
Evaluation of Selected Methods for the Construction of Sustainable Energy Development Index: Application for European Union Member States

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Abstract:

Purpose: The composite sustainable energy index could prove useful to evaluate both the state of the art and the progress of national energy towards sustainable development. However, different methods and procedures of selection and aggregation of variables can produce different results of index values and the ranking of objects. The objective of the paper is to evaluate different methods of data aggregation.

Design/Methodology/Approach: We choose three methods, SAW, TOPSIS and VIKOR in order to obtain the Sustainable Energy Development Aggregated Index (SEDAI) to rank the EU Member States. We apply 47 variables and also test the need to reduce variables due to their collinearity. We apply some measures of the quality of indexes and rankings based on linear correlation of the index with the diagnostic variables, as well as the u_p ratio based on ranks comparison and our modification of u_p measure (u'_p).

Findings: We found that it is not possible to clearly indicate the method of selection and aggregation of variables that gives optimal ranking, however SAW method is most often indicated as the best method, according to evaluation measures applied in our research.

Practical Implications: In this situation, one opportunity is to use the most intuitive SAW method, or we recommend using a set of rankings in order to aggregate the results of different methods as it is used in many machine learning methods.

Originality/Value: The added value of the article is the indication of the SAW method as the best one, according to most analyzed quality measures for creating indexes and rankings. Additionally, we propose a measure of the quality of rankings and a method of aggregating indexes obtained with the use of various methods.

Keywords: SAW, TOPSIS, VIKOR, aggregated index, composite indicator, evaluation measures of index construction methods, sustainable energy.

JEL classification: Q01, C43, C44.

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1. Introduction

Energy systems are some of key focus points in the progress towards sustainable societies. That is why sustainable energy development is a crucial concept of energy policy of governments worldwide. In practice, the concept of sustainable energy is understood as “obtaining energy in a method that causes as little harm to the environment as possible, preferably from renewable sources, and increasing energy efficiency, while ensuring adequate energy security that takes into account the needs of present and future generations, as well as social, economic, and environmental aspects of human development” (Trojanowska and Nęcka, 2020).

Implementation of the concept of sustainable energy requires continuous evaluation of the progress and deviations in this regard from decision-makers. In order to evaluate compliance of energy development with defined objectives, appropriate indicators are required. Various international organizations such as the International Energy Agency (IEA, 1997), the European Environment Agency (EEA, 1999), the Statistical Office of the European Communities (Eurostat, 1999), the International Atomic Energy Agency (IAEA, 2005), the World Energy Council (WEC, 2014) have been trying to develop a credible, universal set of sustainable energy indicators in order to facilitate energy policy-makers. Moreover, many researchers have been putting forward their own suggestions in this area, either referring to the above-mentioned studies or by creating their own sets of indicators (Garcia-Alvarez *et al.*, 2016a; 2016b; Hatefi and Torabi 2018). We also proposed our own set of sustainable energy indicators regarding European Union energy policy objectives (Ligus and Peternek, 2021).

The selected diagnostic variables can be examined individually, or aggregated into one single index with the use of different methods of aggregation. The first widely known simple energy development index (EDI), composed as the arithmetic average of only three indicators, was prepared by IEA in the 2004 edition of the World Energy Outlook (IEA, 2004). Some proposals for energy sustainable development indexes have been developed in the literature (Liu, 2016; Garcia-Alvarez *et al.*, 2016a; 2016b; Cucchiella *et al.*, 2017; Cîrstea *et al.*, 2018). We also proposed an aggregate SEDAI index (Sustainable Energy Development Aggregated Index) to rank the EU Member States and to identify the most advanced, medium-level and worst-performing countries on the path to sustainable energy (Ligus and Peternek, 2021).

However, we noticed that different methods and procedures give different results in the ranking of index values and Member States. One of the crucial steps of the procedure of index construction is the choice of method of selection, preparation and aggregation of variables (Saisana and Tarantola, 2002; Trojanowska and Nęcka, 2020).

In this context the objective of the paper is twofold, first, to verify the need of variables reduction due to their collinearity, and second, to evaluate different methods of data aggregation into one composite index. We test different procedures to obtain aggregate SEDAI index to rank the EU Member States. We apply some measures of indexes and rankings quality based on linear correlation of the index with diagnostic variables, as well as the u_p ratio based on ranks comparison proposed by Kukuła and Luty (2015) and our modification of u_p measure (u'_p).

