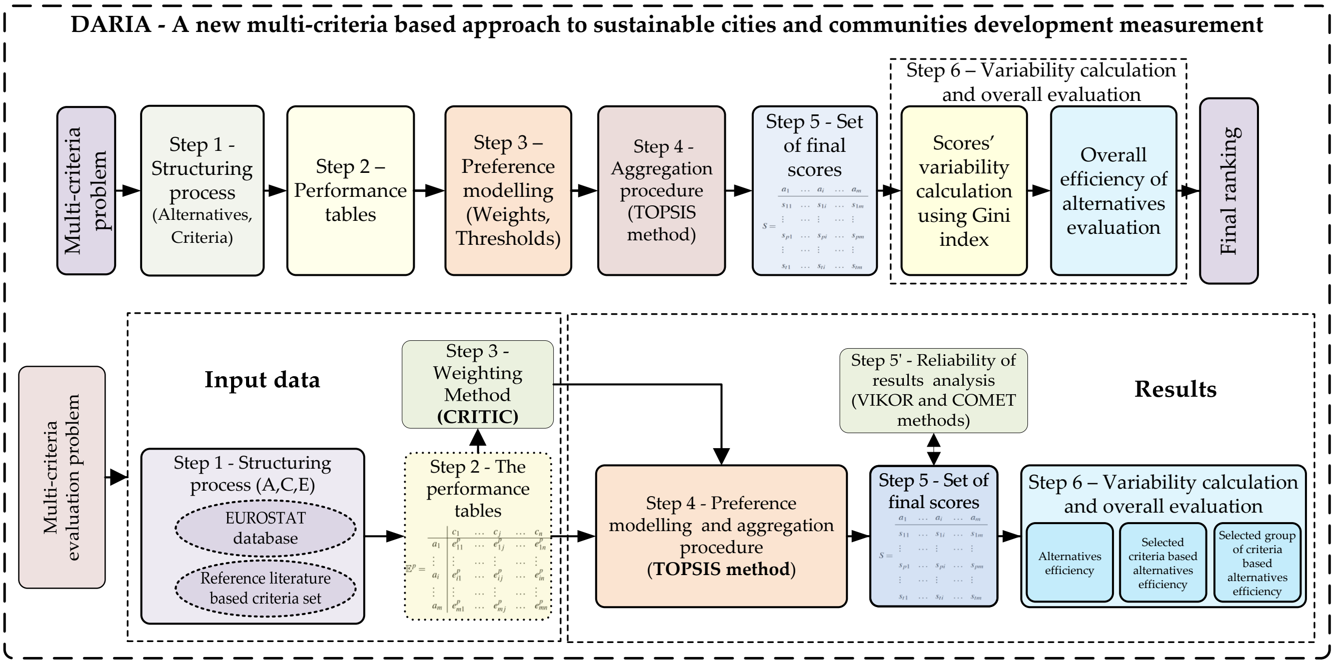
Graphical Abstract

Sustainable cities and communities assessment using the DARIA-TOPSIS method



Sustainable cities and communities assessment using the DARIA-TOPSIS method

Abstract

Effective evaluation of cities' and communities' sustainability is an important aspect of sustainable development. From a methodological point of view, Multi-Criteria Decision Analysis (MCDA) methods proved their usability in the sustainability evaluation domain. The main reason for the popularity of MCDA methods in the sustainability assessment domain is the accurate incorporation of a complex set of often contrasting criteria into a single assessment model. On the other hand, the process of building a model in the classical MCDA paradigm is based on a single set of input data. This may lead to oversimplification, especially in the domain of sustainability, in which, in addition to the current assessment, it is also important to know the dynamics of sustainability change over time. Therefore, this paper proposes an innovative sustainability assessment method that integrates the MCDA approach with the variability of the alternatives' performance measurement called Data vARIability Assessment Technique for Order of Preference by Similarity to Ideal Solution (the DARIA-TOPSIS method). In practical terms, the DARIA-TOPSIS method was used in sustainable cities and communities development measurement for 26 European countries. Time-based analyses conducted using the DARIA-TOPSIS method for aggregated data (countries) and individual sustainability dimensions and alternatives proved usefulness, suitability, and effectiveness in any sustainability assessment problem of the proposed method.

Appendix A. Preliminaries

Appendix A.1. The COMET Method

COMET is an MCDA method based on fuzzy set theory that utilizes characteristic objects (*COs*) distributed in the problem space. *COs* are determined as a combination of characteristic values for each evaluation criteria. This procedure determines the preference for each alternative by calculating the distance from the characteristic objects and their values. Then, the degree of preference for each alternative is determined using fuzzy inference. The preference values range from 0 to 1. The closer the preference value is to 1, the more preferred the object is. The COMET method consists of five steps presented in the following steps, based on [1].

