A Novel Multi-Criteria Temporal Decision Support Method - Sustainability Evaluation Case Study

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Abstract. Moving toward a sustainable society requires the development of reliable indices, indicators, and computational methods that supply the tools, such as decision support systems used in assessing the achievement of sustainable development goals. The aim of this paper is to present an intelligent decision support system that enables multi-criteria evaluation, taking into account the temporal variability of the performance of the assessed alternatives. The framework of this DSS is based on the method called Data vARIability Assessment - Measurement of Alternatives and Ranking according to COmpromise Solution (DARIA-MARCOS). The proposed method was used for an exemplary multi-criteria analysis problem concerning the implementation of the sustainable development goals included in Sustainable Development Goal 11 (SDG 11), focused on sustainable cities and communities. SDG 11 aims to develop toward making cities and human settlements inclusive, safe, resilient, and sustainable. The methodical framework implemented in the demonstrated DSS ensures an efficient, automatized, and objective assessment of a multi-criteria temporal decision-making problem and gives an unequivocal, clear outcome. The results proved the usability of the developed DSS in the multi-criteria temporal evaluation of sustainable development focused on sustainable cities and communities.

Keywords: decision support system · sustainability assessment · multi-criteria temporal assessment · sustainable society · DARIA-MARCOS

1 Introduction

Innovative models, algorithms, and tools involving the implementation of computational methods provide important contributions to the field of sustainability development assessment [2]. The implementation of sustainable development,

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evaluation of this process, and monitoring progress require the development of indicators, indexes, and measurement instruments [3]. Indicators for assessing the implementation of Sustainable Development Goals (SDGs) are a reliable data source. Hence, their use is recommended [10]. Indicators for assessing the sustainable development of the SDGs were officially developed by the United Nations in 2015 with a group of experts [8]. As a result, the development of analytical tools for assessing the achievement of sustainable development goals is essential. From a technical point of view, multiple frameworks, interpretability, and selection of indicators justify the need to use decision support systems (DSSs) powered by objective computational methods for this purpose [5]. The multitude of indicators that need to be considered in sustainability assessment justifies using multi-criteria decision analysis methods (MCDA) in DSS [9]. MCDA methods evaluate compromises between several quantitative and qualitative criteria and facilitate complex decisions [7]. However, MCDA methods evaluate alternatives against a set of criteria for a situation at a single moment in time [12]. This justifies the need to develop methods that take into account the dynamics of results over time [13].

The aim of this research is to present an intelligent decision support system that allows multi-criteria evaluation, considering the temporal variability of the performance of the assessed alternatives. The purpose of the authors is to develop a multi-criteria approach that provides the opportunity to simultaneously include in evaluating the performance of a given time interval in subsequent years, along with the dynamics of fluctuation. The framework of this DSS is based on the method named Data vARIability Assessment - Measurement of Alternatives and Ranking according to COmpromise Solution (DARIA-MARCOS). The classic MARCOS (Measurement of Alternatives and Ranking according to COmpromise Solution) method is employed in the developed DARIA-MARCOS method as a module for the annual assessment of alternatives. Based on the obtained annual utility function values in the DARIA-MARCOS method, parameters such as the value and direction of the variability of annual scores of alternatives used in the next stages of DARIA-MARCOS are then determined. The MARCOS method is based on defining the relationship between alternatives and reference solutions, which are ideal and anti-ideal solutions [28]. Based on the defined relationships, the utility functions of the alternatives are determined, and a ranking of the compromises with respect to the ideal and anti-ideal solutions is created. Utility functions represent the position of an alternative concerning the ideal and anti-ideal solution. The best alternative is the one that is closest to the ideal and, at the same time, furthest from the anti-ideal reference point [21].

The DARIA-MARCOS method gives the possibility of the evaluation of alternatives with simultaneous consideration of multiple assessment criteria and the temporal aggregation of the achieved scores into a single unambiguous score presented as utility function values and rankings. Therefore, the proposed DSS is developed to provide a complete automated assessment, not requiring engagement analysts to assess the variability of performances over time. The demonstrated

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tool automatically considers the temporality of annual scores. The automatic incorporation of variability in the final stage gives reliable results that would be difficult in the case of subjective analysis of individual scores from following years by analysts without the support of supplementary computational methods.

