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Temporal Analysis of Energy Transformation in EU Countries

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Abstract: Due to the environmental policy adopted by the European Union (EU), EU countries are obliged to reduce greenhouse gas emissions. They reduce emissions largely through the energy transformation and switching to renewable energy sources (RES). Therefore, it is important to assess the progress of the energy transformation of individual EU countries. This is related to the aim of the article, which is a temporal analysis of the energy transformation process towards the transition to RES and reducing the use of fossil fuels in energy production. To achieve this goal, a new Temporal/Dynamic Multi-Criteria Decision-Making (T/DMCDM) method called Temporal PROSA was developed, based on the PROMETHEE and PROSA family of methods. The Temporal PROSA method, unlike many other T/DMCDM methods, enables the aggregation of data from many periods into a single final assessment, as well as the direct transfer of information from the examined periods to the overall result. As a result of the research, EU countries that dominated in terms of progress in energy transformation towards RES in the years 2004–2021were identified. Based on the data and methodology used, it was indicated that these countries are primarily Sweden and Portugal, and recently also Denmark and Finland. On the other hand, countries such as Belgium, Bulgaria, Cyprus, Luxembourg, and Poland made the least progress between 2004 and 2021.

Keywords: energy transformation; renewable energy sources; European Union; temporal assessment; PROSA; multi-criteria; Dynamic MCDM

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1. Introduction

Energy is a fundamental factor for sustainable economic development, as well as a key element required to achieve and maintain the stability of the economy and society [1]. Over the last 60 years, energy consumption has increased almost fourfold, from 155.88 EJ in 1960 to 595.15 EJ in 2021 [2]. The global scale of energy needs is well demonstrated by forecasts according to which global energy consumption is expected to increase by 50% by 2050 compared to 2018 [3]. Currently, most energy comes from fossil fuels—the main energy sources are coal, oil and natural gas [4]. According to data from 2022, the share of coal in the global energy mix is approximately 26%, oil—31%, and gas—23% [5]. Unfortunately, fossil fuels, according to research, are responsible for 80% of global CO_2 emissions and are considered the main cause of global warming [6]. Therefore, out of concern for the environment and the threat of climate change, many regions of the world are trying to gradually reduce the use of fossil fuels and replace them with renewable energy [7]. The scale of this phenomenon is shown by a comparison of investments in renewable energy sources (RES) in 2004 and 2018. While in 2004 global investments in RES amounted to USD 50 billion, in 2018 it was already six times more, i.e., USD 300 billion [8]. According to other data, over the years 2010–2019, global investments in RES (excluding hydropower plants) totalled USD 2.7 trillion. The largest financial outlays during this time were made in China (USD 818 billion), United States (USD 392 billion), Japan (USD 211 billion), Germany (USD 183 billion), and United Kingdom (USD 127 billion) [9]. Together with investments in RES, their production capacity increases. The International Energy Agency (IEA) predicts that by 2026, the increase in RES generation capacity will account for approximately 95%

of the total increase in energy capacity in the world [10]. Therefore, fossil fuels will only contribute to 5% of the increase in production capacity.

Growing investments in renewable energy are justified by a number of benefits that the use of RES brings. First of all, it is recognized that RES do not emit (or emit only minimally) pollutants and greenhouse gases, reducing air and water pollution and limiting climate change [8,11]. In addition to the environmental aspect, an important advantage is the diversity of RES, which means that almost every country has some renewable resources [12]. This translates into reduced dependence on energy exporters, because part of the needed energy can be produced locally and does not have to be imported from other countries that have access to fossil fuels [8,11,13]. Another advantage that reduces dependence on energy exporters is the abundance of RES, so there is no risk of running out of energy in a relatively short time [8,11]. Moreover, investments in RES allow for the creation of new jobs and contribute to driving economic growth [8,11,14]. In particular, it was observed that the increase in renewable energy consumption is determined by a higher level of human capital and the stage of country development [15]. A positive relationship was also noted between increasing renewable energy generation capacity and employment, showing an increase in employment of 0.48% for every 1% increase in renewable energy generation capacity [16]. The role of RES in a circular economy is important, as recycling and RES have been shown to be important factors in ensuring sustainable economic development with less climate deterioration [17]. RES also have some disadvantages and limitations, such as the lack of continuity of energy production from RES, the dependence of production on weather conditions and the lack of synchronization of energy generation peaks in RES with energy consumption peaks [18]. However, currently the greatest disadvantage of RES is the high costs of energy transformation consisting in switching from the use of conventional energy sources (fossil fuels) to renewable sources [12]. This means that, despite increasingly larger investments and development of RES, the coexistence of renewable energy and energy from fossil fuels is assumed in the next few decades [13,18].

The advantages and potential benefits of using RES cause individual countries and groups of countries to engage in the development of renewable energy. Particularly ambitious actions in this area are undertaken by the European Union (EU), which is a world leader in introducing pro-environmental legislation [12]. The energy transformation of EU countries includes, among others: reducing investments in the extraction of fossil fuels, eliminating coal-fired power plants, and increasing investments in technological innovations related to energy [18]. Of particular importance in the EU in the context of energy transformation and the transition to the use of RES is the "Green Deal" program adopted in 2019. It assumes that the EU economy will become "zero-emission" by 2050 and gain energy independence [19]. Moreover, in 2021, the EU adopted the "Fit for 55" package requiring member countries to reduce greenhouse gas emissions by 55% by 2030 and assuming further increases in the use of RES [12]. It should be noted that between 2000 and 2019, the consumption of energy from RES in all economic sectors and households in the EU-27 increased by over 200%. The largest increase in the use of renewable energy in the EU-27 occurred in the transport sector (by 2200%), the smallest in industry (by 150%), and in the case of households the increase was 165% [12]. By 2020, nine EU countries have phased out coal-based energy, thirteen countries have set a deadline for phasing out coal, and four more countries are considering possible timetables [20]. In 2000, 60% of RES consumption in EU households belonged to Germany, Spain, France, Poland, and Romania, while in 2019 the share of these countries increased to 67%. In the industrial sector, in 2000, Sweden, Finland, Spain, France and Portugal together accounted for 67% of RES consumption in the EU, while in 2019, 72% of RES consumption in this sector was accounted for (in order of biggest consumers) by Sweden, Finland, Germany, France, Spain and Poland. As for the transport sector, in 2000, 100% of RES consumption belonged to Germany, France, Spain, Austria, the Czech Republic and Romania. In 2019, the largest consumers of RES in the transport sector were Germany, Spain, France, Italy, Sweden, and Poland, which consumed a total of 71% of the energy produced in the EU from RES [12].

The data presented above show that the structure of the energy mix of individual countries changes dynamically over time. The order of leading countries in the EU in terms of energy transformation and the transition from fossil fuels to RES in various sectors of the economy is also changing. Taking into account the potential benefits of switching to RES and the EU requirements for member states in this respect, the assessment of the progress of the energy transformation of individual EU countries is an important research problem. This progress needs to be continuously monitored and reviewed to ensure that all EU countries are moving in the same direction. Constant monitoring of the energy transformation will allow us to support and motivate countries that are coping worse with the transformation, as well as to appreciate countries that are leaders in this field. Moreover, it is important to analyze the transformation over a longer period of time in order to reliably assess the entire energy transformation process of EU countries over the last dozen or so years. Therefore, the aim of the article is a temporal analysis of the energy transformation process towards switching to RES and reducing the use of fossil fuels in energy production. The achievement of the indicated goal is the practical contribution of the article. Unfortunately, there is a shortage of methods in scientific methodology that would broadly take into account data from many periods and the dynamics of changes in subsequent periods in the analysis. In order to fill this methodological gap, the dynamic multi-criteria decision-making (DMCDM) framework allowing for the temporal assessment of the progress of energy transformation of individual countries was developed [21]. The framework uses the Preference Ranking Organization Method for Enrichment Evaluation for Sustainability Assessment (PROSA) [22] to take into account changes in the structure of the energy mix of a given country compared to other countries examined. The developed approach allows to take into account partial data from many periods, the dynamics of changes in these data and the evolution of individual countries in the context of energy transformation, as well as generate a clear quantitative assessment of the transformation process. This approach is based on the application of the DMCDM framework in combination with the PROSA method is a new methodological issue, previously unheard of in the literature, and is the scientific contribution of the article. The developed approach was formalized in the form of the DMCDM method called Temporal PROSA.