2. Methodology of Index Construction

Several groups of methods are proposed in the literature to aggregate indicators into one composite index. The most popular groups of methods are linear programming, covering data envelopment analysis (DEA) method developed by Charnes et al. (1978), multi-criteria decision analysis (MCDA) covering, i.e., AHP, FAHP, TOPSIS, VIKOR methods and the subgroup of simple additive or multiplying methods (Zhou *et al.*, 2006; Zho *et al.*, 2007; Hatefi and Torabi, 2018). Due to the clarity of interpretation, the most often used method of aggregation is the SAW method (Garcia-Alvarez *et al.*, 2016a; 2016b; Ligus and Peternek, 2021). The TOPSIS method is used just as often, due to its many advantages (Roszkowska, 2011). The VIKOR method is used a little less frequently for index construction (Bulgurcu, 2016; Koszela *et al.*, 2020).

However the choice of aggregation method is very important, attempts are also made to verify the need to reduce the set of variables and the construction of reduction methods (Hellwig, 1968; Młodak, 2006; Bąk, 2017; Konarzewska, 2017). Researchers have also made attempts to verify the methods of normalization of variables (Walesiak, 2018; Trojanowska and Nęcka, 2020). An entirely separate problem is the choice of a measure that can be a criterion for the selection of the best method of index construction (Grabiński *et al.*, 1989; Kukuła and Luty, 2015; Zhou *et al.*, 2006). There are measures based on linear correlation of the index with diagnostic variables, the rank correlation and the variability, as well as the concentration of the index. We also propose our own measure.

2.1 Selected Methods of Diagnostic Variables Reduction and Data Aggregation

Our procedure of index construction comprises the following stages. In the first phase, we calculate the main descriptive statistics of indicators. An important issue is to exclude those with irrelevant variation from the set of indicators, because such indicators will not differentiate between objects. We assume the value of the coefficient of variation higher than 0.15 as being significant.

In the second phase, we transform all variables into stimulants, which means that the higher the value of the indicator, the better. The most straightforward transformation of destimulants into stimulants is multiplication by -1.

In the third phase, we apply the formal statistical method in order to decide whether to reduce redundant information from the set of variables. The literature does not clearly indicate whether the full set of substantively selected indicators should be used or, due to the potential repeatability of information, this set should be reduced. Several works, e.g., Saisana and Tarantola (2002), Trojanowska and Nęcka (2020), suggest that there should be reductions of strongly correlated variables, but one can also find approaches that deem this reduction unnecessary (Kukuła and Luty 2015). This lack of reduction of correlated variables is explained, on the one hand, by greater stability of the ranking, and on the other hand, it is indicated that there are no formal (statistical) premises (such as colinearity) that the set should be reduced. In our research we decided to compute the indexes on both full and reduced set of variables.

We can find several methods of reducing indicators (Jarocka, 2013). Hellwig (1968) proposed methods based on correlation coefficients. Młodak (2006) proposed some improvement of Hellwig's method, Konarzewska (2017) suggested to apply factor analysis. Malina and Zeliaś (1998) proposed to use inverse correlation matrix method, which allows to analyze the interdependence of all variables together. It should be noted that Zeliaś and Malina's proposal is just the VIF (Variance Inflation Factor) analysis for each following variable, so the commonly used limit value of VIF is suggested to be 10. We decided to use the method of Malina and Zeliaś.

In the fourth phase we calculate indexes in separate sustainable energy dimensions by three methods:

1. SAW, where in order to ensure comparability of the variables given in different units, we calculate the z -scores for all indicators:

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \quad (1)$$

where, x_{ij} is the value of j -indicator for i -country, \bar{x}_j and s_j are the average and standard deviation of the j -indicator, respectively. In the next phase, we calculate values of the proposed indexes for the separate EU Member States and EU-27 average. The formula is as follows:

$$I_i = \frac{z_i - z_i^{\min}}{z_i^{\max} - z_i^{\min}} = \frac{z_i - \sum_{j=1}^{n_d} \min_i z_{ij}}{\sum_{j=1}^{n_d} \max_i z_{ij} - \sum_{j=1}^{n_d} \min_i z_{ij}} \quad (2)$$

where $Z_i = \sum_{j=1}^{n_d} z_{ij}$ is added values of n_d normalized indicators for i - country in d dimension (standardized sum); $\sum_{j=1}^{n_d} \min_i z_{ij}$ is the sum of the worst variable values in the sample in d dimension (anti-pattern - minimum value for all n_d indicators) and $\sum_{j=1}^{n_d} \max_i z_{ij}$ is constructed as the sum of the best variable values in the sample in d dimension (pattern - maximum value for all n_d indicators).