The application of the proposed DSS was shown in this research through the example of a multi-criteria temporal assessment of Sustainable Development Goal 11 (SDG 11) implementation by selected European countries. SDG 11 was introduced by the United Nations (UN) in the 2030 Agenda for Sustainable Development. It was approved by all United Nations Member States in 2015 [22,24]. SDG 11 encourages making cities and human settlements safe, stable, sustainable, and inclusive [18]. According to the assumptions of SDG 11, cities should develop towards the creation of safe, stable, and sustainable inclusive settlements [15]. At the same time, countries must improve resource efficiency, strive to reduce pollution, and counter poverty [11]. One such example is improving municipal waste management. In the future, cities should provide equal opportunities for all people and access to basic services, energy, housing, transportation, and more [4].

The proposed system powered by the DARIA-MARCOS method can find application in assessing the achievement of the targets contained in SDG 11 by European countries in any chosen time frame, giving a view of the trend of progress or regression in development with respect to sustainable cities and communities, compared to other countries.

The rest of the paper is organized as follows. Section 2 provides the literature review including related works focused on existing multi-criteria methods considering temporality in assessment. Section 3 presents the methodology of the research performed. Research results are demonstrated and discussed in section 4. In the end, in section 5, conclusions are stated, and directions for further work are indicated.

2 Related works

The necessity of applying a temporal approach when evaluating multi-criteria problems requiring consideration of multiple periods is emphasized in several research papers. Martins and Garcez conducted a multidimensional and multi-period assessment of road safety using an aggregation of various road safety indicators recorded for different periods [16]. The authors used the Multi-criteria Multi-Period Outranking Method (MUPOM) proposed by Frini and Amor [12]. The MUPOM method belongs to the outranking methods, thus it considers the sustainability requirements [25]. The application of the proposed method is presented using the example of selecting the most favorable scenario for sustainable forest management. Sustainability assessment problems require consideration of complexity involving multiple criteria and periods. This challenge was successfully addressed by Urli, Frini, and Amor, who, in their research work, proposed the PROMETHEE-MP (PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) for Multi-Period) method based on

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a double aggregation involving multi-criteria aggregation and temporal aggregation [23]. The practical application of the proposed approach was demonstrated for the problem of evaluating sustainable forest management. A temporal extension of the PROMETHEE II method was used to create a ranking of emerging economies in terms of HDI (Human Development Index) in the work of Banamar and Smet [6]. The method is based on aggregating scores over time using an arithmetic mean. Another outranking method, considering both temporality and uncertainty, is the SMAA-TRI generalization based on the ELECTRE TRI (ELimination and Choice Expressing the Reality TRI) method proposed by Mouhib and Frini presented for a problem of temporal assessment of sustainable development in forest management [17]. In addition to outranking methods, another approach that takes into account temporality in multi-criteria evaluation is the multi-period single synthesizing criterion approach based on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method proposed by Frini and Benamor [13]. The presented temporal extension of the TOPSIS method was applied for multi-period assessment of forest management.

However, the methods discussed have some limitations. Temporal extensions of PROMETHEE, such as PROMETHEE-MP and MUPOM, require a complex computational procedure, including multiple aggregations, which makes these algorithms complicated to apply [12, 23]. The SMAA-TRI procedure also requires repetition [17]. The temporal extension of TOPSIS is a more straightforward method than the cited temporal outranking approaches. However, it requires performing a double TOPSIS procedure, first for periods, then for the results achieved for periods. It also has the disadvantage of needing clear rules for determining the weights of periods [13]. Therefore, the authors in the present work aimed to develop an approach that considers a multiplicity of criteria and periods in sustainability assessment that will be simple and, at the same time, automatically take into account the variability of results over time using clear rules.

3 Methodology

This section presents methodical aspects of the proposed DSS, including a novel methodology called DARIA-MARCOS and a multi-criteria assessment model regarding targets incorporated in SDG 11. The proposed DARIA-MARCOS method was applied in this research to evaluate 27 selected European countries against implementing the goals included in the Sustainable Development Goal 11 (SDG 11) framework focused on sustainable cities and communities. SDG 11 is among one of the seventeen SDGs aimed at promoting sustainable development in various aspects set in the 2030 Agenda by the United Nations in 2015. SDG 11 aims to develop toward making cities and human settlements inclusive, safe, resilient, and sustainable. Since the world's population is constantly increasing, it is essential to accommodate everyone and build modern, sustainable cities. Intelligent urban planning creates safe, affordable, and resilient cities with green

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and culturally inspiring living conditions. The particular nine targets included in SDG 11 are listed in Table 1.

