) method involved in several steps of the DARIA-MARCOS is provided on the basis of [18].

Step 1. Build a decision matrix denoted by $X^p = [x_{ij}^p]_{m \times n}$ including performance values for m alternatives in relation to n criteria for each evaluated period, where particular periods are defined by $p = 1, 2, \ldots, t$, and t represents number of periods assessed. One singular decision matrix for a given period is shown in Equation (1).

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$$X^p = [x_{ij}^p]_{m \times n} = \begin{bmatrix} x_{11}^p & x_{12}^p & \cdots & x_{1n}^p \\ x_{21}^p & x_{22}^p & \cdots & x_{2n}^p \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1}^p & x_{m2}^p & \cdots & x_{mn}^p \end{bmatrix} \tag{1}$$

Step 2. Expand every decision matrix built for given period p by ideal (AI^p) and anti-ideal (AAI^p) solutions according to Equation (2).

$$X^p = [x_{ij}^p]_{m+2 \times n} = \begin{bmatrix} x_{aa1}^p & x_{aa2}^p & \cdots & x_{aan}^p \\ x_{11}^p & x_{12}^p & \cdots & x_{1n}^p \\ x_{21}^p & x_{22}^p & \cdots & x_{2n}^p \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1}^p & x_{m2}^p & \cdots & x_{mn}^p \\ x_{ai1}^p & x_{ai2}^p & \cdots & x_{ain}^p \end{bmatrix} \tag{2}$$

The anti-ideal solution (AAI^p) represents the worst alternative and the ideal solution (AI^p) represents the best alternative. AAI^p is created as Equation (3) presents and AI^p is determined using Equation (4), where B defines profit criteria and C denotes cost criteria.

$$AAI^p = x_j^{p\ min}\ if\ j \in B\ and\ x_j^{p\ max}\ if\ j \in C \tag{3}$$

$$AI^p = x_j^{p\ max}\ if\ j \in B\ and\ x_j^{p\ min}\ if\ j \in C \tag{4}$$

Step 3. Conduct normalization procedure of each expanded initial matrix X^p. Normalized matrix $N^p = [n_{ij}^p]_{m+2 \times n}$ are computed according to Equations (5) for cost criteria and (6) for profit criteria, where x_{ij} and x_{ai} represent elements of expanded initial matrix X.

$$n_{ij}^p = \frac{x_{ai}^p}{x_{ij}^p}\ if\ j \in C \tag{5}$$

$$n_{ij}^p = \frac{x_{ij}^p}{x_{ai}^p}\ if\ j \in B \tag{6}$$

Step 4. Compute the weighted normalized matrix $V^p = [v_{ij}^p]_{m+2 \times n}$ performing multiplication of the normalized matrix N by criteria weights w_j^p for j-th criterion, as Equation (7) shows. Criteria weights may be designated subjectively by decision-makers or calculated with objective weighting methods. In this research, criteria weights were computed using the objective weighting method named CRITIC (Criteria Importance Through Inter-criteria Correlation) [1].

$$v_{ij}^p = n_{ij}^p w_j^p \tag{7}$$

Step 5. Compute the utility degree of alternatives K_i^p as Equations (8) show and (9), where S_i^p $(i = 1, 2, \ldots, m)$ defines the sum of the values in the weighted matrix V^p computed by Equation (10).

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$$K_i^{p-} = \frac{S_i^p}{S_{aai}^p} \tag{8}$$

$$K_i^{p+} = \frac{S_i^p}{S_{ai}^p} \tag{9}$$

$$S_i^p = \sum_{j=1}^{n} v_{ij}^p \tag{10}$$

Step 6. Calculate the utility function of alternatives $f(K_i^p)$. The utility function is the compromise of a particular alternative with regard to the ideal and anti-ideal solution. The utility function of alternatives is denoted by Equation (11)

$$f(K_i^p) = \frac{K_i^{p+} + K_i^{p-}}{1 + \frac{1-f(K_i^{p+})}{f(K_i^{p+})} + \frac{1-f(K_i^{p-})}{f(K_i^{p-})}} \tag{11}$$

where $f(K_i^{p-})$ defines the utility function with regard to the anti-ideal solution. then again, $f(K_i^{p+})$ represents the utility function with regard to the ideal solution. Utility functions with regard to the ideal and anti-ideal solutions are determined with Equations (12) and (13).