Step 1. The expert's task is to define the problem's dimensionality under consideration by selecting r criteria $C_1, C_2, \dots, C_r$. Then, for each criterion C_i, a set of triangular fuzzy numbers i.e., $\tilde{C}_{i1}, \tilde{C}_{i2}, \dots, \tilde{C}_{ic_i}$ is determined to represent the domain's characteristic values under consideration. The specified set of triangular numbers is shown in Equation (A.1)

$$\begin{array}{c} C_1 = \{\tilde{C}_{11},\, \tilde{C}_{12},\, \dots,\, \tilde{C}_{1c_1}\} \\ C_2 = \{\tilde{C}_{21},\, \tilde{C}_{22},\, \dots,\, \tilde{C}_{2c_2}\} \\ \dots \\ C_r = \{\tilde{C}_{r1},\, \tilde{C}_{r2},\, \dots,\, \tilde{C}_{rc_r}\} \end{array} \tag{A.1}$$

where $c_1, c_2, \dots, c_r$ represent numbers of the fuzzy numbers for all criteria.

Step 2. The objective of this step is to generate characteristic objects as Cartesian Product of triangular fuzzy number cores assigned to each criterion. This procedure is expressed by Equation (A.2)

$$CO = C(C_1) \times C(C_2) \times \dots \times C(C_r) \tag{A.2}$$

In effect, the ordered set of *COs* shown by Equation (A.3) is obtained

$$\begin{array}{l} CO_1 = \{C(\tilde{C}_{11}),\, C(\tilde{C}_{21}),\, \dots,\, C(\tilde{C}_{r1})\} \\ CO_2 = \{C(\tilde{C}_{11}),\, C(\tilde{C}_{21}),\, \dots,\, C(\tilde{C}_{r2})\} \\ \dots \\ CO_t = \{C(\tilde{C}_{1c_1}),\, C(\tilde{C}_{2c_2}),\, \dots,\, C(\tilde{C}_{rc_r})\} \end{array} \tag{A.3}$$

where t denotes *COs* number calculated by Equation (A.4). The number of necessary comparisons is expressed by the formula $p = \frac{t(t-1)}{2}$, since for each element $\alpha_{i,j}$ it can be noticed that $\alpha_{j,i} = 1 - \alpha_{i,j}$.

$$t = \prod_{i=1}^{r} c_i \tag{A.4}$$

Step 3. At this stage, the expert compares pairwise characteristic objects filling the *MEJ* matrix (Matrix of Expert Judgement) based on specialized knowledge of the problem being solved. The structure of the *MEJ* is represented by the Equation (A.5)

$$MEJ = \begin{pmatrix} \alpha_{11} & \alpha_{12} & \dots & \alpha_{1t} \\ \alpha_{21} & \alpha_{22} & \dots & \alpha_{2t} \\ \dots & \dots & \dots & \dots \\ \alpha_{t1} & \alpha_{t2} & \dots & \alpha_{tt} \end{pmatrix} \tag{A.5}$$

where $\alpha_{i,j}$ denotes effect of CO_i and CO_j comparison. If one object is preferred, it gains one point, while the other object gets zero points. If both objects are judged equally, they are scored with a value of 0.5. The procedure for evaluating characteristic objects is shown in Equation (A.6)

$$\alpha_{ij} = \begin{cases} 0.0, & f_{exp}(CO_i) < f_{exp}(CO_j) \\ 0.5, & f_{exp}(CO_i) = f_{exp}(CO_j) \\ 1.0, & f_{exp}(CO_i) > f_{exp}(CO_j) \end{cases} \tag{A.6}$$

where f_{exp} denotes an expert judgement function. Based on the completed MEJ, a vertical vector of Summed Judgements SJ is calculated according to Equation (A.7).

$$SJ_i = \sum_{j=1}^{t} \alpha_{ij} \tag{A.7}$$

The preference values for COs are then calculated using SJ according to the following pseudocode.

```
1: k = length(unique(SJ));
2: P = zeros(t, 1);
3: for i = 1 : k
4:     ind = find(SJ == max(SJ));
5:     P[ind] = (k - i) / (k - 1);
6:     SJ[ind] = 0;
7: end;
```

In line 1, k denotes the number of all unique values included in the vector SJ, respective to the number of positions in the ranking. Then, in line 2, a vector P including zeros with identical dimensions as the vector SJ is generated. Then, in line 4, the maximum value index in the SJ vector is sought. After that, in line 5, a preference value based on Laplace's indifference principle is placed in vector P at the same position as the obtained index. In the end, in line 6, the maximum value in the SJ vector is reset. Finally, a vertical vector P is received, where the i-th row includes the approximate value of utility function assigned to CO_i.

Step 4. The rule base is created by transforming the characteristic objects and utility values into a fuzzy rule. In generated rule base degree of membership to particular fuzzy sets gives the premise for activation of inference in the form of P. Described procedure is demonstrated by Equation (A.8).

$$IF\ C(\tilde{C}_{1i})\ AND\ C(\tilde{C}_{2i})\ AND\ \ldots\ THEN\ P_i \tag{A.8}$$

As a result, a complete rule base is derived that represents the expert $f_{exp}(CO_i)$ judgment function.