Section 2 presents the state of the art of dynamic and temporal approaches to MCDM. The imperfections of the approaches used and their methodological gaps were pointed out. Section 3 discusses the proposed form of time representation in the MCDM paradigm. In addition, a newly developed Temporal PROSA method is presented, which fills the previously indicated gaps. Section 4 discusses the criteria and results of assessing the progress of the energy transformation of EU countries. Both temporal results from subsequent periods, as well as overall results are presented, aggregating individual periods into one assessment value. Section 5 contains conclusions as well as a discussion of research limitations and further research directions.

2. State of the Art

2.1. Static and Dynamic Approach to Decision-Making

Multi-criteria decision-making problems involve a limited number of alternatives evaluated on the basis of multiple indicators (criteria) to help decision-makers (DMs) determine the best option (alternative) [23]. Multi-criteria decision-making (MCDM) methods are used in this type of decision-making problems. This is a group of advanced analytical methods that help in optimal decision-making by evaluating competing alternatives based on contradictory (conflicting) criteria [24]. Typically, in MCDM methods, each criterion is assigned a single value, which may be, for example, the average of fulfilling the criterion in a given period, the value at the time of making the decision (current data) or other static data [25]. Unfortunately, such reliance on a single set of input data may lead to excessive simplifications of the decision-making model [26].

Although MCDM methods are an effective tool for many real-world problems of selecting and ranking alternatives, they usually only provide an idea of which alternative is preferred. Therefore, their results may become outdated due to changes in the performance of alternatives or in decision-makers' perceptions of value [27]. Most proposed MCDM approaches do not take into account the temporal characteristics of the criteria values, which may be interesting information to investigate to predict future rankings [28]. In other words, MCDM methods deal with the value of the criteria at the moment of decision-making, without taking into account their evolution over time [25]. In practice, due to the dynamic nature of many decision-making problems and changes in alternatives, a static approach to assessing current outcomes is insufficient [29]. Therefore, in recent years there has been a visible development of a new MCDM trend called temporal MCDM (TMCDM). Temporal methods, apart from the classic assessment of the considered alternatives, also allow for accurate capture of the dynamics of changes in outcomes over time and translate them into an easy-to-interpret result [30]. The same assumptions apply to DMCDM methods because they also assume changes over time. In dynamic decision-making problems, both the set of alternatives and the criteria may change. The set of criteria used to measure efficiency may be a function of time and may additionally depend on individual DMs. DMs' preferences and other input information may change, affecting the perception of the solution [31]. It is therefore clear that both TMCDM and DMCDM take into account the development of MCDM methods towards the possibility of capturing changes in the decision-making model and input values over time.

2.2. Applications of DMCDM and TMCDM Methods in Decision-Making Problems

The TMCDM and DMCDM methods are used in the literature for multi-criteria multi-period decision analysis. Liu et al. [32] applied DMCDM to the problem of selecting a wine supplier for a supermarket. They relied on the Bipolar Linguistic Term Set approach, and their dynamic approach allows for changes in the sets of alternatives and criteria in subsequent periods. Tao et al. [33] used the Intuitionistic Fuzzy Set based Dynamic Group Multi-Criteria Decision-Making in a similar decision-making problem that involved the selection of a wine supplier by a group of decision-makers. Furthermore, in this case, the dynamics of the decision-making problem include changes in the sets of alternatives and criteria in particular periods. An approach that allows for changes in the group of decision-makers and in the set of alternatives was developed by Keshavarz-Ghorabaee et al. [34]. They solved the problem of dynamic evaluation of subcontractors in a construction project using the Evaluation based on Distance from Average Solution (EDAS) method. Polomčić et al. [35] used the Fuzzy Dynamic Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to select a groundwater control system for an open-pit mine. In this case, DMCDM allows for changes in the set of criteria, and subsequent periods were aggregated using a weighted average. Frini and Ben Amor [36] used a combination of Analytic Hierarchy Process (AHP) and Multi-criteria multi-Period Outranking Method (MUPOM) in the problem of selecting forest management activities. Temporal aggregation in this work was performed by aggregating the binary relations obtained in each period for each pair of alternatives. The MUPOM method was also used by Martins and Garcez [37] in the problem of building a ranking of roads on which accident prevention measures should be implemented. In turn, Mouhib and Frini [38] used the temporal Stochastic Multi-criteria Acceptability Analysis Tri (SMAA-Tri) in the problem of selecting forest management activities. The approach they propose allows for the aggregation of periods using a weighted average of local acceptability indices or outranking indices. Campello et al. [28], using a combination of Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) and SMAA, assessed the selected countries from a financial and economic perspective. In their study, they predicted countries' failure ratings based on past data. In another study, Campello et al. [25] calculated the human development index of selected countries in many periods. They built country rankings based on statistical characteristics determined from past data. TOPSIS and SMAA methods were used in this study. In both studies, Campello et al. proposed a temporal approach using tensor data representation and time series. Similarly to Campello et al., Banamar and Smet [39] calculated the human development index of selected countries in many periods. In this study, the authors used the PROMETHEE method, and the temporal approach consisted in aggregating subsequent periods using a weighted average. Witt and Klumpp [40] chose a sustainable investment portfolio based on renewable energy technologies. Furthermore, in this case, the PROMETHEE method was used, and the temporal extension allowed for changes in the sets of criteria over time. The authors carried out the aggregation of subsequent periods using the arithmetic mean. Wątróbski et al. [26] developed an approach called Data vARIability Assessment (DARIA) TOPSIS. This approach has been used to assess the sustainability of cities and communities in European countries. Then, the DARIA-TOPSIS method was used by Bączkiewicz and Wątróbski [41] in the problem of assessing energy systems in European countries. The DARIA-TOPSIS method they developed allows for the determination of temporal changes in the efficiency of alternatives based on the studied periods. Temporal change analysis is used to update the efficiency of alternatives in the most recent period under study. The same temporal extension was used by Wątróbski [30] in the PROMETHEE method, when considering the problem of consumption of alternative fuels in road transport. Wen et al. [27] used the Best-Worst method and TOPSIS to select heating systems for residential buildings. They developed a semi-dynamic approach based on the representation of time by decision scenarios. This approach allows criteria weights to change over time. Finally, Ziemba [18] developed a generalized DMCDM framework allowing for temporal decision analysis. In a pilot study, this framework was used to assess the energy security of countries belonging to the Organisation for Economic Cooperation and Development (OECD). The pilot study was based on the Fuzzy Simple Additive Weighting (SAW) and New Easy Approach To Fuzzy PROMETHEE (NEAT F-PROMETHEE) methods. The use of fuzzy methods made it possible to take into account periods from the past, present and future, as well as to forecast future values based on past data. An aggregation of subsequent periods was performed using a weighted average. The discussed applications of the TMCDM and DMCDM methods in multi-criteria multi-period decision analysis problems are presented in Table 1.

Table 1. Decision-making problems solved using temporal/dynamic modifications of MCDM methods.

