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Energy Security Assessment Based on a New Dynamic Multi-Criteria Decision-Making Framework

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Abstract: Access to energy resources and broadly understood energy security are some of the critical factors influencing the economic development of countries. This article deals with the problem of assessing the energy security of countries, considering this problem in various periods of time, examining the past, present and forecasted future conditions at the same time. For this purpose, the Dynamic Multi-Criteria Decision Making (DMCDM) methodology was developed and applied, based on the classic and fuzzy Multi-Criteria Decision Making (MCDM) methods and the International Energy Security Risk Index (IESRI). In particular, the Simple Additive Weighting (SAW)/Fuzzy SAW and New Easy Approach to Fuzzy PROMETHEE II (NEAT F-PROMETHEE) methods were used. These methods are significantly different from each other in the calculation procedures used. The study showed that methodological differences between these methods cause large differences in the results of the assessment of energy security of countries. However, both methodological approaches indicated the high energy security of New Zealand, Norway, Denmark and the United States, and the very low security of Ukraine, Thailand and South Korea. The results of the assessment of energy security of countries over the 2015–2025 period are the main practical contribution of this article. The scientific contribution of the article consists in developing a framework for dynamic energy security assessment that allows for the aggregation of many periods of time and that defines the aggregation strategies, capturing data from the past, present and future state forecasts while taking into account changes in the weights of criteria and changes in the sets of alternatives and criteria.

Keywords: energy security assessment; Dynamic Multi-Criteria Decision Making (DMCDM); energy forecasting; international energy security risk index

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1. Introduction

Energy is one of the factors necessary for the economic and social development of states. Therefore, along with the economic development of individual countries, their energy needs also increase. According to the forecasts of the U.S. Energy Information Administration (EIA), global energy consumption, and thus energy demand, is expected to increase by 50% by 2050 compared with 2018 [1]. Therefore, the critical issue is energy security, in its basic meaning understood as uninterrupted availability of energy sources at an affordable price [2]. However, at present, the concept of energy security is understood more broadly and includes the security of supply and use, economic security, as well as environmental security [3]. An important element of energy security is the security and cyber security of critical energy infrastructure [4], which has a fundamental impact on energy distribution. In the context of the security of energy production, the growing importance of the circular economy is visible [5], which can at least partially solve the problems of scarcity of energy resources and pollution related to energy production. Similarly, renewable energy sources [6,7] and alternative, less conventional sources, such as shale gas [8], are also important for the security of energy resources and the environment. Therefore, it is clear that the problem of research energy security is, in fact, a problem in the field of sustainability because there are environmental, economic and social factors.

Energy security is largely determined by political, economic, social and environmental issues. The political issue having a negative impact on energy security is, first of all, the dependence of many European countries on energy sources imported from Russia. Russia is one of the leading exporters of oil, gas and coal, which entails high political risk [9]. This risk is confirmed by the huge negative impact that the armed conflict between Russia and Ukraine has had on supply chains and the availability of fossil fuels [10]. The social issue is certainly the COVID-19 pandemic and the negative economic consequences associated with it, caused by, for example, lockdowns, occurring mainly in the initial period of the pandemic. The pandemic has caused drastic fluctuations in energy demand, oil price shocks, disruptions in energy supply chains and has hampered energy investment [11]. As for the environmental issues, the global concern about the environmental and climatic consequences of energy production and consumption has a big impact on energy security [12]. As a result of these concerns, the energy transformation of some economically developed countries is underway, consisting in increasing investments in renewable energy sources (RES) and phasing out energy production from coal. Increased investments in RES and record levels of CO_2 emission allowance prices has resulted in a very high increase in electricity prices for end users, which indirectly adversely affects the security of energy supply [13].