Step 5. Each alternative is defined as a set of crisp numbers $A_i = \{\alpha_{1i}, \alpha_{2i}, \ldots, \alpha_{ri}\}$ that correspond to criteria $C_1, C_2, \ldots, C_r$, where values of subsequent attributes $a_{1i}, a_{2i}, \ldots, a_{ri}$ are determined by respect to condition presented in Equation (A.9).

$$\begin{array}{l} a_{1i} \in [C(\tilde{C}_{11}), C(\tilde{C}_{1c_1})] \\ a_{2i} \in [C(\tilde{C}_{21}), C(\tilde{C}_{2c_2})] \\ \ldots \\ a_{ri} \in [C(\tilde{C}_{r1}), C(\tilde{C}_{rc_r})] \end{array} \tag{A.9}$$

Each alternative activates a certain number of rules, for which activation degree is calculated as the product of all the premises' degrees of membership. Next, each alternative's preference value is calculated as the sum of the product of all activated rules' activation degrees and the preference values assigned to them. The final ranking of alternatives is determined by sorting preference degrees in descending order.

Appendix A.2. The VIKOR Method

VIKOR is a method that, similarly to TOPSIS, is based on distance measurement, but in this case, the preferences of alternatives are calculated based on the measurement of the distance from the reference solution, which is the ideal solution. In the case of VIKOR, in contrast to TOPSIS and COMET, alternatives are ranked in ascending order of preference values. The stages of the VIKOR method are provided below, based on [2].

Step 1. For each criteria functions the best f_j^* and the worst f_j^- values are determined, separately for profit (A.10) and cost (A.11) criteria.

$$f_j^* = \max_i f_{ij}, \quad f_j^- = \min_i f_{ij} \tag{A.10}$$

$$f_j^* = \min_i f_{ij}, \quad f_j^- = \max_i f_{ij} \tag{A.11}$$

Step 2. Values of S_i and R_i are calculated with Equations (A.12) and (A.13).

$$S_i = \sum_{j=1}^{n} w_j (f_j^* - f_{ij}) / (f_j^* - f_j^-) \tag{A.12}$$

$$R_i = \max_j [w_j (f_j^* - f_{ij}) / (f_j^* - f_j^-)] \tag{A.13}$$

Step 3. Q_i is calculated according to Equation (A.14)

$$Q_i = v(S_i - S^*)/(S^- - S^*) + (1 - v)(R_i - R^*)/(R^- - R^*) \tag{A.14}$$

where
$S^* = min_i S_i, \quad S^- = max_i S_i$
$R^* = min_i R_i, \quad R^- = max_i R_i$
v denotes the weight assumed for the strategy of "most criteria". In the calculations in this research $v = 0.5$ was chosen.

Step 4. Rankings of alternatives are created by sorting S, R and Q in ascending order. In this way, three ranking lists are received.

Step 5. The compromise solution or set of compromise solutions is proposed based on S, R and Q rankings. Nevertheless, in this research, only Q is considered in the final results.

Appendix A.3. The CRITIC Weighting Method

The CRITIC (Criteria Importance Through Inter-criteria Correlation) technique requires a decision matrix $X = [x_{ij}]_{m \times n}$ containing m alternatives and n criteria, where x_{ij} denotes the performance measure of the i^{th} alternative corresponding to the j^{th} criterion. The computations conducted in aim to assign the weight to the j^{th} criterion w_j using the CRITIC weighting method are presented in the following three steps [3].

Step 1. Normalization of the decision matrix according to Equation (A.15).

$$x_{ij}^* = \frac{x_{ij} - min(x_{ij})}{max(x_{ij}) - min(x_{ij})} \tag{A.15}$$

where x_{ij}^* denotes normalized performance value of the i-th alternative considering the j-th criterion. It is worth noting that the applied formula is a minimum-maximum normalization and does not consider the split of criteria into cost and profit types.

Step 2. The correlation values among criteria pairs are computed using Equation (A.16).

$$\rho_{jk} = \frac{\sum_{i=1}^{m}(r_{ij}-\overline{r}_j)(r_{ik}-\overline{r}_k)}{\sqrt{\sum_{i=1}^{m}(r_{ij}-\overline{r}_j)^2\sum_{i=1}^{m}(r_{ik}-\overline{r}_k)^2}}. \tag{A.16}$$

Step 3. Criteria weights are calculated by Equation (A.17) and (A.18)

$$c_j = \sigma_j \sum_{k=1}^{n}(1-\rho_{jk}); \tag{A.17}$$

$$w_j = \frac{c_j}{\sum_{k=1}^{n} c_k}, \tag{A.18}$$

where $i = 1,2,\ldots,m$; $j,k = 1,2,\ldots,n$. In equations demonstrated above c_j denotes the quantity of information contained in j^{th} criterion, σ_j denotes the standard deviation of the j^{th} criterion and ρ_{jk} denotes the correlation coefficient among the j^{th} and k^{th} criteria.