2. TOPSIS, where we calculate relative closeness of objects to the ideal solution:

$$I_i = \frac{d_i^{min}}{d_i^{max} + d_i^{min}} \quad (3)$$

where $d_i^{max} = \sqrt{\sum_{j=1}^{n_d} (z_{ij} - z_i^{max})^2}$; $d_i^{min} = \sqrt{\sum_{j=1}^{n_d} (z_{ij} - z_i^{min})^2}$

z_i^{min} – anti-ideal solution (anti-pattern)

z_i^{max} – ideal solution (pattern)

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^n x_{ij}^2}}$$

3. VIKOR, where we compute values:

$$I_i = 0,5 \frac{S^- - S^+}{S^- - S^+} + 0,5 \frac{R^- - R^+}{R^- - R^+} \quad (4)$$

where $S^+ = \min_i S_i$; $S^- = \max_i S_i$; $R^+ = \min_i R_i$; $R^- = \max_i R_i$

$$S^i = \sum_{j=1}^{n_d} \frac{z_i^{max} - z_{ij}}{z_i^{max} - z_i^{min}}; R^i = \max_j \frac{z_i^{max} - z_{ij}}{z_i^{max} - z_i^{min}}$$

z_i^{min} – anti-ideal solution (anti-pattern)

z_i^{max} – ideal solution (pattern)

$$z_{ij} = \frac{x_{ij} - \min_j x_{ij}}{\max_j x_{ij} - \min_j x_{ij}}$$

Such methods of index construction result in index values being in the range from 0 to 1.

The above procedure leads to calculation of indexes of the three dimensions of sustainable energy, namely: social, economic, and environmental, and local sub-indexes within dimensional categories. Finally, we calculate the Sustainable Energy Development Aggregated Index (SEDAI) for all dimensions, according to the formula:

$$SEDAI = \sum_{k=1}^{l=3} w_k I_i^k \quad (5)$$

where w_k are weights of sustainable energy dimensions.

Equal weighting and subjective selection of weights are the most frequently used weighting methods in practical situations. Uneven selection of weights may cause difficulty as there may not exist enough objective evidence to support any subjective choices of weighting values. The popular methods to obtain the weights are Delphi and the analytic hierarchy process (AHP), statistical methods such as regression analysis, principal component analysis (PCA), and the entropy method (Saisana and Tarantola, 2002).

In our work, we apply the expert weights found in the work of Ligus (2017). In that research, the FAHP method was used to achieve the weights of the sustainable development dimensions. The FAHP pairwise comparison procedure gave weights to the social, economic, and environmental dimensions of 0.304, 0.42, and 0.276, respectively.

2.2 Evaluation Measures of Index Construction Methods

Different methods of variables selection, normalization and aggregation of data can produce different results of index values and the ranking of objects (Saisana and Tarantola, 2002). We use three different methods of indexes construction, SAW, TOPSIS and VIKOR in two scenarios of a full and reduced set of variables. That is why we need some method of investigation and assessment of the results. We can find two kinds of measures in this regard in the literature. Grabiński, Wydymus and Zeliaś (1989) proposed confirmation of index value to diagnostic variable values. They use linear correlation of the index with the diagnostic variables (measures $M1$ and $M2$), the rank correlation (measures $M3$, $M4$, $M5$), and the variability, as well as the concentration of the index (measures $M6$ and $M7$). As all proposed by Grabiński *et al.* (1989) measures are destimulants they proposed to aggregate with the following formula:

$$M = \sqrt{\sum_{j=1}^g M_j^2} \quad (6)$$

However, it is worth noticing that the proposed aggregated measure is controversial because the values of $M1$ to $M7$ are from different intervals. In our research, we have chosen only two measures based on correlation (in order to avoid the mentioned controversy) to explore:

$$M1 = 1 - \frac{1}{m} \sum_{j=1}^m r_j \quad (7)$$

and

$$M2 = \frac{1}{m} \sum_{j=1}^m l(r_j) \quad (8)$$

where

$$l(r_j) = \begin{cases} 0 & \text{for } r_j \in (0.5; 1) \\ 1 & \text{for } r_j \in (0; 0.5) \\ 2 & \text{for } r_j \in (-0.5; 0) \\ 3 & \text{for } r_j \in (-1; -0.5) \end{cases}$$

Another measure of ranking quality, proposed by Kukuła and Luty (2015) consists of confirming ranking quality by pairwise comparison of positions of objects in the examined ranking with the positions of objects in rankings created according to different procedures or methods, and then aggregating differences with the following formula:

$$u_p = \frac{1}{v-1} \sum_{\substack{q=1 \\ p \neq q}}^v m_{pq} \quad p, q = 1, 2, \dots, v, \quad (9)$$

where $m_{pq} = 1 - \frac{2 \sum_{i=1}^n |c_{ip} - c_{iq}|}{n^2 - z}$ $z = \begin{cases} 0 & \text{for odd } n \\ 1 & \text{for even } n \end{cases}$

c_{ip} — rank of the i -th object in the p -th ranking.

Some disadvantage of Kukuła and Luty (2015) proposal is comparing positions in rankings, not the values of indexes themselves. So our proposition is to count, in addition, the distance between values of indexes according to the formula:

$$m'_{pq} = \sum_{i=1}^n |I_{ip} - I_{iq}|. \quad (10)$$

Note that the measure proposed by Kukuła and Luty (2015) has a desirable property that is standardized in the 0 -1 range. Our measure does not have such a desired property. The smaller the distance of the examined ranking, the better.

3. The Data

The sustainable energy index is based on a system of identified and selected indicators. We propose a set of indicators that have been chosen mainly according to the International Atomic Energy Agency guidelines (IAEA, 2005). We have chosen those variables that are more related to the main targets set by European directives in energy policy. We also considered EC's indicators (EC, 2020) proposed for EU countries, especially to assess and track progress towards achieving goal 7 of the United Nations' "The 2030 Agenda for Sustainable Development" to ensure access to affordable, reliable, sustainable and modern energy for all, reported by Eurostat each year (Eurostat, 2020).

We also drew on literature research, such as Garcia-Alvarez *et al.* (2016a; 2016b), Iddrisu and Bhattacharyya (2011) and proposed our own indicators based on our experience and current challenges of the energy and climate policies of EU Member States, that we noticed. The synthetic index is based on the calculations of 47 indicators, which are grouped in 21 sub-categories and eight categories. Those categories are later grouped into three dimensions: society, economy and environment (for more details and the list of indicators see Ligus and Peternek, 2021).

4. Research Results

The study covered three methods for creating ranking (SAW, TOPSIS and VIKOR) on two sets of diagnostic variables. The first set of variables included all proposed 47 variables, while the second one was limited to 37 variables. The reduction of the number of variables was achieved with the use of the inverted correlation matrix method for the limit value of 10. As a result, the number of variables decreased from 20 to 16 in the set of variables assigned to the economic dimension, and from 22 to 16 in the set of variables assigned to the environmental dimension, and the set of variables assigned to social dimension did not change.

To verify compliance of the SEDAI index computed with the use of different methods, it was decided to use the classic correlation coefficients and the ratio u_p proposed by the Kukuła and Luty (2015) and also our modification of u_p measure (u'_p) (Table 1).

Table 1. Correlation coefficients and measures u_p and u'_p for researched methods of index construction

	SAW	TOPSIS	VIKOR	SAW_red	TOPSIS_red	VIKOR_red	u_p	u'_p
SAW	1.000	0.909	0.869	0.989	0.887	0.835	0.805	2.821
TOPSIS	0.909	1.000	0.872	0.905	0.994	0.874	0.825	2.624
VIKOR	0.869	0.872	1.000	0.843	0.852	0.965	0.815	4.795
SAW_red	0.989	0.905	0.843	1.000	0.895	0.832	0.793	2.779
TOPSIS_red	0.887	0.994	0.852	0.895	1.000	0.862	0.805	2.591
VIKOR_red	0.835	0.874	0.965	0.832	0.862	1.000	0.797	4.733

Source: Own study.