In such a dynamically changing political and economic environment, states should accurately read the changes taking place and effectively prevent threats to energy security [14]. Therefore, measuring energy security with the use of appropriate methods and without ignoring various aspects and multidimensional interdependence is of critical importance, enabling an objective assessment using reliable numerical indicators [15]. Since energy security is difficult to measure with a simple index [16], measurements are usually made with complex indices that can capture multidimensionality and give a broader picture of the problem [17]. Unfortunately, the assessment of energy security is usually based on historical data, while only a few studies contain forecasts for the future as such forecasts are associated with a high degree of uncertainty [18]. Another problem is the fact that usually energy security indices do not allow for evaluation over time [12]. Only a few studies address the problem of assessing energy systems in the time dimension. Franki and Višković [19] proposed an optimization model that predicts the energy security of south-eastern European countries in 2021. In turn, Wang and Zhan [20] examined the sustainability of renewable energy in 18 European countries and trends in each of these countries for a period of 10 years (2007–2016). The basic limitation of this research is that they only capture the time dimension in the past or the present. However, these studies do not take into account the forecast of a slightly more distant future. Moreover, such studies lack a comprehensive assessment of energy security over a longer period of time. In other words, such approaches make it possible to assess, for example, 2014, 2015 and 2016, but they do not allow to collectively assess the 2014–2016 period. In addition, it should be noted that the study [20] does not address the topic of energy security at all. However, in the study [19], only a forecast for 2021 was included, not taking into account earlier or later years. Meanwhile, such an assessment of a longer period of time makes it possible to track changes in the state of energy security, which enables the development of more effective scenarios for further actions to improve the energy situation of a given country or area [3]. Therefore, there is a research gap related to the shortage of approaches that take into account the assessment of the energy security of countries in a broader time perspective.

In connection with the identified research gap, the aim of the research is to develop a framework for assessing the energy security of countries, allowing for the evaluation of the current, past and forecasted future state. An important element of the research is the possibility of aggregating assessments from different periods of time into one global assessment. Due to the complexity of the issue of energy security, the framework is based on the Dynamic Multi-Criteria Decision Making (DMCDM) approach, allowing the capture of the dynamics of assessments over time. At the same time, the use of the Multi-Criteria Decision Making (MCDM) paradigm allows the assessment to include uncertainty and sensitivity analyses [21]. These analyses increase the reliability of the results of the safety assessment [17]. The development of such a complex framework, based on the methodological foundations of DMCDM and verifying it with real data, is a contribution of the article. The second section presents approaches to DMCDM used in the literature. The third section contains the basic research assumptions and a ready framework for energy security assessment along with a discussion of data sources. In the fourth and fifth sections, the obtained results are presented along with a critical discussion. The article ends with the research conclusions presented in the sixth section.

2. Dynamic Multi-Criteria Decision Making

The DMCDM paradigm is an extension of the classic MCDM approach. MCDM methods are used to make and support decisions on the basis of many criteria determining the acceptability of individual alternatives, taking into account the complexity of the decision-making process, conflicting criteria, scenarios, preferences of decision makers, sources of uncertainty and time frames [22]. The MCDM paradigm assumes that the above parameters of the decision problem, and in particular the alternatives, criteria and preferences of decision makers, are constant and stable [23]. However, most of the real decision problems are dynamic. In such problems, the final decision is made at the end of a certain research process in which alternatives and criteria may change [24]. In the practice of dynamic decision-making environments, the alternatives, criteria and preferences of decision-makers evolve over time; therefore, various continuous responses are needed over time [25]. In many dynamic decision problems, the set of alternatives is not fixed, and new alternatives can and should be constantly created and suggested. Likewise, the set of criteria used to measure performance may be a function of time and may also depend on individual decision makers. The preferences and the perception of the possible consequences of decisions may also change, and above all, the input information may change, affecting the perception of all the above-mentioned decision-making elements [23]. The classic MCDM paradigm is not able to capture these dynamics because it assumes that the decision-maker must identify fixed sets of criteria and alternatives before starting the ranking [24].