$$f(K_i^{p-}) = \frac{K_i^{p+}}{K_i^{p+} + K_i^{p-}} \tag{12}$$

$$f(K_i^{p+}) = \frac{K_i^{p-}}{K_i^{p+} + K_i^{p-}} \tag{13}$$

Step 7. Create the matrix $S = [s_{pi}]_{t\times m}$ presented in Equation (14) including annual MARCOS utility function values of alternatives s_{pi} gained for t periods in rows, where following periods are numbered by $p = 1, 2, \ldots, t$ and m alternatives a in columns, where following alternatives are numbered by $i = 1, 2, \ldots, m$. Utility function values are represented by $K_i^p)$ for the MARCOS method. Following periods are denoted by $y_1, \ldots, y_p, \ldots, y_t$.

$$S = \begin{array}{c|ccccc} & a_1 & \ldots & a_i & \ldots & a_m \\ \hline y_1 & s_{11} & \ldots & s_{1i} & \ldots & s_{1m} \\ \vdots & \vdots & \ldots & \vdots & \ldots & \vdots \\ y_p & s_{p1} & \ldots & s_{pi} & \ldots & s_{pm} \\ \vdots & \vdots & \ldots & \vdots & \ldots & \vdots \\ y_t & s_{t1} & \ldots & s_{ti} & \ldots & s_{tm} \end{array} \tag{14}$$

Step 8. Compute the variability of achieved scores in matrix S obtained using the MARCOS method for every evaluated period. The variability value is computed using the entropy method [27] explained in steps 8.1-8.3. Entropy

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was chosen to measure variability as the most popular objective method. Entropy measures uncertainty and provides a quantitative measure of information content.

Step 8.1. Perform matrix S normalization with sum normalization method to obtain normalized matrix $K = [k_{pi}]_{t \times m}$ where $p = 1, 2, \ldots, t$ and $i = 1, 2, \ldots, m$, t denotes nomber of periods and m defines number of alternatives.

$$k_{pi} = \frac{s_{pi}}{\sum_{p=1}^{t} s_{pi}} \tag{15}$$

Step 8.2. Compute the entropy value E_i for each ith alternative as Equation (16) demonstrates [27].

$$E_i = -\frac{\sum_{p=1}^{t} k_{pi} ln(k_{pi})}{ln(t)} \tag{16}$$

Step 8.3. Compute the variability value denoted by d_i according to Equation (17).

$$d_i = 1 - E_i \tag{17}$$

Step 9. Establish the direction of score variability. The threshold value obtained in Equation (19) using Equation (18) is involved in computing the variability direction for every ith alternative.

$$thresh_i = \sum_{p=2}^{t} s_p - s_{p-1} \tag{18}$$

$$dir_i = \begin{cases} 1 & if\ thresh_i > 0 \\ -1 & if\ thresh_i < 0 \\ 0 & if\ thresh_i = 0 \end{cases} \tag{19}$$

Step 10. The MARCOS utility function values for alternatives obtained for the most recent period t are updated with the value of the variability of scores d_i in all analyzed periods according to its direction as Equation (20) presents,

$$S_i = S_i^t + d_i \cdot dir_i \tag{20}$$

where S_i denotes the score received by particular alternative a_i updated by adding variability values multiplied by variability direction, S_i^t defines the score of particular alternative a_i achieved in the most recent period t analyzed, d_i denotes values of the variability of alternative's a_i scores over all analyzed periods $p = 1, 2, \ldots, t$ computed applying entropy method, and dir_i represents directions of variability d_i, which may be equal to 1 for improving scores, -1 for worsening scores or 0 for stable scores. Alternatives are represented by a_i ($i = 1, 2, \ldots, m$).