Decision-Making Problem	Number of Periods	Number of Alternatives	Number of Criteria	MCDM Method	Temporal/Dynamic Modification	Ref.
Selection of a wine supplier for a supermarket	3	3–5	4–5	BLTS DMCDM	Changes in the sets of alternatives and criteria over time	[32]
Selection of a wine supplier for a supermarket by a group of decision-makers	3	5–6	5–6	IFS DGMCDM	Changes in the sets of alternatives and criteria over time, the use of alternative queuing method and feedback mechanism	[33]
Evaluation of subcontractors in a construction project	4	7–10	4	Fuzzy EDAS	Changes in the sets of alternatives and decision-makers over time	[34]
Selection of the groundwater control system for an open-cast mine	4	3	3–4	Fuzzy Dynamic TOPSIS	Changes in the set of criteria over time, aggregation of subsequent periods using a weighted average, use of stochastic diffusion	[35]
Selection of a compromise sustainable forest management option	30	5	5	AHP, MUPOM	Aggregation of subsequent periods based on the average distance between two preorders in each period	[36]

Table 1. *Cont.*

Decision-Making Problem	Number of Periods	Number of Alternatives	Number of Criteria	MCDM Method	Temporal/Dynamic Modification	Ref.
Identification and prioritization of roads in order to implement actions on them to prevent or mitigate accidents	5	11	11	MUPOM	Aggregation of subsequent periods based on the average distance between two preorders in each period	[37]
Organizing sustainable forest management options	30	4	5	Temporal SMAA-Tri	Aggregation of subsequent periods using the weighted average value of local acceptability indices or outranking indices	[38]
Financial and economic assessment of countries	40	5	3	PROMETHEE II, SMAA	Forecasting future states based on past data, using tensor representation and time series	[28]
Human development index study of countries	6	10	3	TOPSIS, SMAA	Ranking alternatives based on statistical features calculated from past data, using tensor representation and time series	[25]
Human development index study of countries	6	10	3	PROMETHEE II	Aggregation of subsequent periods using a weighted average	[39]
Identification of a sustainable investment portfolio specified by capacity expansions of different RES technologies	4	4	1–3	PROMETHEE	Changes in sets of criteria over time, aggregation of subsequent periods using the arithmetic mean	[40]
Assessing the sustainable cities and communities in European countries	5	26	10	DARIA-TOPSIS	Determining the value and direction of variability of alternative efficiency results from the analyzed periods. Update of efficiency from the last period with the variability value.	[26]
Assessment of affordable and clean energy systems in European countries	5	30	11	DARIA-TOPSIS	Determining the value and direction of variability of alternative efficiency results from the analyzed periods. Update of efficiency from the last period with the variability value.	[41]
Evaluation of sustainable consumption of alternative fuels in road transport	8	32	9	Temporal PROMETHEE II	Determining the value and direction of variability of alternative efficiency results from the analyzed periods. Update of efficiency from the last period with the variability value.	[30]

Table 1. *Cont.*

Decision-Making Problem	Number of Periods	Number of Alternatives	Number of Criteria	MCDM Method	Temporal/Dynamic Modification	Ref.
Selection of heating systems for heating residential buildings	3	13	11	BWM, TOPSIS	Changes in criteria weights over time, periods considered as separate scenarios	[27]
Assessment of countries' energy security based on the International Energy Security Risk Index	5	25	29	Fuzzy SAW, NEAT F-PROMETHEE	Aggregation of subsequent periods using a weighted average, taking into account periods from the past, present and future, forecasting future states based on past data	[21]

Abbreviations: BLTS—Bipolar Linguistic Term Set, IFS DGMCDM—Intuitionistic Fuzzy Set based Dynamic Group Multi-Criteria Decision-Making, EDAS—Evaluation based on Distance from Average Solution, TOPSIS—Technique for Order of Preference by Similarity to Ideal Solution, AHP—Analytic Hierarchy Process, MUPOM—Multi-criteria multi-Period Outranking Method, SMAA—Stochastic Multi-criteria Acceptability Analysis, PROMETHEE—Preference Ranking Organization Method for Enrichment Evaluation, DARIA—Data vARIability Assessment, BWM—Best-Worst Method, SAW—Simple Additive Weighting, NEAT F-PROMETHEE—New Easy Approach To Fuzzy PROMETHEE.

Although static MCDM methods are widely used in energy and energy management problems [42,43], only a few studies listed in Table 1 relate TMCDM and DMCDM methods to energy problems. These are the problems of selecting an investment portfolio based on renewable energy [40], assessing the energy systems of European countries [41] and assessing the energy security of OECD countries [18]. In addition, one study examines thermal energy and the choice of heating systems for residential buildings [27], as well as the assessment of the use of alternative fuels in road transport [30]. This indicates the need to develop a temporal and dynamic approach to problems related to energy, and in particular renewable energy.

2.3. Research Gap and Novelty of Research

The main disadvantage of the above-mentioned DMCDM and TMCDM approaches is that they usually:

1. do not aggregate evaluations from different periods into an overall evaluation or
2. linearly aggregate ratings from different periods before comparing these aggregated scores.

In the first case, the use of the DMCDM/TMCDM methodology allows the comparison of alternatives only in individual periods, without the possibility of overall comparison of alternatives based on results aggregated over time. In the second case, comparison of aggregated results is possible, but this approach does not take into account the evolution of alternatives. This way of comparing results is certainly effective for classic MCDM problems, but it is no longer sufficient for DMCDM problems because the alternatives, criteria, and decision environment will change over time [33]. To solve this problem, the evolution of alternatives over time must be taken into account. The PROSA method can be used here, which allows you to consider the balance between elements of the same type in the decision-making model in the final assessment. These elements may be decision criteria (in the PROSA-C method) [44,45], groups of criteria (in the PROSA g method) [22], the results of individual assessment obtained by individual DMs (in the PROSA GDSS method) [46,47] or all these elements at the same time [48]. In the proposed modification of the DMCDM/TMCDM framework, these elements are temporal results (rankings) of alternatives obtained for a given period. This approach to temporal assessment allows the dynamics of changes in results between particular periods to influence the final result of alternatives. This allows for a better capture of the evolution of alternatives over time than in the case of simple (usually linear) aggregation of ratings over successive periods. The PROSA-based approach to DMCDM is formalized later in the paper as the Temporal PROSA method.

The approach used in the proposed Temporal PROSA method is somewhat similar to the approaches used by Campello et al. [25], Wątróbski [41], and also by Wątróbski et al. [26], as well as Bączkiewicz and Wątróbski [41] (DARIA-TOPSIS method). Campello et al. [25] uses the coefficient of variation as one of the statistical data, which is the quotient of the standard deviation of the population from all periods and the average from all periods for the value of the alternative to the criterion. Wątróbski [41] uses efficiency variability, which is in fact the standard deviation of efficiency from all periods, and the DARIA-TOPSIS method 38] uses efficiency variability in the form of the Gini coefficient calculated for efficiency in all periods. The approach proposed by Campello et al. does not enable aggregation of periods into one final efficiency value. In turn, the approaches based on efficiency variability use this variability to adjust aggregated ratings for the most recent period only. Therefore, the basis for the final assessment is basically only the last period, adjusted for the variability of efficiency. This means that information about previous periods is only taken into account to a small extent (they are used only to calculate variability, and the rating values from previous periods do not directly affect the final ratings of the alternatives). The use of the Temporal PROSA method guarantees the direct transfer of information from individual periods and its aggregation into the final assessment. Moreover, the use of an approach based on the PROSA method enables temporal aggregation taking into account the variability of results from individual periods by calculating the weighted mean absolute deviation (WMAD) [49]. WMAD, like range, variance or standard deviation, is a measure of dispersion and provides information about the variability of a data set [50]. Considering the indicated advantages of the PROSA method over other approaches using data variability, the extension of PROSA to a temporal form is justified and constitutes a valuable scientific contribution. These developments were based on the DMCDM framework developed by Ziemba [21].

3. Extension of the PROSA Method with a Temporal Approach

3.1. Time Representation in the MCDM Paradigm

A multi-criteria decision-making problem can be presented as a problem of searching for an optimal decision-making alternative a^*, such that (1):

$$max\{c_1(a^*), c_2(a^*), \ldots, c_n(a^*) \mid a^* \in A\} \tag{1}$$

where A is a finite set of decision-making alternatives $\{a_1, a_2, \ldots, a_m\}$ and $\{c_1(\cdot), c_2(\cdot), \ldots, c_n(\cdot)\}$ is a set of evaluation criteria [51]. Since there is usually no optimal solution, the problem considered by classical MCDM methods comes down to finding a pareto-optimal alternative, i.e., not worse than the others. Individual MCDM method search for a pareto-optimal solution using different computational functions. These functions can be generalized and written as (2):

$$G(a^*) = F\{c_1(a^*), c_2(a^*), \ldots, c_n(a^*) \mid a^* \in A\} \tag{2}$$

where F is a function representing a given MCDM method and $G(a^*)$ is the numerical value of the efficiency of alternative a^* obtained after applying the F function.