DMCDM is used in a wide variety of decision problems and fields as an extension of the MCDM paradigm. Zulueta et al. [25] applied DMCDM to the problem of project life cycle risk assessment. They extended the MCDM to include the dynamics of the decision problem by calculating the dynamic risk exposure and dynamic discriminative index for subsequent periods. Chen et al. [26], Ziemba et al. [27], Chen and Li [28], Li et al. [29], Yang et al. [30], and Polomčić et al. [31] proposed a dynamic approach to MCDM in their research by enabling the aggregation of assessments of alternatives over many consecutive periods of time. Moreover, all of these researchers except Polomčić et al. [31] postulated the use of different aggregation strategies, depending on which period would be the most important. Chen et al. [26] developed an approach to DMCDM in the problem of disaster management. Ziemba et al. [27] extended MCDM to include dynamics in the problem of online marketing campaign management. Chen and Li [28] and Li et al. [29] took up the problem of choosing the target of financial investments. Yang et al. [30] applied DMCDM in energy metering device selection. Polomčić et al. [31] considered the problem of groundwater management scenarios evaluation. Yan et al. [32], trying to solve the problem of vendor selection, proposed to study the trend of changes in alternatives over time and take this trend into account when aggregating subsequent periods of time. Keshavarz-Ghorabaee et al. [33], considering the subcontractor evaluation problem in a construction project, proposed extending the MCDM paradigm to capture changes in collections of alternatives and decision makers, and to aggregate ratings from different time periods. Su et al. [34], investigating the problem of choosing a third-party reverse logistic provider, extended the MCDM to allow for the use of different weights of criteria in particular time periods and aggregation of different periods. Campanella and Ribeiro [16], analysing the issue of selecting a helipad, postulated taking into account the variability in the set of alternatives in DMCDM and pointed to the need to take into account historical and present data in decision-making problems. Liu et al. [35] and Tao et al. [36], in the problem of supplier selection, extended this postulate pointing to the need to capture changes in the set of alternatives and criteria. In both publications, the authors confirmed the necessity of taking into account data from the past and the present when solving dynamic decision problems. Similarly, Jassbi et al. [37], when analysing the problem of choosing a supplier for a car manufacturer company, postulated taking into account the variability of sets of alternatives and criteria. The authors raised a very important postulate, pointing to the need to take into account data from the past, present and future (forecasts) in solving dynamic decision problems. In turn, Wei [38] proposed to capture changes in the weight of criteria and use fuzzy numbers to describe alternatives in the newest periods of time. Table 1 presents an overview of the literature related to the various areas of DMCDM application along with the dynamic extensions of the classic MCDM paradigm proposed by the researchers.

Table 1. Publications and decision problems in which DMCDM approach was developed.

Application Field	MCDM Methods	DMCDM Extensions	Reference
Emergency management	DEA	Aggregation of different periods of time, different aggregation strategies	[26]
Project risk management	MAUT	Calculation of dynamic risk exposure and dynamic discriminative index for different periods	[25]
Air traffic	SAW	Changeability of the set of alternatives over time, taking into account historical and present data	[24]
Automotive manufacturing	SAW	Changeability of the set of alternatives and the set of criteria over time, taking into account historical, present and projected future data	[37]
Construction industry	Fuzzy EDAS	Changeability of the set of alternatives and the set of decision makers over time, aggregation of different periods of time	[33]
Marketing management	PROMETHEE GDSS	Aggregation of different periods of time, different aggregation strategies	[27]
Enterprise Resources Planning system implementation	GRA/Fuzzy GRA	Changeability of criteria weights over time, aggregation of different periods of time, the use of real numbers for the oldest periods, interval numbers for intermediate periods and triangular fuzzy numbers for the most recent periods	[38]
Investment management	TIFN-WAA	Aggregation of different periods of time, different aggregation strategies	[28]
Investment management	Fuzzy TOPSIS	Variability of criterion weights over time, aggregation of different periods of time	[29]
Vendor selection	TPIGN	Study of the trend of changes in alternatives on the criteria in subsequent periods, aggregation of different periods of time, taking into account the trend of changes	[32]
Reverse logistics management	DIF-MAGDM	Variability of criteria weights over time, aggregation of different time periods, aggregation of assessments of many experts	[34]
Electric energy metering device selection	DINFWAA/DINFWGA	Aggregation of different periods of time, different aggregation strategies	[30]
Supplier selection	BLTS DMCDM	Variability of the set of alternatives and the set of criteria over time, taking into account historical and present data	[35]
Groundwater management	Fuzzy TOPSIS	Aggregation of different periods of time	[31]
Supplier selection	IFS DGMCDM	Variability of the set of alternatives and the set of criteria over time, taking into account historical and present data	[36]

DEA—Data Envelopment Analysis, MAUT—Multi-Attribute Utility Theory, SAW—Simple Additive Weighting, EDAS—Evaluation based on Distance from Average Solution, PROMETHEE GDSS—Preference Ranking Organization Method for Enrichment Evaluation—Group Decision Support System, GRA—Grey Relational Analysis, TIFN-WAA—Triangular Intuitionistic Fuzzy Numbers-Weighted Averaging Operator, TOPSIS—Technique for Order of Preference by Similarity to Ideal Solution, TPIGN—Three-Parameter Interval Grey Number, DIF-MAGDM—Dynamic Intuitionistic Fuzzy Multi-Attribute Group Decision Making, DINFWAA—Dynamic Intuitionistic Normal Fuzzy Weighted Arithmetic Average, DINFWGA—Dynamic Intuitionistic Normal Fuzzy Weighted Geometric Average, BLTS—Bipolar Linguistic Term Set, IFS DGMCDM—Intuitionistic Fuzzy Set based Dynamic Group Multi-Criteria Decision Making.