Appendix A.4. The Pearson Correlation Coefficient

The Pearson correlation coefficient measures the convergence of two vectors, x and y containing numerical values. Formally, it is defined as the covariance of two variables divided by the product of their standard deviations. For MCDA analysis, the Pearson correlation coefficient estimates the similarity between vectors with preference values or rankings of evaluated alternatives [4]. Pearson coefficient is calculated as Equation (A.19) demonstrates

$$r_{xy} = \frac{\sum_{i=1}^{N}(x_i-\overline{x})\sum_{i=1}^{N}(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\overline{x})^2}\sqrt{\sum_{i=1}^{N}(y_i-\overline{y})^2}} \tag{A.19}$$

where N denotes size of compared vectors, $\overline{x} = \frac{1}{n}\sum_{i=1}^{N} x_i$ represents the average value of x and $\overline{y} = \frac{1}{n}\sum_{i=1}^{N} y_i$ represents the average value of y. The value of Pearson's coefficient takes the range from -1 to 1. The higher the value of this measure, the stronger the correlation between the examined vectors of variables.

Appendix A.5. The Standard Deviation

The standard deviation is presented based on [5]. Calculate the standard deviation according to Equation (A.20) where $X = [x_{ij}]_{m\times n}$ is the decision matrix with m alternatives and n criteria. N denotes number of criteria (columns) in decision matrix X.

$$\sigma_j = \sqrt{\frac{\sum_{j=1}^{N}(x_{ij}-\overline{x}_j)^2}{N}} \tag{A.20}$$

Appendix A.6. The Statistical Variance

The statistical variance is described based on [6]. Statistical variance measures the dispersion of a set of values concerning their mean value. In contrast to statistical analyses that analyze mainly outliers, statistical variance analyzes all data points and then determines their distribution. In this way, statistical variance provides valuable information about data distribution. Calculate the statistical variance according to Equation (A.21) where $X = [x_{ij}]_{m\times n}$ is the decision matrix with m alternatives and n criteria. N denotes the number of criteria (columns) in the decision matrix X.

$$v_j = \frac{\sum_{j=1}^{N}(x_{ij}-\overline{x}_j)^2}{N} \tag{A.21}$$

Appendix A.7. Coefficient of Variation

The coefficient of variation is described based on [7]. The coefficient of variation is a statistical measure of the dispersion of data around a mean value. It represents the ratio of the standard deviation to the mean. It is valuable for comparing the degree of variability in data. This coefficient is useful to measure the variance of options similar to Entropy.

Step 1. Normalize the decision matrix using the Sum normalization method as for profit criteria according to Equation (A.22), where $X = [x_{ij}]_{m\times n}$ is the decision matrix with m alternatives and n criteria.

$$b_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{A.22}$$

Step 2. Calculate the mean value of the jth column in normalized decision matrix as Equation (A.23) shows.

$$\overline{b}_j = \frac{\sum_{i=1}^{m} b_{ij}}{m} \tag{A.23}$$

Step 3. Calculate the standard deviation of the jth column according to Equation (A.24).

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(b_{ij}-\overline{b}_j)^2}{m-1}} \tag{A.24}$$

Step 4. Calculate the coefficient of variation of the jth criterion as Equation (A.25) shows.

$$e_j = \frac{\sigma_j}{\overline{b}_j} \tag{A.25}$$

Appendix A.8. The Entropy method

The Entropy method is described based on [8].

Step 1. Normalize decision matrix $X = [x_{ij}]_{m\times n}$ using sum normalization method to get normalized decision matrix $P = [p_{ij}]_{m\times n}$ where $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,n$, m denotes alternatives number and n represents criteria number.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{A.26}$$

Step 2. Calculate the entropy E_j for each jth criterion according to Equation (A.27).

$$E_j = -\frac{\sum_{i=1}^{m} p_{ij} ln p_{ij}}{lnm} \tag{A.27}$$

Step 3. Calculate d_j as Equation (A.28) shows.

$$d_j = 1 - E_j \tag{A.28}$$

Appendix B. Pseudocodes

Algorithm 1 Pseudocode calculating variability of alternatives' efficiency scores in subsequent periods.

Require: Matrix with efficiency scores for each alternative in m columns from every surveyed period in t rows S

Ensure: Vector with values of variabilities of efficiency scores for alternatives G

```
t, m ← rows_number(S), cols_number(S)
declare array of zeros G_{1:m}
for i = 1 to m do
    G_i ← gini_coeff(S_{1:t,i})
end for
```

Algorithm 2 Pseudocode determinating direction of rankings variability in subsequent periods for alternatives.

Require: Matrix with efficiency scores for each alternative in m columns from every surveyed period in t rows S

Ensure: Vector of efficiency scores' variability directions for each country dir

```
t, m ← rows_number(S), cols_number(S)
declare array of zeros dir_{1:m}
for i = 1 to m do
    thresh ← 0
    for p = 2 to t do
        thresh ← thresh + (S_{p,i} − S_{p−1,i})
    end for
    if thresh < 0 then
        dir_i ← −1
    else if thresh > 0 then
        dir_i ← 1
    end if
end for
```

Algorithm 3 Pseudocode calculating variability of criteria in subsequent years for countries in dataset.