Adding time representation to the MCDM paradigm causes the decision-making problem to be considered in t subsequent periods (3):

$$G^k(a^*) = F\left\{{c_1}^k(a^*), {c_2}^k(a^*), \ldots, {c_n}^k(a^*) \mid a^* \in A\right\} \forall k = 1, \ldots, t \tag{3}$$

where k stands for the k-th period.

Aggregation of all periods is possible using the aggregation function $H\left(G^k(a^*)\right) \forall k = 1, \ldots, t$ [21].

It should be noted that both in the classical–static MCDM approach, as well as in the dynamic approach taking into account time representation, in order to find alternative a^*, all alternatives $a_i \in A \; \forall i = 1, \ldots, m$ are considered.

In the classic MCDM approach, alternatives are considered based on the efficiency matrix E presenting the efficiency of alternatives based on criteria (4) [52]:

$$E = \begin{bmatrix} c_1(a_1) & c_2(a_1) & \cdots & c_n(a_1) \\ c_1(a_2) & c_2(a_2) & \cdots & c_n(a_2) \\ \vdots & \vdots & \ddots & \vdots \\ c_1(a_m) & c_2(a_m) & \cdots & c_n(a_m) \end{bmatrix} \quad (4)$$

The efficiency matrix can also be used in temporal/dynamic extensions of MCDM to represent the aggregated efficiencies of alternatives over particular periods. The matrix will then take the following form (5):

$$T = \begin{bmatrix} G^1(a_1) & G^2(a_1) & \cdots & G^t(a_1) \\ G^1(a_2) & G^2(a_2) & \cdots & G^t(a_2) \\ \vdots & \vdots & \ddots & \vdots \\ G^1(a_m) & G^2(a_m) & \cdots & G^t(a_m) \end{bmatrix} \quad (5)$$

The above-mentioned form of time representation was used in the Temporal PROSA method.

3.2. Temporal PROSA Method

The Temporal PROSA method consists of two main stages. The first is to calculate the efficiency of all alternatives in each of the considered periods. This action is described by Formula (6):

$$G^k(a_i) = F\left\{ {c_1}^k(a_i), {c_2}^k(a_i), \ldots, {c_n}^k(a_i) \right\} \forall i = 1, \ldots, m \; \forall k = 1, \ldots, t \quad (6)$$

where $G^k(a_i)$ is the efficiency of the i-th alternative in the k-th period. In the Temporal PROSA method, any MCDM method can be used as the F function. This method receives data about alternatives in the form of efficiency matrices E^k described by Formula (7):

$$E^k = \begin{bmatrix} {c_1}^k(a_1) & {c_2}^k(a_1) & \cdots & {c_n}^k(a_1) \\ {c_1}^k(a_2) & {c_2}^k(a_2) & \cdots & {c_n}^k(a_2) \\ \vdots & \vdots & \ddots & \vdots \\ {c_1}^k(a_m) & {c_2}^k(a_m) & \cdots & {c_n}^k(a_m) \end{bmatrix} \quad (7)$$

The second step is to aggregate the efficiencies calculated in all periods into one numerical value. This value represents the overall efficiency of each alternative. As noted earlier in Section 3.1, the aggregation of all periods into a single numerical value is performed using the function $H\left(G^k(a_i)\right) \forall i = 1, \ldots, m \; \forall k = 1, \ldots, t$. The set of data passed to the H function takes the form of the T matrix described in Section 3.1 by Formula (5). The PROSA calculation procedure is used as the aggregation function H.

At the beginning of the PROSA procedure adapted to the aggregation of subsequent periods, in each k-th period the difference between the efficiencies of each pair of alternatives $(a_i, a_j) \; \forall i = 1, \ldots, m \; \forall j = 1, \ldots, m$ is calculated. Based on the calculated difference, the preference P_k between the examined pair of alternatives is determined using the preference function f_k according to Formula (8):

$$P_k(a_i, a_j) = f_k\left[G^k(a_i) - G^k(a_j)\right] \quad (8)$$

Then, temporal net flow ϕ_k (9) is calculated for each alternative:

$$\phi_k(a_i) = \frac{1}{m-1}\sum_{j=1}^{m}\left[P_k(a_i, a_j) - P_k(a_i, a_j)\right] \tag{9}$$

Temporal net flows calculated for alternatives in individual periods are aggregated into global net flows ϕ_{net}. Normalized weights (w_k) of individual periods (10) can also be used in this aggregation:

$$\phi_{net}(a_i) = \sum_{k=1}^{t}\phi_k(a_i)w_k \tag{10}$$

The next step is to calculate the WMAD for each alternative using the compensation (balance) factor s_k (11):

$$WMAD(a_i) = \sum_{k=1}^{t}|\phi_{net}(a_i) - \phi_k(a_i)|w_k\, s_k \tag{11}$$

As noted in Section 2, WMAD is a measure of dispersion and provides information about the variability of a data set. In practice, WMAD is the weighted average distance of the global solution $\phi_{net}(a_i)$ from the temporal solutions $\phi_k(a_i)$. In other words, WMAD describes how far all temporal solutions $\phi_k(a_i)$ together are from $\phi_{net}(a_i)$. In turn, s_k is an additional weight that determines how important the distance between the k-th temporal solution, and the global solution is when aggregating subsequent periods. Based on WMAD and the global solution $\phi_{net}(a_i)$, PROSA net value (PSV_{net}) is calculated, correcting the ϕ_{net} net solution by the value of the weighted deviation (12):

$$PSV_{net}(a_i) = \phi_{net}(a_i) - WMAD(a_i) \tag{12}$$

The PSV_{net} values allow you to rank the alternatives in the final alternative ranking.

To sum up, it should be noted that the PROSA method aggregates temporal solutions $\phi_k(a_i)$ into the global net flow $\phi_{net}(a_i)$, which is then corrected based on WMAD.

At the stage of determining the global net flow $\phi_{net}(a_i)$, information about the temporal efficiency of alternatives in subsequent periods is aggregated. Therefore, temporal efficiencies directly affect the final efficiency of each alternative. In turn, determining WMAD and correcting the global net flow $\phi_{net}(a_i)$ by the WMAD value causes PROSA to take into account the evolution of alternatives over time and the relationships between different temporal values of the same alternative against the background of other options. In other words, PROSA (via WMAD) takes into account the variability of alternatives over time. Moreover, correcting the global net flow $\phi_{net}(a_i)$ by the WMAD value causes alternatives with the lowest possible variability to be preferred. This means that in the case of a stable alternative, its efficiencies in particular periods support this alternative. In turn, in the case of an alternative with high variability, the efficiency of this alternative in particular periods are in mutual conflict and detrimental to this alternative. Therefore, the approach proposed in Temporal PROSA is consistent with the concepts of temporal support and temporal conflict, formulated already in 1995 by Östermark [53].

4. Results

4.1. Criteria for Assessing the Progress of Energy Transformation

The energy transformation study used 11 criteria related to energy productivity, energy consumption, the share of RES in the energy mix and energy prices. It should be explained here that the analysis of the energy transformation process of individual EU countries cannot be based on absolute values, because each country has different energy needs, depending on population, industrialization, etc. A country that has a larger population and a more developed industry will consume more energy than a country that is less economically developed and has a smaller population. Therefore, a direct comparison of, for example, Germany and Cyprus would be a methodological error. Therefore, the study was based on relative criteria, taking into account, among others, population or energy consumption in previous years. In assessing the progress of the energy transformation of EU countries, the criteria presented in Table 2 were taken into account.