As we can see from Table 1, values of the correlation coefficients between individual indexes are high - all the statistical tests performed indicate their significance. However, the indexes constructed with the use of the TOPSIS method have the highest compliance with other indexes. The Kukuła and Luty measure based on the comparison of ranks indicates TOPSIS method applied for the full set of variables to be the most similar to other approaches, while our proposition based on distances points out TOPSIS method on the reduced data set as the most similar to others.

In order to confirm the correctness of pointing out the TOPSIS method as the best one, it was also decided to use the measures of accordance to the index value with the values of diagnostic variables. The results are presented in Table 2. As it can be seen, these measures indicate the SAW method as the most consistent. Moreover, the TOPSIS method for the reduced set on variables occurred to be the second-worst method according to the $M2$ measure.

Table 1. Measures $M1$ and $M2$ for researched methods of index construction

	SAW	TOPSIS	VIKOR	SAW_red	TOPSIS_red	VIKOR_red
M1	0.720	0.738	0.751	0.728	0.748	0.754
M2	0.915	1.021	0.979	0.915	1.043	1.085

Source: Own study.

This ambiguity of the obtained results forced us to repeat the analysis carried out in social, economic and environmental dimensions separately. The results of these analyses are presented in Tables 3 and 4 for the economic dimension, Tables 5 and 6 for the environmental dimension, and Tables 7 and 8 for the social dimension.

Table 3. Correlation coefficients and measures u_p and u'_p for economic dimension

	SAW	TOPSIS	VIKOR	SAW_red	TOPSIS_red	VIKOR_red	u_p	u'_p
SAW	1.000	0.764	0.694	0.930	0.708	0.605	0.660	3.84
TOPSIS	0.764	1.000	0.674	0.790	0.993	0.729	0.693	3.056
VIKOR	0.694	0.674	1.000	0.680	0.650	0.902	0.701	5.448
SAW_red	0.930	0.790	0.680	1.000	0.774	0.723	0.716	4.136
TOPSIS_red	0.708	0.993	0.650	0.774	1.000	0.740	0.676	3.063
VIKOR_red	0.605	0.729	0.902	0.723	0.740	1.000	0.726	4.958

Source: Own study.

Table 4. Measures $M1$ and $M2$ for the economic dimension

	SAW	TOPSIS	VIKOR	SAW_red	TOPSIS_red	VIKOR_red
M1	0.705	0.775	0.795	0.726	0.791	0.822
M2	0.955	1.045	1.091	0.818	1.091	1.091

Source: Own study.

In the economic dimension, the ambiguity of the results seems to be even greater than for SEDAI index. The $M1$ and $M2$ coefficients, proving compliance of the index value with the values of the diagnostic variables, indicate the SAW method (Table 4) to be the best, while completely different results can be seen when the u_p and u'_p measures are taken into account. The u_p measure points to the VIKOR method on the reduced set of data as providing the most similar ranking to the others, while the distance-based measure u'_p , we have proposed indicates the TOPSIS method.\

Table 5. Correlation coefficients and measures u_p and u'_p for environmental dimension

	SAW	TOPSIS	VIKOR	SAW_red	TOPSIS_red	VIKOR_red	u_p	u'_p
SAW	1.000	0.944	0.817	0.960	0.936	0.819	0.804	3.368
TOPSIS	0.944	1.000	0.799	0.858	0.968	0.780	0.823	3.955
VIKOR	0.817	0.799	1.000	0.815	0.838	0.991	0.777	5.425
SAW_red	0.960	0.858	0.815	1.000	0.917	0.848	0.804	3.377

TOPSIS_red	0.936	0.968	0.838	0.917	1.000	0.845	0.813	3.619
VIKOR_red	0.819	0.780	0.991	0.848	0.845	1.000	0.782	6.24

Source: Own study.

Table 6. Measures $M1$ and $M2$ for environmental dimension

	SAW	TOPSIS	VIKOR	SAW_red	TOPSIS_red	VIKOR_red
M1	0.551	0.576	0.633	0.569	0.580	0.632
M2	0.550	0.750	0.850	0.700	0.600	0.800

Source: Own study.