Require: List DMs of matrices DM for each alternative (country) with criteria's values in n columns for each surveyed year in t rows

Ensure: Vector with values of variabilities of criteria for countries $var\_crit\_countries$

```
t, n ← rows_number(DM), cols_number(DM)
var_crit_countries ← empty_list
for DM in DMs do
    declare array of zeros G_{1:n}
    for j = 1 to n do
        G_j ← gini_coeff(DM_{1:t,j})
    end for
    var_crit_countries.append(G)
end for
```

Algorithm 4 Pseudocode determinating direction of criteria variability in subsequent years for countries in dataset.

Require: List DMs including: (1) matrices DM for each country with n criteria's values in columns for each surveyed year in t rows and (2) vectors with criteria types $crit\_types$ corresponding to matrices DM

Ensure: Vector with values of variability directions considering criteria values for countries $dir\_crit\_countries$

```
t, n ← rows_number(DM), cols_number(DM)
dir_crit_countries ← empty_list
for DM in DMs do
    declare array of zeros dir_{1:n}
    for j = 1 to n do
        thresh ← 0
        for p = 2 to t do
            thresh ← thresh + (DM_{p,j} − DM_{p−1,j})
        end for
        if thresh < 0 then
            dir_i ← −1
        else if thresh > 0 then
            dir_i ← 1
        end if
    end for
    dir_crits ← dir ∗ crit_types
    dir_crit_countries.append(dir_crits)
end for
```

Algorithm 5 Pseudocode calculating variability of efficiency scores in subsequent years for countries.

Require: Matrix with efficiency scores for each country in columns from every surveyed year in rows S

Ensure: Vector with values of variabilities of efficiency scores for countries G

$t, m \leftarrow rows\_number(S), cols\_number(S)$
$declare\ array\ of\ zeros\ G_{1:m}$
for i = 1 to m **do**
    $G_i \leftarrow gini\_coeff(S_{1:t,i})$
end for

Algorithm 6 Pseudocode determinating direction of efficiency scores variability in subsequent years for countries.

Require: Matrix with efficiency scores for each country in columns from every surveyed year in rows S

Ensure: Vector with values of efficiency scores' variability directions for each country dir

$t, m \leftarrow rows\_number(S), cols\_number(S)$
$declare\ array\ of\ zeros\ dir_{1:m}$
for i = 1 to m **do**
    $thresh \leftarrow 0$
    for p = 2 to t **do**
        $thresh \leftarrow thresh + (S_{p,i} - S_{p-1,i})$
    end for
    if $thresh < 0$ **then**
        $dir_i \leftarrow -1$
    else if $thresh > 0$ **then**
        $dir_i \leftarrow 1$
    end if
end for

Appendix C. Supplementary materials

References

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Table C.1: Decision matrix with values of criteria C_1–C_{10} for the evaluated countries in 2015.

A_i	Country	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	Belgium	1.6	18	581.6	6.8	13.5	53.5	18.2	80.46	18.8	16.1
A_2	Bulgaria	41.4	9.7	613.5	9.9	25	29.4	12.9	60.63	16.9	26.3
A_3	Czechia	18.7	13.9	616.1	7	17.4	29.7	8.9	80.7	25.9	12
A_4	Denmark	8.1	16.5	1052.3	3.1	11.3	47.4	16.1	91.3	19.1	7.7
A_5	Germany	7	25.8	564.8	4.2	13.4	66.7	12.8	95.766	14.4	13.8
A_6	Estonia	13.4	9.4	1540.5	5.1	6.7	28.3	13.4	87.61	21.8	11.8
A_7	Ireland	3.8	8.2	961.3	3.4	8	39.8	13.6	60.56	16.7	10.9
A_8	Greece	28.1	19.2	627.7	7.3	16.4	15.8	15.1	93.4	18.6	12.8
A_9	Spain	5.5	15.7	572.9	3.6	13	30	15.2	84.68	18.6	10
A_{10}	France	7.4	16.4	835.2	5.2	13.5	40.7	12.6	80.2	17.2	14.2
A_{11}	Croatia	41.7	8.3	670.7	8.3	21.9	18	10.9	36.9	14.1	2.8
A_{12}	Italy	27.8	18.3	471.5	5.6	22	44.3	24.1	59.6	18.6	19.4
A_{13}	Latvia	41.4	14.6	1297.2	9.5	15.9	28.7	24.4	90.29	19.3	11.8
A_{14}	Lithuania	26.4	15.4	1053.1	8.3	10.9	33.1	17	72.282	10.8	4.6
A_{15}	Luxembourg	6.8	20.1	511.7	6.3	11.7	47.4	14.4	96.6	17.1	14.9
A_{16}	Hungary	41.1	13.7	704.3	6.5	20.2	32.2	25.4	76.47	31.8	10.6
A_{17}	Netherlands	3.3	24.7	471.6	3.1	12.7	51.8	15.7	99.43	13.8	17.4
A_{18}	Austria	15	17.5	703.6	5.5	14.5	56.9	11.7	95	21.3	12.9
A_{19}	Poland	43.4	12.4	623.9	7.7	23.8	32.5	11.9	72.6	21.5	5.8
A_{20}	Portugal	10.3	23	621.2	5.7	10.3	29.8	28.1	84.64	11.1	10.5
A_{21}	Romania	49.7	22.2	364.8	9.6	17.1	13.2	12.8	39.7	22.1	13.1
A_{22}	Slovenia	13.7	12.9	609.2	5.8	21.6	54.1	26.9	57.4	13.9	9.2
A_{23}	Slovakia	37.8	12.8	536.2	5.7	19	14.9	6.3	63.6	24.2	7.3
A_{24}	Finland	6.7	11.7	2458.7	4.9	6	40.6	4.4	85	15	7.3
A_{25}	Sweden	13.9	12.6	2343.8	2.6	6.1	47.5	7.7	95	16.8	10.9
A_{26}	United Kingdom	7.3	16.5	430.5	2.8	10	43.3	14.8	100	14.1	16.6