Table 2. Criteria for assessing the progress of the energy transformation of EU countries.

No.	Name	Unit of Measure
C1	Energy productivity	Euro per kilogram of oil equivalent (KGOE)
C2	Primary energy consumption	Index, 2005 = 100
C3	Final energy consumption	Index, 2005 = 100
C4	Final energy consumption in households per capita	Kilogram of oil equivalent (KGOE)
C5	Greenhouse gas (GHG) emissions intensity of energy consumption	Index, 2000 = 100
C6	Share of energy from RES	Percentage
C7	Share of energy from RES in transport	Percentage
C8	Share of energy from RES in electricity	Percentage
C9	Share of energy from RES in heating and cooling	Percentage
C10	Electricity prices for medium size households	Euro per Kilowatt-hour
C11	Electricity prices for medium size industrial consumers	Euro per Kilowatt-hour

The C1 criterion (Energy productivity) assesses the quantity of economic output generated per unit of gross available energy. Gross available energy signifies the amount of energy products required to fulfill the demands of entities within the specified geographical area. The economic output is presented in Euros, adjusted for inflation, referencing the year 2010 and utilizing exchange rates from that same year. This allows you to observe the evolution of a given country over time.

The C2 (Primary energy consumption) and C3 (Final energy consumption) criteria measure energy efficiency taking into account energy consumption expressed in Million Tonnes of Oil Equivalent (MTOE). Energy consumption in each country was related to 2005 (base year) for that country. In this way, indexes were established describing the progress of each country in reducing energy consumption over the years.

The C4 criterion (Final energy consumption in households per capita) gauges the amount of electricity and heat an individual utilizes at home, excluding energy devoted to transportation. This metric specifically focuses on the energy consumed by end-users, disregarding the internal energy consumption of the energy sector.

The C5 criterion (GHG emissions intensity of energy consumption) is determined by the ratio of energy-related GHG emissions to the gross inland consumption of energy. This criterion quantifies the number of tonnes of CO_2 equivalents emitted from energy-related GHGs in a specific economy per unit of energy consumed. This value was expressed in the form of an index, for which the reference year was 2000. This allowed the assessment to take into account the progress of a given country in reducing greenhouse gas emissions related to energy consumption.

The C6 (Share of energy from RES), C7 (Share of energy from RES in transport), C8 (Share of energy from RES in electricity), and C9 (Share of energy from RES in heating and cooling) criteria measure the share of renewable energy in total energy consumption. The C6 criterion refers to total energy consumption in all sectors of the economy and in households, while C7–C9 criteria refer to specific areas in which energy is used.

The C10 (Electricity prices for medium size households) and C11 (Electricity prices for medium size industrial consumers) criteria present electricity prices charged to final consumers. For household consumers, electricity prices are determined as the average national price in Euros per kWh, encompassing taxes and levies, applicable for the first half of each year. This calculation pertains to medium-sized household consumers falling within a consumption band with an annual consumption ranging from 2500 to 5000 kWh. On the other hand, for non-household consumers, electricity prices are defined as the average national price in Euros per kWh, excluding taxes, applicable for the first half of each year. This calculation applies to medium-sized industrial consumers within a consumption band with an annual consumption ranging from 500 to 2000 MWh. The C1–C9 criteria were previously used in a study of energy systems in European countries presented by Bączkiewicz and Wątróbski [41]. The C1 and C4–C9 criteria in our study were used in the same form as in the work by Bączkiewicz and Wątróbski, but the data in both works come from different periods. However, the C2 and C3 criteria differ significantly from those used by Bączkiewicz and Wątróbski. In the work by Bączkiewicz and Wątróbski [41], C2 and C3 were expressed in relations to the number of inhabitants, while in our study we used indexes referring to 2005. The difference is that in the work by Bączkiewicz and Wątróbski, the C2 and C3 criteria present raw numerical data, while in our study these criteria provide direct information about a given country's progress in reducing energy consumption over subsequent years in relation to previous years. Together with the C5 criterion expressed as an index in relation to the year 2000, the C2 and C3 criteria allow to capture the dynamics of changes in energy consumption and the related dynamics of changes in the intensity of GHG emissions. The C2 and C3 criteria are complemented by the C4 criterion, which measures energy consumption in households; however not as an index, but in absolute values. The other important criteria are C1, C6–C9, C10 and C11. The C1 criterion allows us to determine how efficient the energy sector of a given country is, i.e., what is the economic production per unit of energy. The C6–C9 criteria allow you to measure progress in the transition to renewable energy sources in various sectors of the economy. In turn, the C10 and C11 criteria show to some extent the impact of the energy transition on energy prices. Of course, this is an indirect impact, excluding factors such as inflation.

4.2. Temporal Study of Individual Periods

The data included in the study were expressed in annual periods from 2004 to 2021. The values of the criteria for the examined EU countries are included in Supplementary File S1. It should be noted that in the case of C10 and C11 criteria, the data referred to the years 2011–2021, while there was no data for the years 2004–2010. The preference model used in the temporal study for each period is presented in Table 3. The criteria weights were normalized to 100%. The energy productivity criterion (C1) was given a weight of 10%, the energy consumption criteria (C2–C4) were given a total weight of 20%, the single environmental criterion (C5) was given a weight of 20%, the criteria regarding the share of energy from RES (C6–C9) were given a total weight of 40%, and the criteria related to energy prices (C10 and C11) were assigned a weight of 10% in total. For the C1, C6–C9 criteria, the highest possible values are desired, while the remaining criteria are of a cost nature, so their values are expected to be as low as possible. A linear preference function (V-shaped criterion) was used for each criterion. The preference threshold for this function was each time twice the population standard deviation calculated on the basis of the values of all alternatives for a given criterion in the examined period.

Table 3. Preference model used to study the degree of advancement of the energy transformation of EU countries in each period from 2004 to 2021.

Criterion	Weight [%]	Preference Direction	Preference Function	Preference Threshold
C1	10	Max	V-shaped	2 × Population standard deviation from the values of all alternatives on the *j*-th criterion in the *k*-th period $2\sigma_j{}^k = 2 \times \sqrt{\frac{\sum_{i=1}^{m}\left(c_j{}^k(a_i)-\overline{c_j{}^k(a)}\right)^2}{m-1}}$
C2	6.67	Min		
C3	6.67	Min		
C4	6.67	Min		
C5	20	Min		
C6	25	Max		
C7	5	Max		
C8	5	Max		
C9	5	Max		
C10	5	Min		
C11	5	Min		

The PROMETHEE II method was used o aggregate preferences in each period, the steps of which are identical to the initial steps of the PROSA method, up to the moment of calculating global net flows ϕ_{net} [51,54]. For each analyzed period, separate values of the $\phi_{net}(a_i)$ assessment and country rankings were obtained, showing the degree of advancement of the energy transformation in a given year compared to other EU countries. The evaluation results in individual periods are presented in Table 4, while the country rankings are presented in Table 5. Additionally, Figure 1 presents the country rankings in subsequent years in a graphical form.