In the environmental dimension the SAW method on the full dataset appears to be the best method according to three out of four evaluation measures. Only the measure proposed by the Kukuła and Luty indicates the TOPSIS method as the best one.

Table 7. Correlation coefficients and measures u_p and u'_p for the social dimension

	SAW	TOPSIS	VIKOR	u_p	u'_p
SAW	1.000	0.955	0.942	0.943	1.394
TOPSIS	0.955	1.000	0.874	0.926	3.837
VIKOR	0.942	0.874	1.000	0.937	6.386

Source: Own study.

Table 8. Measures $M1$ and $M2$ for the social dimension

	SAW	TOPSIS	VIKOR
M1	0.541	0.516	0.509
M2	0.400	0.400	0.400

Source: Own study.

In the last social dimension, the set of indicators has not been reduced so the range of methodical variants is definitely smaller. The measures of compliance with the indexes indicate the SAW method as the best, while the measures of indexes accordance with the diagnostic variables give an ambiguous result. The $M1$ measure indicates VIKOR method as the best one, while the $M2$ measure evaluates all 3 methods equally well.

Unfortunately, the conducted research proves that it is not possible to clearly indicate one recommended method for creating ranking. This finding complies with the findings of the other studies on this subject (Kisielińska, 2016). It is also ambiguous whether the set of variables should be reduced or not. In most cases the measures confirmed the full set of indicators being a better option, but there were some cases where better results were achieved for the reduced set of data. In such situations Kisielińska (2016) proposed averaging the results (rankings) of all analyzed ranking creation methods and procedures in order to create an unambiguous ranking. We also propose a similar solution, but as we rely on the

index, i.e., the value of the measure, and not on the ranking, we suggest that the values of all counted indexes for a given area and under a given method should be unitized. Such prepared dimensional indexes should be averaged and become components of an aggregated SEDAI index calculated according to the formula:

$$SEDAI = \sum_{k=1}^{l=3} w_k \frac{\sum_{m=1}^r \frac{I_{im}^k - \min_i I_{im}^k}{\max_i I_{im}^k - \min_i I_{im}^k}}{r} \quad (11)$$

where m – number of selected methods

I_{im}^k – index for i – country computed by m – method in k -dimension.

Such calculated SEDAI indexes were subjected to the same research, while the averaging of the index values was performed in three groups for methods, SAW, TOPSIS and VIKOR on the full set of indicators (FULL - 3 methods), SAW, TOPSIS and VIKOR calculated for reduced set of variables (RED - 3 methods) and by aggregating indexes calculated with the use of all mentioned methods and data sets (ALL - 6 methods).

Tables 9 and 10 present the results of the chosen measures of indexes and consistency of rankings. It can be noticed that the indexes calculated in this way are very similar to each other. This is indicated both by the values of u_p and u'_p measures and the correlation coefficients. They indicate the SEDAI based on the mean calculated from all methods as the closest to the others. The same result is achieved with the use of M1 measure of index value compliance with the values of the variables - it also indicates the index calculated from all possible methods (ALL) as the most consistent. The only deviation occurs with the results of M2 measure, which indicates the ranking calculated on the reduced data set as the most consistent.

Table 9. Correlation coefficients and measures u_p and u'_p of consistency for applied index construction methods

	FULL	RED	ALL	u_p	u'_p
FULL	1	0,978	0,995	0.968	0.175
RED.	0.978	1	0,995	0.962	0.175
ALL	0.995	0.995	1	0.977	0.117

Source: Own study.

Table 10. M1 and M2 consistency measures of applied index construction methods

	FULL	RED	ALL
M1	0.746	0.746	0.745
M2	1.043	0.979	1.000

Source: Own study.

Additionally, it was decided to calculate the variance inflation factor for all methods of index creation for each dimension (it was not calculated for the entire set of variables due to the insufficient number of objects in relation to the variables, which resulted in bad conditioning of the matrix). Let us recall that the higher the VIF, the stronger the dependence of the value of a given index on the variables of a given dimension. Table 11 indicates that the highest coefficients for each dimension were obtained by the use of SAW method on the full data set.