Table C.2: Decision matrix with values of criteria C_1–C_{10} for the evaluated countries in 2016.

A_i	Country	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	Belgium	3.5	15.8	581.6	5.9	13.3	53.5	19.2	81.93	18.2	13.3
A_2	Bulgaria	42.5	10	613.5	9.9	20.2	31.8	12.3	61.84	16.3	25
A_3	Czechia	17.9	14.5	616.1	5.8	18.1	33.6	8.2	81.2	26.5	11.7
A_4	Denmark	8.2	18.3	1052.3	3.7	10	48.3	15.9	92	18.6	8.4
A_5	Germany	7.2	25.1	564.8	3.9	12.9	67.1	13.1	95.974	14.4	14.1
A_6	Estonia	13.4	10.4	1540.5	5.4	5.4	28.1	13.9	87.79	19.9	9.2
A_7	Ireland	3.4	7.7	961.3	3.8	8.9	40.7	13.3	61.15	16.6	9.7
A_8	Greece	28.7	19.9	627.7	7.6	14.7	17.2	14.7	93.4	18.1	11.8
A_9	Spain	5.4	16.2	572.9	3.9	11.3	33.9	15.9	86.62	18.4	10.3
A_{10}	France	7.7	17.7	835.2	5.2	12.7	42.9	14	80.1	16.8	14.8
A_{11}	Croatia	41.1	8.5	670.7	7.4	20.6	21	11.5	36.9	15	3
A_{12}	Italy	27.8	16.2	471.5	5.4	19.3	45.9	21	59.6	18	14.7
A_{13}	Latvia	43.2	13.3	1297.2	8.1	15.4	25.2	21.9	91.62	18.5	10
A_{14}	Lithuania	23.7	13.4	1053.1	6.7	9.3	48	18.2	73.529	10.1	3.4
A_{15}	Luxembourg	8.1	19.7	511.7	5.5	14.4	49.2	18.7	96.9	16.9	12.2
A_{16}	Hungary	40.4	12.2	704.3	6.2	20.2	34.7	26.7	78.1	30.8	9.7
A_{17}	Netherlands	4	24.9	471.6	3.1	11.2	53.5	16.3	99.45	14	16.9
A_{18}	Austria	15.2	17.3	703.6	4.9	13.1	57.6	11.2	99.75	21.4	12.4
A_{19}	Poland	40.7	13	623.9	8	23.3	34.8	11.6	73.4	21.5	5.6
A_{20}	Portugal	10.3	23.1	621.2	5.5	10.1	30.9	30.5	84.64	11.6	7.8
A_{21}	Romania	48.4	20.3	364.8	9.7	17.2	13.4	13.3	43.8	21.7	14.1
A_{22}	Slovenia	12.6	13.4	609.2	6.3	21.6	55.6	23.8	63.3	13.7	8.5
A_{23}	Slovakia	37.9	12.1	536.2	5.1	14.7	23	6.2	63.6	25.2	6.9
A_{24}	Finland	6.6	12	2458.7	4.7	5.7	42	4.7	85	17.5	6.5
A_{25}	Sweden	14.4	17.1	2343.8	2.7	5.6	48.4	7.4	95	16.5	12.7
A_{26}	United Kingdom	8	17	430.5	2.8	10.4	44	16.4	100	13.5	16.8

Table C.3: Decision matrix with values of criteria C_1–C_{10} for the evaluated countries in 2017.