Step 11. The aim of the last step is to rank the alternatives following the descending order of the final scores S as for the MARCOS method.

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3.2 The Dataset

Sustainable Development Goal (SDG) 7 focuses on ensuring access to affordable, reliable, sustainable, and modern energy for everyone. It aims for universal access to such energy, which involves improving energy efficiency, increasing the use of renewable energy sources, and diversifying the energy mix while ensuring affordability for all [5]. Within the European Union context, the monitoring of SDG 7 includes analyzing changes in energy consumption, energy supply, and access to affordable energy [17]. The criteria that serve as indicators for the implementation of the SDG 7 strategy are detailed in the accompanying Table 1. Symbol ↑ represents criteria with the aim of maximization and on the other hand ↓ denotes criteria with the aim of minimization. Decision matrices for the years 2017-2022 are available in the GitHub repository mentioned previously.

Table 1: Set of criteria involved in multi-criteria model assessment of SDG 7 realization.

Symbol	Name	Unit	Type
C_1	Primary energy consumption	Tonnes of oil equivalent (TOE) per capita	↑
C_2	Final energy consumption	Tonnes of oil equivalent (TOE) per capita	↑
C_3	Final energy consumption in households per capita	Kilogram of oil equivalent (KGOE)	↑
C_4	Energy productivity	Euro per kilogram of oil equivalent (Euro per KGOE)	↑
C_5	Share of renewable energy sources in gross final energy consumption	Percentage (%)	↑
C_6	Share of renewable energy sources in transport in gross final energy consumption	Percentage (%)	↑
C_7	Share of renewable energy sources in electricity in gross final energy consumption	Percentage (%)	↑
C_8	Share of renewable energy sources in heating and cooling in gross final energy consumption	Percentage (%)	↑
C_9	Energy import dependency by products	Percentage (%)	↓
C_{10}	Population unable to keep home adequately warm	Percentage (%)	↓

4 Results

This section presents the results of evaluating countries based on their progress toward achieving the goals of Sustainable Development Goal 7 (SDG 7) using the DARIA-MARCOS method. The assessment covers multiple periods from 2017 to 2022. Table 2 displays the annual scores and ranks derived from the classic MARCOS approach. When scores fluctuate in consecutive years, it becomes challenging to derive a clear and definitive assessment based on a single value.

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Table 3 presents the results of the DARIA-MARCOS method. The "Var." column includes variability scores from the individual periods under consideration. The "D.-MARCOS sc." column contains the DARIA-MARCOS scores, while the "D.-MARCOS rank" column represents the ranking of alternatives based on these temporal DARIA-MARCOS scores. The "MARCOS AVG sc." column displays the scores obtained using the classical MARCOS approach that arose based on the averaged performances from the considered periods. Finally, the "MARCOS AVG rank" column provides the ranking for the classical MARCOS method, constructed according to its average scores.

Table 2: Results including annual scores and rankings of classical MARCOS approach.