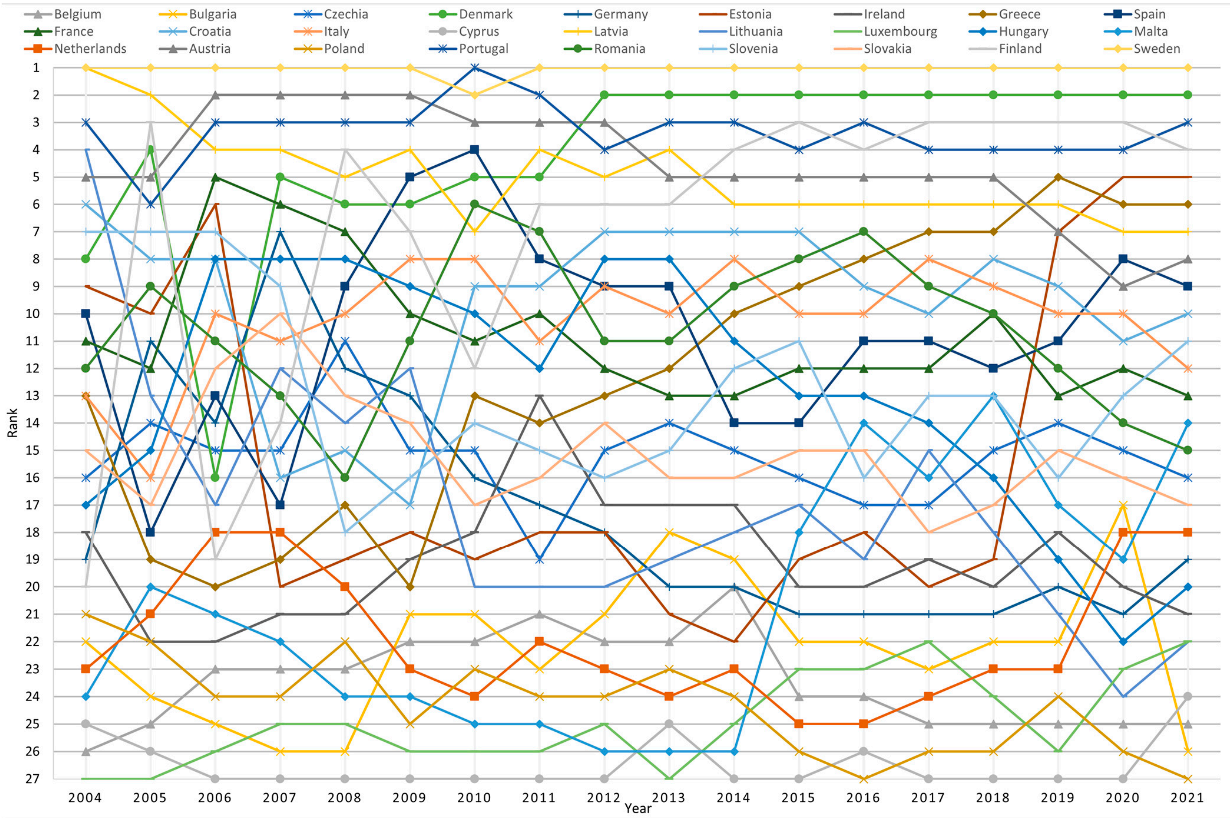

Figure 1. Graphical form of rankings of the energy transformation of EU countries in subsequent periods.

The analysis of temporal results allows us to see the EU countries that have dominated over the last 20 years in terms of energy transformation. The first position in almost all periods was taken by Sweden, only in 2010 it was overtaken by Portugal. Portugal has also been consistently high compared to other countries over the last 20 years. In the case of several countries that have been dynamically modernizing their energy sector in recent years and switching to RES, we can see the progress that has been made since 2004. In particular, we are talking about Finland and Denmark. In the ranking for 2004, Denmark ranked 8th, in 2006–2016, but since 2012 only Sweden has overtaken it. Similarly, Finland was ranked 20th in 2004, while since 2014 it has consistently occupied the 3rd or 4th place in the ranking. The C5 criterion is largely responsible for the distant positions in the rankings of Finland in 2004 and 2006, as well as in Denmark in 2006. In these years, the value of the GHG emissions intensity of energy consumption (C5) index read from Eurostat data increased significantly for the indicated countries. For some countries, e.g., Spain, a "jump" in the ranking can be observed in 2005 compared to other years. These anomalies result from the fact that the values of the C2 and C3 criteria in 2005 for all countries were exactly the same (100%), because it was the base year for the indices represented by C2 and C3. Therefore, these criteria did not in any way influence the ratings of individual countries in 2005, while in the neighbouring years 2004 and 2006 such an influence existed.

Table 4. Results of assessing the degree of advancement of the energy transformation of EU countries in subsequent periods.

Country	Period [$\phi_{net}(a_i)$]																	
	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Belgium	−0.317	−0.261	−0.209	−0.187	−0.219	−0.203	−0.219	−0.155	−0.197	−0.221	−0.182	−0.269	−0.231	−0.223	−0.255	−0.280	−0.268	−0.246
Bulgaria	−0.156	−0.206	−0.264	−0.307	−0.264	−0.193	−0.172	−0.189	−0.183	−0.084	−0.164	−0.205	−0.202	−0.203	−0.140	−0.148	−0.106	−0.261
Czechia	−0.032	0.005	−0.006	−0.015	0.024	−0.017	−0.021	−0.075	−0.028	−0.014	−0.007	−0.032	−0.058	−0.052	−0.052	−0.038	−0.082	−0.076
Denmark	0.088	0.201	−0.013	0.134	0.183	0.144	0.169	0.242	0.338	0.288	0.326	0.363	0.358	0.414	0.420	0.453	0.401	0.404
Germany	−0.069	0.025	0.013	0.100	0.009	0.000	−0.035	−0.062	−0.104	−0.186	−0.182	−0.192	−0.187	−0.151	−0.127	−0.123	−0.144	−0.141
Estonia	0.035	0.042	0.095	−0.129	−0.109	−0.042	−0.114	−0.074	−0.104	−0.200	−0.220	−0.094	−0.071	−0.140	−0.119	0.126	0.225	0.244
Ireland	−0.045	−0.156	−0.168	−0.134	−0.191	−0.062	−0.045	0.005	−0.038	−0.080	−0.102	−0.131	−0.143	−0.093	−0.122	−0.111	−0.133	−0.179
Greece	0.000	−0.095	−0.075	−0.126	−0.094	−0.111	0.029	−0.018	0.030	0.071	0.059	0.074	0.096	0.109	0.137	0.180	0.184	0.192
Spain	0.028	−0.085	0.016	−0.052	0.065	0.146	0.203	0.093	0.069	0.092	0.043	−0.007	0.059	0.009	−0.007	0.028	0.106	0.064
France	0.023	0.020	0.099	0.109	0.136	0.058	0.060	0.062	0.045	−0.001	0.044	0.007	0.010	0.004	0.032	0.005	−0.024	−0.040
Croatia	0.144	0.073	0.060	−0.018	−0.016	−0.041	0.080	0.084	0.121	0.121	0.119	0.110	0.070	0.044	0.069	0.052	0.018	0.028
Italy	0.000	−0.016	0.044	0.046	0.058	0.118	0.104	0.060	0.069	0.090	0.074	0.058	0.068	0.101	0.065	0.040	0.051	−0.014
Cyprus	−0.225	−0.283	−0.316	−0.354	−0.351	−0.391	−0.295	−0.393	−0.368	−0.283	−0.305	−0.296	−0.292	−0.325	−0.266	−0.336	−0.304	−0.228
Latvia	0.390	0.353	0.231	0.159	0.190	0.207	0.126	0.250	0.235	0.255	0.219	0.191	0.171	0.174	0.158	0.132	0.145	0.155
Lithuania	0.209	0.006	−0.049	0.024	0.000	0.003	−0.130	−0.110	−0.113	−0.103	−0.112	−0.049	−0.090	−0.047	−0.117	−0.140	−0.205	−0.191
Luxembourg	−0.342	−0.380	−0.313	−0.234	−0.259	−0.293	−0.286	−0.323	−0.327	−0.312	−0.294	−0.240	−0.204	−0.197	−0.225	−0.287	−0.194	−0.191
Hungary	−0.042	−0.001	0.060	0.083	0.088	0.099	0.075	0.056	0.105	0.101	0.058	0.001	−0.011	−0.043	−0.068	−0.117	−0.160	−0.151
Malta	−0.198	−0.098	−0.105	−0.184	−0.224	−0.234	−0.276	−0.308	−0.344	−0.293	−0.298	−0.093	−0.027	−0.051	−0.050	−0.089	−0.127	−0.059
The Netherlands	−0.196	−0.145	−0.071	−0.077	−0.188	−0.205	−0.261	−0.184	−0.207	−0.262	−0.229	−0.276	−0.251	−0.204	−0.201	−0.197	−0.119	−0.118
Austria	0.187	0.173	0.314	0.396	0.393	0.368	0.326	0.302	0.310	0.254	0.262	0.214	0.208	0.176	0.190	0.126	0.102	0.095
Poland	−0.147	−0.156	−0.238	−0.211	−0.207	−0.237	−0.227	−0.211	−0.237	−0.239	−0.257	−0.280	−0.296	−0.315	−0.258	−0.263	−0.303	−0.312
Portugal	0.214	0.154	0.300	0.361	0.382	0.288	0.384	0.339	0.282	0.280	0.305	0.245	0.256	0.191	0.210	0.241	0.286	0.349
Romania	0.018	0.058	0.043	0.002	−0.053	0.053	0.142	0.103	0.049	0.087	0.068	0.092	0.116	0.081	0.032	0.022	−0.064	−0.060
Slovenia	0.124	0.101	0.076	0.064	−0.108	−0.036	0.009	−0.035	−0.030	−0.015	0.050	0.022	−0.048	−0.035	−0.050	−0.048	−0.030	0.001
Slovakia	−0.010	−0.070	0.031	0.057	0.003	−0.005	−0.040	−0.039	−0.018	−0.063	−0.013	−0.011	−0.046	−0.057	−0.073	−0.047	−0.083	−0.109
Finland	−0.070	0.247	−0.073	−0.014	0.206	0.139	0.033	0.140	0.183	0.238	0.272	0.324	0.251	0.331	0.306	0.316	0.324	0.345
Sweden	0.390	0.493	0.516	0.504	0.546	0.446	0.382	0.441	0.462	0.481	0.466	0.472	0.495	0.502	0.513	0.503	0.504	0.498