3. Framework for Dynamic Multi-Criteria Evaluation of the Energy Security of States

3.1. Basic Assumptions

When analysing the dynamic extensions of MCDM presented in Section 2, it should be noted that the basis of DMCDM is the possibility of aggregating the performance of alternatives from successive periods of time. The possibility of selecting an appropriate aggregation strategy for individual periods is also very often postulated so that the most important periods have higher weights than the less important periods. These requirements are also very important in the framework under development. A natural solution for assessing the energy security of countries in the longer term is to give more importance to the most recent periods of time and a lower weight to periods from the more distant past.

An interesting proposition is to take into account the variability of sets of alternatives and criteria along with their weights. The possibility of modifying the set of criteria and their weights in particular periods seems to be justified because in different periods, the assessment of energy security may be influenced by other criteria. For example, now, when the transit of gas from Russia to many European countries has been stopped, the importance of countries having diversified sources of gas supplies has increased significantly. On the other hand, the possibility of modifying the set of decision alternatives (studied countries) may seem redundant. However, one can imagine a situation where a decision-maker would like to eliminate from the study of a given country the period in which that country was, for example, under sanctions, involved in war or other events.

A very important postulate is the need to take into account not only past and present data, but also forecasts relating to the future, as proposed by Jassbi et al. [37]. Thanks to this, when assessing the energy security of a given country, the forecasted future level of security can also be taken into account. Complementary to this proposal seems to be the suggestion of Wei [38] to use fuzzy numbers to describe alternatives in the latest periods of time, which can capture the uncertainty and imprecision of data. It is the forecast-based assessment of the future that is uncertain and imprecise. Therefore, in the framework under development, it is proposed to use fuzzy numbers to assess the future state of energy security of countries.

The last assumption is related to the suggestion in the work of Yan et al. [32] to study the trend of changes in alternatives over time in DMCDM problems and to take this trend into account when making assessments. When it comes to assessing the energy security of countries, the analysis of the trend is also important because the energy policy of countries is usually stable and does not undergo major changes over at least a few years. Of course, changes in the direction of energy policy may occur, but they are caused by unexpected global events rather than by the political decisions of the new authorities. Therefore, the trend analysis is important and it is proposed to use the trend study in the developed framework to forecast the future energy security of countries.

3.2. Conceptual Framework

The approach to DMCDM proposed in this article is a direct extension of the classic MCDM paradigm, in which the multi-criteria decision problem is presented as a three (1):

$$(A, C, E) \tag{1}$$

where A is the m-element set of alternatives $A = \{a_1, a_2, \ldots, a_m\}$, C is the n-element set of criteria $C = \{c_1, c_2, \ldots, c_n\}$, and E represents performance table $E = C(A)$ [39].

The optimal solution of the multi-criteria decision problem is the one that maximizes all criteria [40], according to the Formula (2):

$$a^* = \max(c_1(a_i), c_2(a_i), \ldots, c_n(a_i)) \ \forall i = 1, \ldots, m \tag{2}$$

In discrete decision problems where the number of alternatives is finite, there are usually no optimal solutions. Therefore, MCDM methods are to indicate optimal solutions in the sense of Pareto and, therefore, not worse than others [41]. In order to indicate Pareto solutions, the method must differentiate individual alternatives by determining their performance. Each of the MCDM methods uses different functions and computational procedures for this purpose, which however, can be generalized [42]. Assuming that F is a transformation representing the mathematical procedure used in any MCDM method to determine the performance of G of the i-th alternative, the performance of each alternative in the table E can be written as (3):

$$G(a_i) = F(C(a_i)) = F(c_1(a_i), c_2(a_i), \ldots, c_n(a_i)) \; \forall i = 1, \ldots, m \quad (3)$$