Table 11. VIF measures for researched index construction methods

VIF	SAW	TOPSIS	VIKOR	SAW_red	TOPSIS_red	VIKOR_red	Full	Red.	All
Social	2.88	2.3	2.86	2.26	2.27	1.81	1.38	1.48	1.43
Economic	36.66	19.35	27.45	32.79	18.11	25.94	29.07	26.11	27.82
Environmental	16.29	11.17	10.8	11.49	9.4	7.09	13.68	14.94	14.58

Source: Own study.

5. Conclusions

The conducted research proves that it is not possible to clearly indicate a method that results in optimal ranking. Different measures of suitability of rankings indicate different methods and procedures as being the best. In this situation, one approach is to use a set of rankings in order to aggregate the results of different methods - similar prediction methods are used in many machine learning methods. It is also impossible to unequivocally prove whether the correlated variables should be removed from the data set or not.

However, if the researcher would like to choose only one method of ranking construction, then the SAW method should be considered - it is the most intuitive and also most often indicated in our study as the best method.

It should be noted that our research was carried out with the use of transformation types dedicated to specific aggregation methods applied. It seems that it would be reasonable to repeat the research carried out, by additionally examining various methods of data normalization and various methods of transforming the nature of the variables (change of destimulants into stimulants).

References:

- Bąk, A. 2017. Statystyczne metody doboru zmiennych w porządkowaniu liniowym. Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu, 468, 29-37.
- Bulurcu, B. 2016. Investment Destination Decision by Using the VIKOR Method in the European Union Countries. American International Journal of Contemporary Research, 6(2), 16-24.
- Charnes, A., Cooper, W.W., Rhodes, E. 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429-444.
- Cîrstea, S.D., Moldovan-Teselios, C., Cîrstea, A., Turcu, A.C., Darab, C.P. 2018. Evaluating renewable energy sustainability by composite index. Sustainability, 10(3), 811.

- Cucchiella, F., D'Adamo, I., Gastaldi, M., Koh, S.L., Rosa, P. 2017. A comparison of environmental and energetic performance of European countries: A sustainability index. *Renewable and Sustainable Energy Reviews*, 78, 401-413.
- European Commission. 2020. Circular economy action plan for a cleaner and more competitive Europe, COM(2020) 98 final. Available online: https://eur-lex.europa.eu/resource.html?uri=cellar:9903b325-6388-11ea-b735-01aa75ed71a1.0017.02/DOC_1&format=PDF.
- European Environment Agency. 1999. Workshop on Indicators as a Tool for Managing and Monitoring a Sustainable Local and Regional Planning Process. Brussels.
- Eurostat. 1999. Integration-indicators for Energy. Data 1985-97, Office for Official Publications of the European Communities. Luxembourg.
- Eurostat. 2020. Sustainable development in the European Union - Monitoring report on progress towards the SDGS in an EU context — 2020 edition, EC. Available online: <https://ec.europa.eu/eurostat/web/products-statistical-books/-/KS-02-20-202>.
- García-Álvarez, M.T., Moreno, B., Soares, I. 2016a. Analyzing the environmental and resource pressures from European energy activity: A comparative study of EU Member States. *Energy* 115, 1375-1384.
- García-Álvarez, M.T., Moreno, B., Soares, I. 2016b. Analyzing the sustainable energy development in the EU-15 by an aggregated synthetic index. *Ecological Indicators*, 60, 996-1007.
- Grabiński, T., Wydymus, S., Zeliaś, A. 1989. *Metody Taksonomii Numerycznej w Modelowaniu Zjawisk Społeczno- Gospodarczych*. PWN, Warszawa, Poland.
- Hatefi, S.M., Torabi, S.A. 2018. Slack analysis framework for improving composite indicators with applications to human development and sustainable energy indices. *Econometric Reviews*, 37, 3, 247-259.
- Hellwig, Z. 1968. Zastosowanie metody taksonomicznej do typologicznego podziału krajów ze względu na poziom ich rozwoju oraz zasoby i strukturę wykwalifikowanych kadr. *Przegląd statystyczny*, 4, 307-326.
- International Atomic Energy Agency, United Nations Department of Economic and Social Affairs (UNDESA), International Energy Agency (IEA), Eurostat, European Environment Agency (EEA). 2005. Energy indicators for sustainable development: guidelines and methodologies, Vienna. Available online: <http://www.iaea.org/Publications/index.html>.
- Iddrisu, I., Bhattacharyya, S.C. 2011. Sustainable Energy Development Index: A multi-dimensional indicator for measuring sustainable energy development. *Renewable and Sustainable Energy Reviews*, 50, 513-530.
- International Energy Agency. 1997. Indicators of Energy Use and Efficiency -Understanding the Link between Energy and Human Activity. OECD, International Energy Activity, Paris.
- International Energy Agency. 2004. World Energy Outlook, OECD/International Energy Agency, Paris, France. Available online: <https://www.oecd-ilibrary.org/docserver/weo-2004-en.pdf?expires=1601222340&id=id&accname=ocid53014339&checksum=28DB02A67A5A287E77D02113E1F4AEDE>.
- Jarocka, M. 2013. Wpływ metody doboru cech diagnostycznych na wynik porządkowania liniowego na przykładzie rankingu polskich uczelni. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 279, 85-94.