Table 1: Multi-criteria model of assessment in relation to the achievement of SDG 11 goals.

Criterion	Description	Unit	Aim
C_1	Severe housing deprivation rate	Percentage	$\downarrow$
C_2	Population living in households considering that they suffer from noise	Percentage	$\downarrow$
C_3	Settlement area per capita	Square metres per capita	$\uparrow$
C_4	Road traffic deaths - considering total type of roads	Rate	$\downarrow$
C_5	Premature deaths due to exposure to fine particulate matter (PM2.5)	Rate	$\downarrow$
C_6	Recycling rate of municipal waste	Percentage	$\uparrow$
C_7	Population connected to at least secondary wastewater treatment	Percentage	$\uparrow$
C_8	Share of buses and trains in inland passenger transport	Percentage	$\uparrow$
C_9	Population reporting occurrence of crime, violence or vandalism in their area	Percentage	$\downarrow$

3.1 The DARIA-MARCOS Method

This section provides the basics and assumptions of the newly developed multi-criteria temporal DARIA-MARCOS. Software developed for the proposed DSS, including, among other items, a DARIA class providing five methods for determining variability, including the entropy and datasets used in this study, is available in an open GitHub repository at link `https://github.com/energyinpython/DARIA-MARCOS`. Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) method included in stages of the DARIA-MARCOS is described based on [21].

Step 1. Create a decision matrix defined by $X^p = [x_{ij}^p]_{m \times n}$ with performance values of m alternatives concerning n criteria for each evaluated period of time, where following periods are represented by $p = 1, 2, \ldots, t$ and t denotes number of time periods evaluated. Single decision matrix for a single period of time is presented in Equation (1).

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

Step 2. Extend each decision matrix created for partical period of time p by ideal (AI^p) and anti-ideal (AAI^p) solutions as shown in Equation (2)

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

The anti-ideal solution (AAI^p) is the worst alternative and the ideal solution (AI^p) is the best alternative. AAI^p is determined according to Equation (3) and AI^p is established with Equation (4), where B denotes profit criteria and C represents 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. Normalize the extended initial matrix X^p. Normalized matrix $N^p = [n_{ij}^p]_{m+2\times n}$ are calculated using Equations (5) for cost criteria and (6) for profit criteria, where x_{ij} and x_{ai} are elements of extended 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. Calculate the weighted matrix $V^p = [v_{ij}^p]_{m+2\times n}$ by multiplying the normalized matrix N by criteria weight values w_j^p for j-th criterion, according to Equation (7). Criteria weights can be determined subjectively by decision-makers or by using objective weighting methods that determine weights based on a decision matrix. In this research, criteria weights were determined using the objective weighting method called CRITIC (Criteria Importance Through Inter-criteria Correlation) method for objective determination of criteria weights [1].

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

Step 5. Calculate the utility degree of alternatives K_i^p with Equations (8) and (9), where S_i^p $(i = 1, 2, \ldots, m)$ denotes the sum of the elements in the weighted matrix V^p calculated by Equation (10).

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

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

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

Step 6. Determine the utility function of alternatives $f(K_i^p)$. The utility function is the compromise of a given alternative in relation to the ideal and anti-ideal solution. The utility function of alternatives is represented 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 $f(K_i^{p-})$ denotes the utility function in relation to the anti-ideal solution. On the other hand, $f(K_i^{p+})$ denotes the utility function in relation to the ideal solution. Utility functions in relation to the ideal and anti-ideal solutions are established using 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. Construct the matrix $S = [s_{pi}]_{t \times m}$ shown in Equation (14) containing annual MARCOS utility function values of alternatives s_{pi} (for MARCOS method they are represented by K_i^p) collected for t periods in rows, where following periods are numbered by $p = 1, 2, \ldots, t$ and m alternatives a in columns, where subsequent alternatives are numbered by $i = 1, 2, \ldots, m$. Subsequent periods are represented 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. Calculate the variability of obtained scores in matrix S received using the MARCOS method for each assessed period. The variability value is calculated using the entropy method [27] provided in steps 8.1-8.3. Entropy was selected for measuring variability as the most common objective method. Entropy measures uncertainty and provides a quantitative measure of information content.