Extending the MCDM paradigm and taking into account the dynamics (DMCDM) in the form of time periods $1 \ldots t$ causes the expression (3) to take the form (4):

$$G^k(a_i) = F\left(C^k(a_i)\right) = F\left({c_1}^k(a_i), {c_2}^k(a_i), \ldots, {c_n}^k(a_i)\right) \; \forall i = 1, \ldots, m; \; \forall k = 1, \ldots, t \quad (4)$$

Additionally, there is a function H which allows the aggregation of all performances of G of the alternative a_i from all k-th time periods. Therefore, the overall performance of the alternative in the proposed DMCDM framework is described by the Formula (5):

$$G(a_i) = H\left(G^k(a_i)\right) \; \forall i = 1, \ldots, m; \; \forall k = 1, \ldots, t \quad (5)$$

As noted earlier, F represents the MCDM method procedure for determining the performance of G [42]. If, for example, the PROMETHEE II [43] procedure is used as the F transformation, then the expression (4) can be converted to the form (6):

$$G^k(a_i) = \phi^k_{net}(a_i) \; \forall i = 1, \ldots, m; \; \forall k = 1, \ldots, t \quad (6)$$

On the other hand, if the SAW method [40] is used as the transformation of F, then the Formula (4) is transformed to (7):

$$G^k(a_i) = \frac{\sum_{j=1}^{n} w_j^k r_{ij}^k}{\sum_{j=1}^{n} w_j^k} \; \forall i = 1, \ldots, m; \; \forall k = 1, \ldots, t \quad (7)$$

A weighted average (8) can be used as a function of H:

$$G(a_i) = \frac{\sum_{k=1}^{t} G^k(a_i) \times \omega_k}{\sum_{k=1}^{t} \omega_k} \; \forall i = 1, \ldots, m \quad (8)$$

where ω_k is the significance of the k-th period of time.

Data from the past and present are certain; therefore, for calculations in time periods relating to the past and present, methods based on crisp data can be used, for example, the classic PROMETHEE II [44] or SAW [40]. Forecasts are inherently uncertain; therefore, for time periods relating to the future, it is recommended to use methods that perform calculations of trapezoidal fuzzy numbers (TFNs), which allows us to capture the uncertainty and imprecision of the data. Such methods may be, for example, NEAT F-PROMETHEE II [45] or Fuzzy SAW [46]. Moreover, it is proposed to use a two-parameter Holt prognostic model to determine future forecasts [47]. This model is used when there is a time series with a component in the form of a linear trend with random fluctuations. The Holt model allows us to capture the trend and smooth out random fluctuations using a moving average of the time series [48].

The proposed DMCDM framework allows for the determination of any significance of data from individual time periods thanks to the ω_k coefficient. Moreover, as shown by Formula (4), different sets of criteria may be used in successive k-th periods of time. Due to the fact that in Formula (5) the performance of G is determined separately for each alternative, they can occur in a different number of time periods. Therefore, the framework meets the basic assumptions set out at the beginning. The framework:

- Enables the aggregation of the performance of alternatives from successive periods of time;
- Allows the definition of any strategies of aggregation of individual periods through the coefficient ω_k;
- Takes into account the variability of sets of alternatives and criteria along with weights;
- Is adapted to capture certain data from the past and present and uncertain data which are predictions of the future;
- Takes into account the trend of changes of alternatives over time when forecasting future data values, and thus takes the trend into account in the evaluation.

3.3. Data Sources

The report of the Global Energy Institute on the International Energy Security Risk Index (IESRI) [49] was used as the source of data on energy security. This report was issued in 2020 and covers the 1980–2018 period. The report contains data for 25 countries that are large energy users. These are European countries (Denmark, France, Germany, Italy, Netherlands, Norway, Poland, Russia, Spain, Turkey, Ukraine, United Kingdom), African countries (South Africa), countries located in North America (Canada, Mexico, United States) and South America (Brazil), Oceania (Australia, New Zealand) and Asia (China, India, Indonesia, Japan, South Korea, Thailand). The data included in the report come from BP (formerly British Petroleum), the Energy Information Administration, Freedom House, the International Energy Agency, and the World Bank. The data covers eight groups measuring different aspects of energy security, as presented in Table 2.

Table 2. The importance of individual groups of data included in the IESRI report.