- Kisielińska, J. 2016. Ranking państw UE ze względu na potencjalne zaspokojenie zapotrzebowania na produkty rolne z wykorzystaniem metod porządkowania liniowego. *Problemy rolnictwa światowego*, 16(3), 142-152. Warszawa.
- Konarzewska, I. 2017. Rankingi wielokryteriowe w warunkach zależności liniowej kryteriów – przykład badania ładu środowiskowego w Polsce w roku 2014. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 468, 99-107.
- Koszela, G., Gostkowski, M., Ochnio, L., Kostoglou, V. 2020. A comparison of logistics infrastructure development level of European Union countries using TOPSIS and VIKOR methods. *Zeszyty Naukowe Szkoły Głównej Gospodarstwa Wiejskiego w Warszawie. Ekonomika i Organizacja Logistyki*, 5(1).
- Kukuła, K., Luty, L. 2015. Propozycja procedury wspomagającej wybór metody porządkowania liniowego. *Przegląd Statystyczny*, R. LXII – ZESZYT 2.
- Ligus, M. 2017. Evaluation of economic, social and environmental effects of low-emission energy technologies development in Poland: A multi-criteria analysis with application of a fuzzy analytic hierarchy process (FAHP). *Energies*, 10(10), 1550.
- Ligus, M., Peternek, P. 2021. The Sustainable Energy Development Index - An Application for European Union Member States. *Energies*, 14, 1117.
- Liu, G. 2014. Development of a general sustainability indicator for renewable energy systems: a review. *Renew. Sustain. Energy Rev.*, 31, 611-621.
- Malina, A., Zeliaś, A. 1998. On Building Taxonomic Measures on Living Conditions Statistics in Transition, 3, 523-544.
- Młodak, A. 2006. Analiza taksonomiczna w statystyce regionalnej. Difin, Warszawa.
- Roszkowska, E. 2011. Multi-criteria decision making models by applying the TOPSIS method to crisp and interval data. *Multiple Criteria Decision Making/University of Economics in Katowice*, 6(1), 200-230.
- Saisana, M., Tarantola, S. 2002. State-of-the-art report on current methodologies and practices for composite indicator Development. European Commission.
- Trojanowska, M., Nęcka, K. 2020. Selection of the Multiple-Criteria Decision-Making Method for Evaluation of Sustainable Energy Development: A Case Study of Poland. *Energies*, 13, 6321.
- Walesiak, M. 2018. The choice of normalization method and rankings of the set of objects based on composite indicator values. *Statistics in Transition, New Series*, 19(4), 693-710.
- World Energy Council. 2014. Energy trilemma index. Benchmarking the sustainability of national energy systems, London. Available online: http://www.wec-france.org/DocumentsPDF/Etudes_CME/Energy-Trilemma-Index-2014-ENG.pdf.
- Zho, P., Ang, B.W., Poh, K.L. 2007. A mathematical programming approach to constructing composite indicators. *Ecological Economics*, 62, 291-297.
- Zhou, P., Ang, B.W., Poh, K.L. 2006. Comparing aggregating methods for constructing the composite environmental index: An objective measure. *Ecological Economics*, 59, 305-311.