Step 8.1. Normalize matrix S using sum normalization method to get normalized matrix $K = [k_{pi}]_{t \times m}$ where $p = 1, 2, \ldots, t$ and $i = 1, 2, \ldots, m$, t represents periods number and m denotes alternatives number.

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

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Step 8.2. Calculate the entropy value E_i for each ith alternative according to Equation (16) [27].

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

Step 8.3. Calculate the variability value represented by d_i as Equation (17) shows.

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

Step 9. Determine the direction of score variability. The threshold value provided in Equation (19) with Equation (18) is employed to calculate the variability direction for each 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 received for the most recent period t is updated with the value of the variability of scores d_i in all investigated periods according to its direction using Equation (20),

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

where S_i defines the score achieved by given alternative a_i updated by adding variability values multiplied by variability direction, S_i^t represents the score of given alternative a_i reached in the most recent period t investigated, d_i represents values of the variability of alternative's a_i scores over all analyzed periods $p = 1, 2, \ldots, t$ calculated using entropy method, and dir_i defines directions of variability d_i, which may be equal to 1 for increasing scores, -1 for decreasing scores or 0 for stable scores. Alternatives are defined by a_i $(i = 1, 2, \ldots, m)$.
Step 11. The purpose of the final step is to rank the alternatives according to the final scores S following the descending order as for the MARCOS method.

4 Results

This section provides results given by the DARIA-MARCOS method. In the first stage, individual evaluation of each year was carried out. The list of European countries evaluated in this research is provided in Table 2. The selection of just these 27 countries is justified by the availability of data against all criteria of the SDG 11 framework. The analysis considers the most recent seven years (2015-2022) for which data is available in the Eurostat database. The data were accessed on 23 January 2024. Table 2 presents sample performance values of

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evaluated countries collected for 2022. The datasets for the other years included in the analysis are made available in an open GitHub repository.

Table 2: Sample dataset with performances regarding implementation of targets included in SDG 11 collected for 2022.

Country	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Belgium	2.3	14.5	583.5	4.6	44	55.5	84.03	14.4	10.8
Bulgaria	8.6	8.8	623.4	8.2	158	28.2	65.05	10.1	19.1
Czechia	2	13.3	634.4	5.1	81	43.3	84.7	15	6.1
Denmark	2.8	18.2	1053.8	2.6	21	57.6	97.8	13.3	7.3
Germany	1.2	21.6	586.7	3.3	39	67.8	96.32	11.2	8.2
Estonia	2.1	8	1484.4	3.6	7	30.3	82	10.7	5.5
Ireland	1.4	10.3	972.7	2.7	9	40.8	62.3	14.3	11.3
Greece	5.8	20.1	710.2	5.9	95	21	94.7	12.9	18.1
Spain	3.4	21.9	577.5	3.2	30	36.7	86.93	12.6	14.1
France	3.8	20.7	845.1	4.8	30	43.8	79.85	14	17.7
Croatia	5.1	8.1	722.5	7.4	96	31.4	31.39	11.2	2.4
Italy	6.1	14.3	484.3	5.4	79	51.9	59.6	17.2	8.4
Cyprus	1.6	14	939	5	70	15.3	83.48	12.7	10.4
Latvia	11.5	12.5	1276.1	7.8	75	44.1	76.48	11.5	5.3
Lithuania	5.4	14.7	1090.5	4.2	77	44.3	76.94	5.3	3.3
Luxembourg	1.6	19.7	565.2	5.5	12	55.3	97	13.7	11
Hungary	7.6	9.3	811.5	5.6	107	34.9	84.23	20.7	5.3
Malta	1	30.8	201.4	1.7	37	13.6	7.4	14.1	11.4
Netherlands	1.5	25.5	456.9	2.9	32	57.8	99.52	10.6	15.7
Austria	3	16.8	740.1	4.1	36	62.5	99.1	18.8	5.7
Poland	7.9	12.6	633.7	5.9	125	40.3	75.2	13.7	4.4
Portugal	3.9	25.1	689.1	5.4	20	30.4	55.8	8.7	6.6
Romania	14.3	16.1	528.4	9.3	103	11.3	52.6	17	8.8
Slovenia	3.1	15	625.1	5.4	56	60.8	67.61	10	7.3
Slovakia	3.2	9.9	631.8	4.9	98	48.9	69.9	16.3	4.3
Finland	1	14.1	2447.6	4.1	3	39	85	12.3	7
Sweden	2.5	17.3	2223	2	6	39.5	96	15.9	13.8