Country	2017	2018	2019	2020	2021	2022	2017	2018	2019	2020	2021	2022
BEL	-0.3700	-0.3067	-0.3282	-0.3017	-0.3406	-0.3399	8	5	7	6	7	10
BGR	-0.8402	-0.8499	-0.8138	-0.7369	-0.8160	-0.8147	22	24	25	25	25	25
CZE	-0.8601	-0.8107	-0.7229	-0.6946	-0.6812	-0.6754	23	23	24	24	21	23
DNK	-2.9963	-1.3043	-0.6796	-0.5287	-0.8117	-0.6005	28	26	23	18	24	21
DEU	-0.4238	-0.3945	-0.3611	-0.3818	-0.3812	-0.3636	13	13	12	14	12	14
EST	-7.8166	-27.6676	-7.1928	-2.8090	-22.4651	-5.1912	29	29	29	29	29	29
IRL	-0.3934	-0.3550	-0.3470	-0.3046	-0.2799	-0.2924	11	9	9	7	5	6
GRC	-0.4089	-0.3889	-0.3673	-0.2976	-0.3512	-0.3283	12	12	13	5	9	9
ESP	-0.3796	-0.3590	-0.3500	-0.3693	-0.3712	-0.3503	9	10	10	12	10	11
FRA	-0.6147	-0.6082	-0.6047	-0.6022	-0.6188	-0.5338	20	20	20	22	19	19
HRV	-0.5587	-0.5286	-0.4860	-0.4736	-0.4738	-0.4403	16	17	17	17	15	17
ITA	-0.3464	-0.3318	-0.3246	-0.3242	-0.3344	-0.3124	6	8	6	8	6	8
CYP	-0.2879	-0.2775	-0.2778	-0.2509	-0.2721	-0.2705	4	3	4	3	4	4
LVA	-0.6776	-0.6252	-0.6408	-0.5604	-0.7080	-0.7267	21	21	21	20	23	24
LTU	-0.3934	-0.3598	-0.3545	-0.3256	-0.3471	-0.3570	10	11	11	9	8	13
LUX	-0.1995	-0.1945	-0.1936	-0.2064	-0.2007	-0.2060	2	2	2	2	2	2
HUN	-0.4805	-0.4973	-0.3979	-0.4631	-0.5080	-0.4213	14	16	15	15	16	16
MLT	-0.2810	-0.2796	-0.2804	-0.2568	-0.2597	-0.2577	3	4	5	4	3	3
NLD	-0.5810	-0.4494	-0.4077	-0.3488	-0.4273	-0.3039	17	14	16	10	13	7
AUT	-0.3616	-0.3202	-0.2685	-0.3610	-0.4359	-0.2797	7	6	3	11	14	5
POL	-0.8627	-0.6901	-0.6607	-0.6381	-0.6952	-0.6233	24	22	22	23	22	22
PRT	-0.3300	-0.3233	-0.3386	-0.3699	-0.3737	-0.3540	5	7	8	13	11	12
ROU	-1.4541	-1.3043	-1.0372	-1.0137	-0.9217	-0.9266	26	27	27	27	26	26
SVN	-0.5856	-0.5382	-0.5144	-0.5643	-0.5108	-0.4831	18	19	18	21	17	18
SVK	-0.4839	-0.4610	-0.3943	-0.4673	-0.5189	-0.3876	15	15	14	16	18	15
FIN	-0.5934	-0.5337	-0.5729	-0.5434	-0.6231	-0.5826	19	18	19	19	20	20
SWE	-1.0989	-0.9262	-0.8830	-0.7660	-1.2743	-1.0123	25	25	26	26	27	27
ISL	-1.6453	-1.4360	-1.7890	-2.3051	-1.7793	-1.8316	27	28	28	28	28	28
NOR	0.4022	0.3796	0.4009	0.3186	0.3012	0.2883	1	1	1	1	1	1

The results demonstrate that Norway has consistently performed exceptionally well over the years analyzed, topping the rankings in every instance. It leads the DARIA-MARCOS ranking and also ranks first in the traditional MARCOS method, which is based on averaged performance values from the consecutive

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years studied. A similar trend is noted for Luxembourg, which reliably holds the second position across all rankings. Malta secured third place in both the DARIA-MARCOS ranking and the MARCOS ranking based on average performances. In the DARIA-MARCOS ranking, Cyprus secured the fourth position. While Malta and Cyprus performed similarly in previous years, Malta surpassed Cyprus in the last two years. These recent years are particularly important for stakeholders involved in the adopted strategy. Malta's notable improvement during this period, which Cyprus did not experience, allowed Malta to achieve a higher score and ranking than Cyprus.

Table 3: Results of the DARIA-MARCOS method, including variability, scores, and rankings compared to the classical MARCOS approach.