Data Group	Description
Global Fuels	Reliability and diversity of the world's oil, natural gas and coal reserves and supplies.
Fuel Imports	Exposure to unreliable supplies of crude oil, natural gas and coal.
Energy Expenditures	Energy costs and the risk of consumer exposure to price shocks.
Price & Market Volatility	Susceptibility of economies to large fluctuations in energy prices.
Energy Use Intensity	Energy consumption in relation to population and economic performance.
Electric Power Sector	Reliability of electricity generation capacity.
Transportation Sector	Efficiency of energy use in the transport sector per unit of GDP and population.
Environmental	The degree of exposure to orders to reduce greenhouse gas emissions.

All groups of data included in Table 2 include a total of 29 individual indicators with weights given in Table 3.

The methodology of aggregating the indicator values into one risk/energy security index value used in IESRI is based on the SAW method. The direction of preferences is the minimum, so the lower the final value, the better the result of a given country. Due to the fact that the IESRI is based on the MCDM methodology as a standard and contains values from various periods of time, it is perfect for the needs of verifying the framework for assessing the energy security of countries. It should be emphasized that IESRI served as a case study. However, it is not the only possible source of data. It is important that the potential sources give the possibility of obtaining data from subsequent periods, necessary for the assessment of the past and present and for forecasting the future.

Table 3. Detailed indicators included in the IESRI report.

Data Group	Indicator	Weight
Global Fuels	C1—Security of World Oil Reserves	2
	C2—Security of World Oil Production	3
	C3—Security of World Natural Gas Reserves	2
	C4—Security of World Natural Gas Production	3
	C5—Security of World Coal Reserves	2
	C6—Security of World Coal Production	2
Fuel Imports	C7—Petroleum Import Exposure	3
	C8—Natural Gas Import Exposure	3
	C9—Coal Import Exposure	2
	C10—Total Energy Import Exposure	4
	C11—Fossil Fuel Import Expenditures per GDP	5
Energy Expenditures	C12—Energy Expenditure Intensity	4
	C13—Energy Expenditures per Capita	3
	C14—Retail Electricity Prices	6
	C15—Crude Oil Prices	7
Price and Market Volatility	C16—Crude Oil Price Volatility	5
	C17—Energy Expenditure Volatility	4
	C18—World Oil Refinery Utilization	2
	C19—GDP per Capita	4
Energy Use Intensity	C20—Energy Consumption per Capita	4
	C21—Energy Intensity	7
	C22—Petroleum Intensity	3
Electric Power Sector	C23—Electricity Diversity	5
	C24—Non-CO_2 Emitting Share of Electricity Generation	2
Transportation Sector	C25—Transportation Energy per Capita	3
	C26—Transportation Energy Intensity	4
Environmental	C27—CO_2 Emissions Trend	2
	C28—Energy-Related Carbon Dioxide Emissions per Capita	2
	C29—Energy-Related Carbon Dioxide Emissions Intensity	2

4. Results

The data underlying the study was taken from the IESRI 2020 report, which includes data up to and including 2018. The data relating to the past were the values of indicators (criteria) from 2015–2017. The values for 2018 were used as present data, i.e., the latest data published in the report. On the other hand, the forecasted index values were determined using the Holt model borrowed from the work of Ziemba et al. [50]. These forecasts were prepared for 2025 using the 1980–2015 time series (for Russia and Ukraine it was the 1995–2015 time series due to the lack of previous data) with a step of 5 years. Such a time series allowed the capture of long-term trends in the forecast, without the noise in the form of short-term local trend changes. The value of $h = 2$ was assumed as the forecast horizon so that the forecast refers to the year 2025. TFNs were constructed in order to take into account the forecast uncertainty. The forecast values for 2025 were the centre of TFN. The supports of the number were the value of the indicator from 2015 and the value determined for the forecast horizon $h = 4$ (in a sense, a forecast for 2035). The core of the number was contained in the halves of the distance between the centre of the number and its support. The data on which the study was based is included in Supplementary Materials.