Results of DARIA-MARCOS comprise variability value of annual scores, direction of variability, DARIA-MARCOS utility function value and final ranking. Mentioned results are included in Table 4. It can be noted that Malta achieved the highest variability of annual performance toward improvement (0.00298). As a result, even though Malta was ranked 26th in 2015-2019, the improvement in 2020-2022 resulted in the country moving up to rank 24 in 2020 and up to rank 23 in 2021-2022 and achieving rank 23 in the temporal ranking of DARIA-MARCOS. The DARIA-MARCOS gives greater relevance to these most recently evaluated years because it is the most important from the perspective of policy-makers and stakeholders. Results involving utility function values of alternatives

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for each year and annual rankings created based on utility function values are displayed in Table 3.

Table 3: Annual MARCOS utility function values and ranks.

Country	Utility function values								Ranks							
	2015	2016	2017	2018	2019	2020	2021	2022	2015	2016	2017	2018	2019	2020	2021	2022
Belgium	0.455	0.458	0.445	0.463	0.462	0.454	0.459	0.457	9	10	12	15	16	14	14	14
Bulgaria	0.361	0.357	0.365	0.371	0.384	0.372	0.351	0.350	22	23	23	23	23	23	24	24
Czechia	0.407	0.426	0.448	0.456	0.472	0.482	0.467	0.467	18	14	11	16	12	10	11	11
Denmark	0.522	0.525	0.511	0.536	0.500	0.486	0.533	0.519	4	4	5	5	6	9	5	7
Germany	0.464	0.485	0.474	0.480	0.476	0.520	0.524	0.520	7	7	8	10	11	5	6	6
Estonia	0.510	0.521	0.583	0.564	0.595	0.551	0.564	0.571	5	5	4	4	4	3	3	3
Ireland	0.573	0.593	0.621	0.656	0.602	0.515	0.539	0.538	3	3	3	2	3	6	4	4
Greece	0.341	0.342	0.342	0.362	0.350	0.342	0.334	0.334	24	24	24	24	24	25	26	26
Spain	0.449	0.457	0.483	0.473	0.466	0.397	0.395	0.394	10	11	7	11	15	21	22	22
France	0.423	0.420	0.426	0.440	0.433	0.395	0.400	0.395	11	15	15	18	21	22	21	21
Croatia	0.413	0.416	0.419	0.464	0.477	0.472	0.461	0.460	14	17	17	14	10	11	13	13
Italy	0.359	0.377	0.396	0.438	0.427	0.406	0.411	0.407	23	21	21	19	22	20	19	20
Cyprus	0.407	0.377	0.387	0.435	0.433	0.412	0.408	0.408	17	22	22	20	20	19	20	19
Latvia	0.389	0.393	0.397	0.400	0.446	0.429	0.432	0.432	20	20	20	22	17	17	16	16
Lithuania	0.392	0.460	0.407	0.464	0.469	0.434	0.440	0.448	19	9	19	13	13	15	15	15
Luxembourg	0.416	0.446	0.443	0.468	0.483	0.469	0.497	0.481	13	12	13	12	9	12	9	10
Hungary	0.421	0.440	0.454	0.527	0.501	0.490	0.482	0.482	12	13	10	6	5	8	10	9
Malta	0.318	0.267	0.290	0.325	0.314	0.354	0.375	0.373	26	26	26	26	26	24	23	23
Netherlands	0.480	0.487	0.499	0.491	0.468	0.455	0.466	0.465	6	6	6	9	14	13	12	12
Austria	0.459	0.481	0.471	0.509	0.498	0.520	0.523	0.522	8	8	9	7	7	4	7	5
Poland	0.408	0.408	0.409	0.420	0.435	0.415	0.426	0.425	16	19	18	21	19	18	18	18
Portugal	0.318	0.337	0.323	0.358	0.337	0.316	0.338	0.337	25	25	25	25	25	26	25	25
Romania	0.255	0.260	0.271	0.285	0.297	0.305	0.294	0.293	27	27	27	27	27	27	27	27
Slovenia	0.410	0.419	0.432	0.455	0.437	0.430	0.426	0.426	15	16	14	17	18	16	17	17
Slovakia	0.381	0.414	0.421	0.496	0.496	0.510	0.500	0.496	21	18	16	8	8	7	8	8
Finland	0.691	0.738	0.740	0.708	0.727	0.695	0.684	0.686	1	1	1	1	1	1	1	1
Sweden	0.647	0.640	0.632	0.640	0.638	0.580	0.597	0.597	2	2	2	3	2	2	2	2