Table 5. Rankings of the degree of advancement of the energy transformation of EU countries in subsequent periods.

Country	Period [Rank ϕ_{net}]																	
	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Belgium	26	25	23	23	23	22	22	21	22	22	20	24	24	25	25	25	25	25
Bulgaria	22	24	25	26	26	21	21	23	21	18	19	22	22	23	22	22	17	26
Czechia	16	14	15	15	11	15	15	19	15	14	15	16	17	17	15	14	15	16
Denmark	8	4	16	5	6	6	5	5	2	2	2	2	2	2	2	2	2	2
Germany	19	11	14	7	12	13	16	17	18	20	20	21	21	21	21	20	21	19
Estonia	9	10	6	20	19	18	19	18	18	21	22	19	18	20	19	7	5	5
Ireland	18	22	22	21	21	19	18	13	17	17	17	20	20	19	20	18	20	21
Greece	13	19	20	19	17	20	13	14	13	12	10	9	8	7	7	5	6	6
Spain	10	18	13	17	9	5	4	8	9	9	14	14	11	11	12	11	8	9
France	11	12	5	6	7	10	11	10	12	13	13	12	12	12	10	13	12	13
Croatia	6	8	8	16	15	17	9	9	7	7	7	7	9	10	8	9	11	10
Italy	13	16	10	11	10	8	8	11	9	10	8	10	10	8	9	10	10	12
Cyprus	25	26	27	27	27	27	27	27	27	25	27	27	26	27	27	27	27	24
Latvia	1	2	4	4	5	4	7	4	5	4	6	6	6	6	6	6	7	7
Lithuania	4	13	17	12	14	12	20	20	20	19	18	17	19	15	18	21	24	22
Luxembourg	27	27	26	25	25	26	26	26	25	27	25	23	23	22	24	26	23	22
Hungary	17	15	8	8	8	9	10	12	8	8	11	13	13	14	16	19	22	20
Malta	24	20	21	22	24	24	25	25	26	26	26	18	14	16	13	17	19	14
The Netherlands	23	21	18	18	20	23	24	22	23	24	23	25	25	24	23	23	18	18
Austria	5	5	2	2	2	2	3	3	3	5	5	5	5	5	5	7	9	8
Poland	21	22	24	24	22	25	23	24	24	23	24	26	27	26	26	24	26	27
Portugal	3	6	3	3	3	3	1	2	4	3	3	4	3	4	4	4	4	3
Romania	12	9	11	13	16	11	6	7	11	11	9	8	7	9	10	12	14	15
Slovenia	7	7	7	9	18	16	14	15	16	15	12	11	16	13	13	16	13	11
Slovakia	15	17	12	10	13	14	17	16	14	16	16	15	15	18	17	15	16	17
Finland	20	3	19	14	4	7	12	6	6	6	4	3	4	3	3	3	3	4
Sweden	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1

In addition to countries such as Denmark, Finland, Greece, and Estonia, which have made significant progress in energy transformation and switching to RES in recent years, there are also countries that have significantly slowed down the transformation. These countries certainly include Latvia, Hungary, Austria, and Germany, which in the following years occupy lower and lower positions in the rankings. The countries making the least progress each year include Belgium, Bulgaria, Cyprus, Luxembourg, and Poland. These countries occupy the last positions in each period in terms of the degree of advancement of the energy transformation.

4.3. Study of the Progress of the Energy Transformations of EU Countries over the Years 2004–2021

In order to generally assess the progress of the energy transformation, the temporal results included in Table 4 have been aggregated into an overall assessment. Table 6 shows the preference model used to aggregate the individual periods into a single rating. For all periods, the compensation (balance) coefficient $s_k = 0.5$ and the linear preference function f_k z progiem preferencji $p_k = 2$ were used. For all periods, the highest possible ϕ_{net} values obtained by individual countries were preferred. When weighing individual periods, a "forgetting" strategy was used, so older periods were assigned a correspondingly lower weight.

Table 6. Preference model used in the general assessment of the progress of the energy transformation of EU countries.

Period	Year	Weight	Compensation (Balance) Coefficient	Preference Direction	Preference Function	Preference Threshold
1	2004	1.00	0.5	Max	V-shaped	2
2	2005	1.05				
3	2006	1.10				
4	2007	1.15				
5	2008	1.20				
6	2009	1.25				
7	2010	1.30				
8	2011	1.35				
9	2012	1.40				
10	2013	1.45				
11	2014	1.50				
12	2015	1.55				
13	2016	1.60				
14	2017	1.65				
15	2018	1.70				
16	2019	1.75				
17	2020	1.80				
18	2021	1.85				

The results of the overall assessment of the progress of individual EU countries are presented in Table 7. Table 7 contains the assessment results and ranking based on the PROSA method ($PSV_{net}(a_i)$), as well as WMAD values describing the variability of individual countries' results over time. Additionally, Table 7 contains the ratings and ranking obtained using the PROMETHEE II method for comparative purposes.

The ranking determined using the Temporal PROSA method confirms observations from temporal rankings regarding countries that have made the greatest and least progress in energy transformation over the years 2004–2021. Sweden tops the overall ranking, ahead of Portugal and Denmark, followed by Austria, Latvia, and Finland. The ranking is closed by Cyprus, Luxembourg, Poland, Belgium, The Netherlands, and Bulgaria. The Czech Republic and Italy are characterized by the lowest variability over time, and the highest variability over time had Estonia, Denmark, and Finland. By comparing the ranking based on PSV_{net} (Temporal PROSA) and ϕ_{net} (PROMETHEE II), it is possible to observe how the variability of the alternatives influenced their final results. In the case of Estonia, the variability over time resulted in a two-position decline in the ranking based on PSV_{net} (Temporal PROSA) compared to the ranking based on ϕ_{net} (PROMETHEE II). In the case of Denmark, Finland, as well as Germany, Croatia, Hungary, Malta and Finland, the relatively high variability resulted in these countries deteriorating by one position in the PROSA ranking compared to PROMETHEE II ranking. An exception in this study is Greece, where relatively high variability caused a drop in the PROSA ranking by as much as three positions in relation to the PROMETHEE II ranking. In turn, low variability is responsible for the advancement of some countries in the Temporal PROSA ranking compared to the PROMETHEE II ranking. Relatively low variability contributed to Bulgaria, Ireland, Spain, France, Italy, Latvia, Portugal, Romania, Slovenia, and Slovakia moving up one place in the ranking.