Country	Var.	Dir. var.	D.-MARCOS sc.	D.-MARCOS rank	MARCOS AVG sc.	MARCOS AVG rank
BEL	0.0013	↑	-0.3386	10	-0.3345	6
BGR	0.0006	↑	-0.8142	25	-0.8230	24
CZE	0.0024	↑	-0.6729	23	-0.7457	23
DNK	0.1267	↑	-0.4738	18	-0.8647	25
DEU	0.0008	↑	-0.3628	14	-0.3924	13
EST	0.1571	↑	-5.0341	29	-6.9588	29
IRL	0.0041	↑	-0.2883	6	-0.3305	5
GRC	0.0030	↑	-0.3253	9	-0.3604	10
ESP	0.0003	↑	-0.3500	11	-0.3692	12
FRA	0.0007	↑	-0.5331	20	-0.6047	20
HRV	0.0017	↑	-0.4386	17	-0.4987	17
ITA	0.0003	↑	-0.3121	8	-0.3351	7
CYP	0.0005	↑	-0.2701	4	-0.2768	4
LVA	0.0020	↓	-0.7288	24	-0.6636	21
LTU	0.0009	↑	-0.3561	13	-0.3618	11
LUX	0.0002	↓	-0.2061	2	-0.2029	2
HUN	0.0021	↑	-0.4192	16	-0.4646	16
MLT	0.0005	↑	-0.2572	3	-0.2716	3
NLD	0.0117	↑	-0.2922	7	-0.4124	14
AUT	0.0077	↑	-0.2720	5	-0.3366	8
POL	0.0035	↑	-0.6198	22	-0.6994	22
PRT	0.0008	↓	-0.3548	12	-0.3540	9
ROU	0.0088	↑	-0.9178	26	-1.0994	27
SVN	0.0012	↑	-0.4820	19	-0.5399	18
SVK	0.0031	↑	-0.3845	15	-0.4534	15
FIN	0.0008	↑	-0.5818	21	-0.5805	19
SWE	0.0074	↑	-1.0049	27	-0.9868	26
ISL	0.0058	↓	-1.8374	28	-1.7806	28
NOR	0.0051	↓	0.2831	1	0.3493	1

Another noteworthy case is Austria, which secured fifth place in the DARIA-MARCOS ranking. Austria's score was better than that obtained through the classical MARCOS method, which relies on averaged data. Austria improved from 7th to 3rd place in the first three years of the analysis, but then experienced a decline, falling to 11th and 14th place in subsequent years. However, in the final significant year, Austria made a notable comeback and rose to 5th place, reflecting a pattern of volatility with overall improvement. In the DARIA-

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MARCOS ranking, this resulted in receiving 5th place by this country. It is important to note that the classical MARCOS method, which is based on averaged data, does not consider variability, the direction of changes, or the specific periods of time during which advancements occurred. As a result, the MARCOS ranking did not adequately recognize Austria's progress, leaving it in a lower 8th place compared to the more nuanced DARIA-MARCOS method.

The case of the Netherlands is particularly interesting. In the DARIA-MARCOS ranking, the country was positioned seventh, while it was significantly lower, in 14th place, in the MARCOS ranking based on averaged data. The DARIA-MARCOS methodology allowed for the inclusion of a notable performance improvement, resulting in a rise from 17th to 7th place. This significant leap in the Netherlands' performance occurred in the most critical year for this analysis, which contributed to its high seventh position in the DARIA-MARCOS ranking.

Belgium has not sufficiently improved its performance over the past year compared to other countries, resulting in a decline from the 7th position to the 10th. The DARIA-MARCOS method reflected this downturn, ranking Belgium at 10th place. In contrast, when averaged data is used without considering these changes, the MARCOS ranking places Belgium at 6th position.