It can be observed that Finland is the leader of all annual rankings for the years included in this analysis. This confirms Finland's strong and stable position over the seven years investigated. On the other hand, the last rank in all the annual rankings received in the research is held by Romania, which indicates the country's poor implementation of the goals of SDG 11 compared to the other countries analyzed.

The cases presented above show that temporal analysis of the performance of countries such as Finland and Romania, whose performance in all years is maintained at constant positions, is easy to carry out using classical MCDA methods that give results for single moments in examined time. However, it can be observed that a high variability of results over the time range studied is evident in the significant majority of the countries considered. This variability is expressed in variable utility function values achieved by countries in subsequent years, as reflected in shifts in rankings. In such situations, in order to obtain a single unambiguous and easy-to-interpret result that takes into account the

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full range of time under study, additional computational methods are needed to complement classical MCDA methods.

Table 4: Results of temporal assessment performed with DARIA-MARCOS.

Country	Variability	Direction	Score	Rank	Country	Variability	Direction	Score	Rank
Belgium	0.00003	↑	0.4574	14	Lithuania	0.00084	↑	0.4488	15
Bulgaria	0.00021	↓	0.3502	24	Luxembourg	0.00067	↑	0.4815	10
Czechia	0.00065	↑	0.4673	11	Hungary	0.00111	↑	0.4826	9
Denmark	0.00022	↓	0.5190	7	Malta	0.00298	↑	0.3762	23
Germany	0.00051	↑	0.5207	6	Netherlands	0.00021	↓	0.4647	12
Estonia	0.00059	↑	0.5714	3	Austria	0.00053	↑	0.5220	5
Ireland	0.00141	↓	0.5370	4	Poland	0.00012	↑	0.4251	18
Greece	0.00015	↓	0.3339	26	Portugal	0.00035	↑	0.3378	25
Spain	0.00158	↓	0.3922	22	Romania	0.00088	↑	0.2940	27
France	0.00037	↓	0.3947	21	Slovenia	0.00020	↑	0.4262	17
Croatia	0.00077	↑	0.4612	13	Slovakia	0.00252	↑	0.4982	8
Italy	0.00086	↑	0.4079	20	Finland	0.00023	↓	0.6860	1
Cyprus	0.00050	↑	0.4084	19	Sweden	0.00037	↓	0.5962	2
Latvia	0.00060	↑	0.4327	16					

Slovakia (0.00252) was another country that received a large variability towards improvement. Slovakia was ranked 21st in 2015 but performed much better in subsequent years, which enabled the country to be ranked 7th-8th in 2018-2022. Slovakia's improved performance promoted the country to eighth place in the DARIA-MARCOS temporal ranking. A different situation due to high variability in performance towards worsening (0.00158) occurs for Spain. Spain ranked 7-11 in 2015-2018, dropped to 15th in 2019, 21st in 2020, and 22nd in 2021-2022. The significance of the most recent year, decreasing annual performances, and a drop in subsequent rankings caused Spain to rank only 22nd in the final DARIA-MARCOS temporal ranking. If the variability is minor, then even if it is associated with worsening, it will not result in a degradation of the DARIA-MARCOS ranking, as in the case of Sweden. For this country, there was a variability of 0.00037 toward worsening, which is nevertheless small enough that Sweden maintained its second place with annual rankings in the DARIA-MARCOS temporal ranking. Other countries can be analyzed analogously to the examples discussed.