Table 7. Results of the general assessment of the progress of the energy transformation of EU countries.

Country	Rank PSV_{net}	$PSV_{net}(a_i)$	$WMAD(a_i)$	$\phi_{net}(a_i)$	Rank ϕ_{net}
Belgium	24	−0.128049633	0.007984855	−0.12	24
Bulgaria	21	−0.108669459	0.011036868	−0.098	22
Czechia	15	−0.024666835	0.00618809	−0.018	16
Denmark	3	0.124778715	0.028241528	0.153	2
Germany	20	−0.068983262	0.018026784	−0.051	19
Estonia	17	−0.046457865	0.030721023	−0.016	15
Ireland	19	−0.067226496	0.010833783	−0.056	20
Greece	12	0.005212232	0.022128861	0.027	9
Spain	9	0.013441352	0.012585976	0.026	10
France	11	0.006719242	0.009123875	0.016	12
Croatia	8	0.021886152	0.010176601	0.032	7
Italy	7	0.022977433	0.006733093	0.03	8
Cyprus	27	−0.17053625	0.009497788	−0.161	27
Latvia	5	0.090921971	0.012662037	0.104	6
Lithuania	18	−0.058766532	0.016985155	−0.042	18
Luxembourg	26	−0.150347129	0.012671015	−0.138	26
Hungary	14	−0.021415373	0.019930556	−0.001	13
Malta	22	−0.108924014	0.024565714	−0.084	21
The Netherlands	23	−0.110621964	0.011784919	−0.099	23
Austria	4	0.10034531	0.020821694	0.121	4
Poland	25	−0.139988998	0.009372601	−0.131	25
Portugal	2	0.132917473	0.012794066	0.146	3
Romania	10	0.009395505	0.012469879	0.022	11
Slovenia	13	−0.014101477	0.011405121	−0.003	14
Slovakia	16	−0.027862779	0.008242334	−0.02	17
Finland	6	0.084008341	0.027322631	0.111	5
Sweden	1	0.242044403	0.007663087	0.25	1

5. Discussion

The ranking obtained using the Temporal PROSA method was compared with the DARIA-TOPSIS ranking obtained in the assessment of energy systems in European countries in the article by Bączkiewicz and Wątróbski [41]. Comparing these rankings is justified due to the similar subject matter of both studies, the similarity of the methodological approach (temporal analysis), as well as the use of a similar set of criteria (see: Section 4.1) and decision-making alternatives. A comparison of the rankings is presented in Table 8, but it should be explained that in [41] 30 countries were taken into account, but Table 8 omitted three non-EU countries (Iceland, Norway, and United Kingdom).

Analyzing Table 8, it can be seen that the results obtained only partially overlap. The same or similar position in individual rankings is occupied by: Sweden (Temporal PROSA: 1, DARIA-TOPSIS: 1), Denmark (3, 3), Austria (4, 5), Latvia (5, 7), Croatia (8, 11), Hungary (14, 14), Slovakia (16, 18), Germany (20, 19), Cyprus (27, 25). In turn, the largest differences in terms of positions in the rankings occur in the following countries: Estonia (17, 4), Ireland (19, 6), Spain (9, 23), Italy (7, 21), Luxembourg (26, 10), The Netherlands

(23, 13), Poland (25, 12), Portugal (2, 24), Romania (10, 22). It can be concluded that for some countries the differences in rankings are significant. One of the reasons for such large differences in the rankings are the methodological differences between the PROSA and TOPSIS methods. Another reason is the use of completely different approaches to capture variability during temporal aggregation (see: Section 2.3). In particular, the DARIA-TOPSIS method examines variability over time using the Gini coefficient, and Temporal PROSA uses WMAD for this purpose. Moreover, DARIA-TOPSIS simply corrects the latest temporal ranking using the measured variability, while Temporal PROSA verifies the variability between each subsequent period and based on this variability, adjusts the weighted average of all rankings. Both studies also referred to different periods because the study using the DARIA-TOPSIS method covered the years 2016–2020, while the study using the Temporal PROSA method covered the 2004–2021 period. The final reason for the differences between the DARIA-TOPSIS and Temporal PROSA rankings are differences in the criteria used. Both studies used the same seven criteria, two criteria differed in that one study used numerical criteria and the other used index criteria (see: Section 4.1). Additionally, in the case of energy consumption criteria (C2 and C3) in the DARIA-TOPSIS study, minimum was indicated as the direction of preference. This is quite strange because energy sustainability is about reducing energy consumption, not increasing it.

Table 8. Comparison of the results obtained in the assessment of the energy transformation of EU countries with the results contained in the literature.

Country	Rank PSV_{net}	Rank DARIA-TOPSIS [41]
Belgium	24	16
Bulgaria	21	26
Czechia	15	8
Denmark	3	3
Germany	20	19
Estonia	17	4
Ireland	19	6
Greece	12	20
Spain	9	23
France	11	17
Croatia	8	11
Italy	7	21
Cyprus	27	25
Latvia	5	7
Lithuania	18	27
Luxembourg	26	10
Hungary	14	14
Malta	22	15
The Netherlands	23	13
Austria	4	5
Poland	25	12
Portugal	2	24
Romania	10	22
Slovenia	13	9
Slovakia	16	18
Finland	6	2
Sweden	1	1

6. Conclusions

The aims of the article were a temporal analysis and assessment of the progress made by individual EU countries towards the transition to RES. The study showed that the leaders in this respect among EU countries are Sweden and Portugal. They are followed by Denmark and Finland, which have significantly accelerated their energy transformation in recent years, and Austria and Latvia, which in turn have slowed down the transformation process in recent years. At the opposite extreme are countries such as Bulgaria, The

Netherlands, Belgium, Poland, Luxembourg, and Cyprus. Considering the positions of the countries informally managing EU policy, the distant ranking of Germany and the Benelux countries may seem surprising. It is largely Germany and The Netherlands that are lobbying for the EU to pursue an increasingly restrictive energy policy. This time, it turns out that they themselves have a lot to improve in this area.

The analytical study carried out was a practical contribution to the article. In turn, the methodological contribution was the development of the PROSA family of MCDM methods and the development of a new dynamic MCDM method called Temporal PROSA. This method is based on the DMCDM framework and PROSA-C/PROMETHEE II methods. Like other recent temporal approaches, PROSA also uses the dispersion measure to provide information about the variability of a temporal data set. Moreover, PROSA, thanks to the appropriate mathematical formulation, unlike many other temporal methods, allows, among others, for the aggregation of data from many periods into a single final assessment and direct transfer of information from the examined periods to the overall result.

The research conducted and the results obtained obviously have their limitations. The main research limitation is related to the construction of the decision-making model. The study used 11 criteria regarding productivity, consumption, and energy prices, as well as the share of RES in the energy mix. Of course, using different criteria could yield different results. However, the indicated criteria, thanks to their relative nature, made the assessment results largely independent of the economic and population characteristics of the countries. The criteria used are objective measures and indices of energy transformation. The second research limitation concerns the methodology used. The Temporal PROSA method allows the use of any MCDM method giving a total order of alternatives in the first stage. Therefore, the use of a method other than PROMETHEE II in the first stage could also produce slightly different results. However, the use of PROMETHEE II resulted from the fact that it belongs to the same family of methods as the PROSA methods (in practice, the PROSA methods are an extension of the PROMETHEE methods). The above-mentioned research limitations indicate potential directions for further research. This research will include modifying and expanding the set of criteria to include other indicators to measure the progress of the energy transformation. Future research must also take into account the diversity of MCDM methods and the possibility of using a different method than PROMETHEE II in the first stage of Temporal PROSA, which was used in this study.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en16237703/s1, Supplementary File S1.xlsx. The supplement file contains source data, i.e., criterion values for individual examined countries in successive time periods.

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