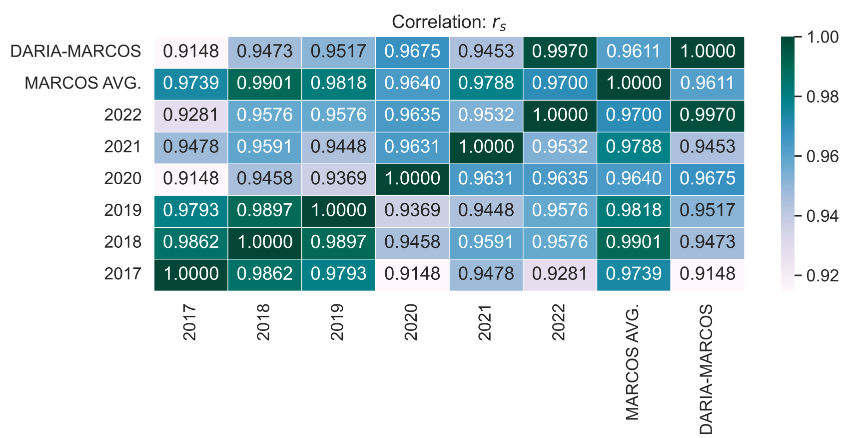

Fig. 1: The convergence of the DARIA-MARCOS rankings compared to classical MARCOS approach.

The DARIA-MARCOS method effectively captures gradual improvements in performance, particularly in the most recent year, leading to higher rankings compared with the traditional MARCOS method. This is evident in countries such as Denmark, Spain, and Greece. Conversely, the DARIA-MARCOS method also identifies deteriorating performance, which results in lower rankings for

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countries experiencing decline, unlike the classic MARCOS method, which does not account for these changes. This trend can be observed in the cases of Latvia and Portugal, for example.

In the aim to analyze the differences in rankings produced by the DARIA-MARCOS method compared to the MARCOS method, both based on averaged and annual data, the Spearman correlation coefficient was applied. The results of this investigation are displayed in Figure 1. The correlation between the DARIA-MARCOS ranking and the MARCOS ranking derived from averaged data is 0.9611. This high correlation indicates that, while the rankings are similar, there are notable differences for certain countries that may rank differently in DARIA-MARCOS due to variations over time. The strongest correlation between the DARIA-MARCOS ranking and the annual MARCOS ranking was observed for the year 2022. This finding aligns with our research assumption that the most recent data is most relevant for policymakers and stakeholders.

5 Discussion

In a recent survey, Norway emerged as the leader in meeting the indicators outlined in the Sustainable Development Goal 7 (SDG 7) strategy. This goal aims to ensure universal access to affordable, reliable, sustainable, and modern energy. Compared to other European countries, Norway is distinguished by its high percentage of renewable energy in total final energy consumption and significant investments in green infrastructure development. These efforts not only advance the objectives of SDG 7 but also serve as a model for other countries pursuing sustainable energy development [13].

The results indicate that the DARIA-MARCOS method effectively captures trends in the variability of alternatives' performance, whether it is improving or deteriorating, and reflects these trends in the final outcomes and rankings. However, further benchmarking studies are necessary to compare performance convergence with results from other multi-criteria methods across multiple periods. Additionally, it would be beneficial to conduct benchmarking studies that assess the impact of different variability measurement methods on the final results. Such studies could help identify the optimal parameters for multi-criteria methods across various periods that enhance the stability of solutions.

6 Conclusions

The research results confirm that the DARIA-MARCOS method effectively represents the performance variability of alternatives over different periods of time in the final ranking. For MCDA extensions that consider result variability across multiple periods, the final outcomes are affected by the type of algorithm used in the MCDA method's temporal approach and the variability measure applied.

Future work should focus on developing extensions for other Multi-Criteria Decision Analysis (MCDA) methods that enable them to account for multiple

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periods included in the analysis simultaneously. This includes a precise evaluation of the significance of individual periods in the newly developed approaches. Additionally, benchmarking studies should be conducted to compare the effects of various temporal MCDA extensions and the measures of variability on performance.

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