A_i	Country	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	Belgium	4.8	15.6	581.6	5.4	12.8	53.9	18.4	82.96	18.2	12.4
A_2	Bulgaria	41.9	9.8	613.5	9.6	23.8	34.6	12.2	63.19	15.2	23.6
A_3	Czechia	16	13.6	616.1	5.4	18.4	32	8	82.3	27.1	9.3
A_4	Denmark	8.6	18.8	1052.3	3	9.2	47.6	14.9	92.8	18.5	7.8
A_5	Germany	7.2	26.1	564.8	3.8	12.8	67.2	12.5	95.974	14.7	14.2
A_6	Estonia	13.5	8.2	1540.5	3.6	5.3	28.4	13.9	87.87	19.5	7.3
A_7	Ireland	2.8	9	961.3	3.2	8	40.4	12.6	61.15	17.4	9.7
A_8	Greece	29	20.1	627.7	6.8	13.5	18.9	13.5	93.4	17.5	13.8
A_9	Spain	5.1	15.2	572.9	3.9	12.1	36.1	11.5	86.62	14.8	8.7
A_{10}	France	7.7	16.8	835.2	5.1	12	44.1	11.1	79.8	17.2	13.9
A_{11}	Croatia	39.9	8.6	670.7	8	19	23.6	11.4	36.9	15.7	3
A_{12}	Italy	27.1	12.5	471.5	5.6	19.2	47.8	16.1	59.6	17.3	12.5
A_{13}	Latvia	41.9	14.1	1297.2	7	13.6	24.8	22.8	94.95	17.3	8
A_{14}	Lithuania	23.7	13.2	1053.1	6.8	8.6	48.1	15.7	73.78	8.9	8.2
A_{15}	Luxembourg	8.3	21.6	511.7	4.2	13.2	48.7	17.4	97	17.1	12
A_{16}	Hungary	40.5	11	704.3	6.4	20.9	35	24.8	79.119	30	7.2
A_{17}	Netherlands	4.1	25.6	471.6	3.1	11.3	54.6	13.5	99.5	14.3	15
A_{18}	Austria	15.1	17.9	703.6	4.7	14.1	57.7	11.9	99.75	21.4	10.9
A_{19}	Poland	40.5	12.4	623.9	7.5	24.1	33.8	11.9	73.5	21.5	5.4
A_{20}	Portugal	9.3	23.5	621.2	5.8	12	29.1	25.5	84.64	11.5	7.9
A_{21}	Romania	47	19.3	364.8	10	20.4	14	11.1	46.5	22.2	11.3
A_{22}	Slovenia	12.8	13.3	609.2	5	19.7	57.8	22	67.4	13.5	8
A_{23}	Slovakia	36.4	12.8	536.2	5.1	17.5	29.8	6.7	65	25.6	6.2
A_{24}	Finland	6.1	12.5	2458.7	4.3	4.9	40.5	4.2	85	15.8	6.2
A_{25}	Sweden	13.5	16.9	2343.8	2.5	5.4	46.8	7	95	16.7	13
A_{26}	United Kingdom	3.4	17.3	430.5	2.8	9.9	43.8	17	100	13.3	20.3

Table C.4: Decision matrix with values of criteria C_1–C_{10} for the evaluated countries in 2018.

A_i	Country	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	Belgium	5.7	17.7	583.5	5.3	12.8	54.4	17.9	82.96	18.4	12.3
A_2	Bulgaria	41.6	9.4	623.4	8.7	20.1	31.5	13	63.72	14.2	21.8
A_3	Czechia	15.7	14.6	634.4	6.2	19.5	32.2	7.7	82.3	26.7	7.9
A_4	Denmark	9.2	18.2	1053.8	3	12	49.9	16.4	92.9	18	7.4
A_5	Germany	7.4	27.8	586.7	4	13.1	67.1	13.4	95.974	14.9	13.3
A_6	Estonia	12.6	8.6	1484.4	5.1	6.3	28	13.6	87.87	19.4	7.4
A_7	Ireland	2.7	9.4	972.7	2.9	8.8	37.6	11.9	61.15	18.3	10
A_8	Greece	29.2	19.3	710.2	6.5	13.4	20.1	12.9	93.4	17.3	13.5
A_9	Spain	4.7	17	577.5	3.9	11.7	34.8	15.9	86.62	15.1	10.9
A_{10}	France	8.2	18.2	845.1	4.8	11.7	45.1	12.7	79.3	16.7	14.9
A_{11}	Croatia	39.3	8	722.5	7.7	20.3	25.3	11.2	36.9	15.2	2.6
A_{12}	Italy	27.8	10.9	484.3	5.5	16	49.8	13.2	59.6	18	11.3
A_{13}	Latvia	43.4	13.7	1276.1	7.7	16.1	25.2	23.5	98.69	17.2	8.6
A_{14}	Lithuania	22.8	14.8	1090.5	6.2	8.5	52.5	14.8	75.8	9.6	3.7
A_{15}	Luxembourg	8.4	19.3	565.2	5.9	11.1	49	18.3	97	17.1	11.3
A_{16}	Hungary	20.1	8.5	811.5	6.5	17.7	37.4	22.5	80.36	29.4	4.8
A_{17}	Netherlands	4.1	27.1	456.9	3.5	11.8	55.9	15.8	99.5	14.3	17.5
A_{18}	Austria	13.5	17.5	740.1	4.6	15.5	57.7	10.4	99.78	22.9	9.7
A_{19}	Poland	39.2	13.8	633.7	7.5	24.3	34.3	11.6	74	20.7	4.8
A_{20}	Portugal	9.6	23	689.1	6.8	10.8	29.1	26.9	84.64	11.6	6.5
A_{21}	Romania	46.3	20.1	528.4	9.6	20	11.1	10.1	48.1	21.2	11.5
A_{22}	Slovenia	12.5	14.3	625.1	4.4	18.3	58.9	22.7	68.9	13.6	7.9
A_{23}	Slovakia	35.5	11.2	631.8	4.8	16.9	36.3	5.1	65.7	26.1	4.8
A_{24}	Finland	7.3	13.4	2447.6	4.3	6.4	42.3	4.6	85	15.8	7
A_{25}	Sweden	15.2	17	2223	3.2	6.2	45.8	7.8	95	16.9	14.4
A_{26}	United Kingdom	4.8	19.8	426.9	2.8	10.1	44.1	17.6	100	12.9	24.2