Finally, the comparative analysis involving determining the correlation for the following annual rankings and the temporal DARIA-MARCOS ranking was performed in order to compare the convergence between them. For this aim, the Weighted Spearman correlation coefficient r_w was employed [26]. Results are visualized in the form of a heatmap in Figure 1. It can be outlined that the DARIA-MARCOS ranking involving six analyzed years 2015-2022 demonstrates the lowest convergence for the ranking generated for the very earliest year in the investigation. On the other hand, for the successive years investigated, the correlation grows. In the end, the highest correlation is noticed when comparing

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the DARIA-MARCOS ranking with the annual ranking generated for the most recent year, 2022. This is proved by the fact that in the temporal DARIA-MARCOS method employed in this research, the most recent period is the most important, which is updated with the variability of the scores for the successive years analyzed. In the approach of this novel method, the highest significance of the most recent year was established, as this is the period of most importance and interest to decision-makers and stakeholders from the perspective of sustainable development.

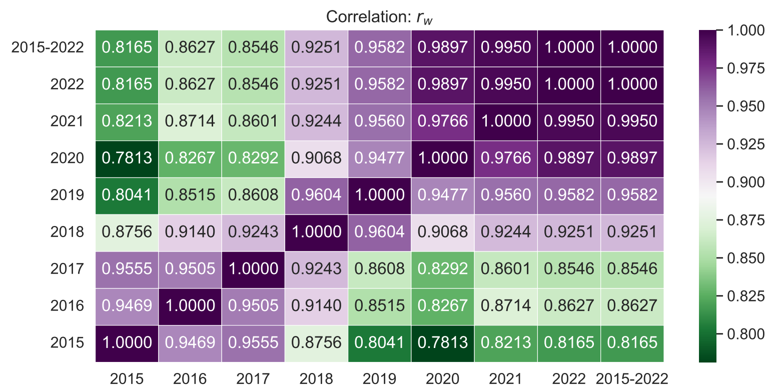

Fig. 1: r_w correlation of the DARIA-MARCOS ranking with annual rankings.

However, in accordance with individual analytical requirements for particular decision-making problems, the DARIA-MARCOS method is adaptable, and its idea enables this concept to be easily modified. Creating the final score may include updating the average score of all periods instead of the score achieved for the most recent period. Measures of variability other than entropy, such as the Gini coefficient [14], standard deviation [20], and statistical variance [19] can also be used to measure variability in performance.

5 Conclusions

The research work demonstrated in this paper a novel method DARIA-MARCOS employed in DSS for multi-criteria temporal assessment of any decision problem. The practical application of the presented DSS was shown using a practical example of evaluation of the implementation of targets included in SDG 11, which calls for making cities and human settlements inclusive, safe, resilient, and sustainable. A multi-criteria temporal assessment employing DARIA-MARCOS was performed for selected European countries in the time interval covering eight years, 2015-2022. The methodical framework implemented in the demonstrated DSS ensures an efficient, automatized, and objective assessment of a

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multi-criteria temporal decision-making problem and gives an unequivocal, clear outcome. The results proved the usability of the developed DSS in the multi-criteria temporal evaluation of sustainable development focused on sustainable cities and communities. The comparative analysis demonstrated that the results delivered by the presented DSS are reliable. Therefore, it can also be employed for multi-criteria temporal evaluation in other development areas.

Advantages of the proposed method over other existing temporal approaches include low computational complexity due to the lack of need to perform multiple aggregations, the use of a measure of variability to aggregate results that reflects variability over time more adequately than simple methods such as the arithmetic mean, the lack of need to determine the significance of individual periods, and the possibility of expanding the approach in the future to include measures of variability other than entropy. The DARIA-MARCOS method can be a valuable tool for researchers and practitioners, as it reflects the impact of data variability on the final form of the model. Replacing oversimplifications that smooth out variability over time introduces new analytical possibilities into the model. Directions for further work involve developing multi-criteria temporal methods based on other multi-criteria decision analysis (MCDA) methods and measures of variability and comparative analysis of the results.

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