Table C.5: Summary of results provided with TOPSIS and with DARIA-TOPSIS method.

		TOPSIS efficiency					TOPSIS Rank					DARIA-TOPSIS	
Ai	Country	2015	2016	2017	2018	2019	2015	2016	2017	2018	2019	Efficiency	Rank
A_1	Belgium	0.5366	0.5643	0.5642	0.5670	0.5565	13	10	9	9	11	0.5664	12
A_2	Bulgaria	0.3361	0.3419	0.3447	0.3527	0.3603	25	25	25	25	25	0.3739	26
A_3	Czechia	0.5135	0.5324	0.5534	0.5562	0.5726	14	15	12	13	7	0.5935	8
A_4	Denmark	0.6416	0.6341	0.6333	0.6363	0.6066	4	4	4	5	5	0.5973	7
A_5	Germany	0.5601	0.5643	0.5536	0.5566	0.5481	10	9	11	12	12	0.5425	15
A_6	Estonia	0.6558	0.6554	0.6767	0.6652	0.6807	3	3	3	3	3	0.6893	3
A_7	Ireland	0.6181	0.6261	0.6318	0.6407	0.6331	5	5	5	4	4	0.6398	4
A_8	Greece	0.4284	0.4263	0.4320	0.4557	0.4194	20	21	22	21	24	0.4050	24
A_9	Spain	0.5659	0.5779	0.5818	0.5683	0.5601	8	7	7	8	10	0.5523	14
A_{10}	France	0.5627	0.5582	0.5737	0.5703	0.5649	9	11	8	7	9	0.5704	11
A_{11}	Croatia	0.3741	0.3839	0.4013	0.4172	0.4347	23	24	24	24	23	0.4655	21
A_{12}	Italy	0.3673	0.4076	0.4438	0.4926	0.4755	24	23	21	19	20	0.5337	17
A_{13}	Latvia	0.4200	0.4362	0.4528	0.4388	0.4913	21	20	19	22	19	0.5198	18
A_{14}	Lithuania	0.4659	0.5348	0.5247	0.5569	0.5248	15	14	15	11	16	0.5542	13
A_{15}	Luxembourg	0.5474	0.5429	0.5430	0.5578	0.5702	12	13	14	10	8	0.5802	10
A_{16}	Hungary	0.4294	0.4399	0.4467	0.5554	0.5461	19	19	20	14	13	0.6053	6
A_{17}	Netherlands	0.5522	0.5560	0.5528	0.5419	0.5267	11	12	13	15	15	0.5165	19
A_{18}	Austria	0.5867	0.6053	0.5952	0.6230	0.6063	6	6	6	6	6	0.6174	5
A_{19}	Poland	0.4124	0.4114	0.4222	0.4316	0.4395	22	22	23	23	22	0.4537	23
A_{20}	Portugal	0.4615	0.4748	0.4584	0.4701	0.4614	16	17	18	20	21	0.4543	22
A_{21}	Romania	0.2643	0.2638	0.2870	0.3102	0.3285	26	26	26	26	26	0.3767	25
A_{22}	Slovenia	0.4546	0.4744	0.5012	0.5211	0.5075	17	18	16	18	18	0.5345	16
A_{23}	Slovakia	0.4443	0.4766	0.4852	0.5402	0.5423	18	16	17	16	14	0.5840	9
A_{24}	Finland	0.7311	0.7553	0.7522	0.7439	0.7553	2	1	1	1	1	0.7617	1
A_{25}	Sweden	0.7579	0.7220	0.7228	0.7001	0.7090	1	2	2	2	2	0.6946	2
A_{26}	United Kingdom	0.5847	0.5737	0.5594	0.5371	0.5130	7	8	10	17	17	0.4869	20