For data from individual periods (2015, 2016, 2017, 2018, and 2025), the SAW method was used, as was also used in the original IESRI. It should be explained here that for the forecast for 2025, Fuzzy SAW was used to capture the uncertainty of the forecast. For all periods, the weight values used in the original IESRI (given in Table 3) were used. In this way, the Risk Score values were determined, which for the periods 2015–2018, were equal to the values given in the IESRI 2020 report. This confirms the correctness of the calculations and compliance of the SAW calculation method with IESRI. The results from subsequent periods of time have been aggregated into one overall assessment describing the energy security of countries in the period 2015–2025. By aggregating the periods of time, a strategy was adopted, according to which the most important are the current results, as they are the most up-to-date, and at the same time reliable and certain. The projected assessments of the future are slightly less important due to the fact that they are subject to uncertainty. The values of the past are the least important, although the past periods are the most numerous. Based on the adopted aggregation strategy, the following weights were assigned to individual time periods: 2015—10%, 2016—10%, 2017—10%, 2018—40%, 2025—30%.

Table 4 shows the energy security rankings obtained for individual time periods and the ranking aggregating all partial rankings. Security rankings are also presented graphically in Figure 1.

Table 4. The results of the energy security assessment in subsequent periods of time and the aggregate assessment of all periods based on the SAW methodology.

Country (Alternative)	k = 1 (2015)		k = 2 (2016)		k = 3 (2017)		k = 4 (2018)		k = 5 (2025)		2015–2025	
	Risk Score	Rank	Risk Score	Rank	Risk Score	Rank	Risk Score	Rank	Risk Score	Rank	Risk Score	Rank
A1-Australia	824.63	4	845.97	5	842.38	4	805.37	4	866.4346	5	833.3764	5
A2-Brazil	1077.87	13	1065.05	13	1058.23	13	1059.04	13	1106.213	13	1075.595	13
A3-Canada	832.59	5	834.24	4	830.15	3	802.05	3	832.6732	4	820.32	4
A4-China	917.83	9	956.64	10	955.6	9	912.09	8	927.4488	8	926.0776	8
A5-Denmark	861.02	6	864.51	6	875.99	6	864.36	5	889.9508	6	872.8812	6
A6-France	1133.04	15	1137.06	15	1160.19	15	1128.04	15	1220.567	14	1160.415	15
A7-Germany	1087.07	14	1100.46	14	1118.98	14	1084.78	14	1246.538	15	1138.524	14
A8-India	1216.16	19	1205.31	17	1169.71	17	1144.63	16	1348.524	19	1221.527	19
A9-Indonesia	930.37	10	920.06	7	929.66	8	931.96	9	912.3883	7	924.5095	7
A10-Italy	1225.02	20	1239.57	21	1269.55	21	1240.15	20	1340.313	18	1271.568	20
A11-Japan	1292.8	22	1277.66	22	1307.14	22	1280.56	22	1496.696	22	1348.993	22
A12-Mexico	899.61	7	947.77	8	975.32	10	966.19	11	1015.753	11	973.472	10
A13-Netherlands	1172.44	16	1163.36	16	1162.95	16	1146.65	17	1362.414	20	1217.259	16
A14-New Zealand	779.31	3	771.32	2	774.19	2	757.39	2	780.674	3	769.6402	2
A15-Norway	683.42	1	686.87	1	865.86	5	869.39	6	668.605	1	771.9525	3
A16-Poland	985.25	12	1010.42	12	1010.2	12	967.43	12	1011.327	10	990.9571	12
A17-South Africa	1185.7	17	1226.52	20	1185.47	18	1155.67	18	1328.364	17	1220.546	18
A18-South Korea	1487.92	24	1489.86	24	1492.33	24	1453.2	24	1621.731	23	1514.81	24
A19-Spain	1209.45	18	1211.11	18	1225.49	19	1189.13	19	1262.946	16	1219.141	17
A20-Thailand	1456.31	23	1442.6	23	1440.73	23	1396.36	23	1662.608	24	1491.29	23
A21-Turkey	1228.48	21	1225.65	19	1261.93	20	1266.61	21	1392.034	21	1295.86	21
A22-United Kingdom	907.29	8	956.26	9	978.7	11	943.85	10	1050.369	12	976.8756	11
A23-United States	772.25	2	775.42	3	769.17	1	727.44	1	708.9944	2	735.3583	1
A24-Russian Federation	943.54	11	975.81	11	914.25	7	875.04	7	984.1553	9	928.6226	9
A25-Ukraine	1765.67	25	1734.17	25	1594.36	25	1462.82	25	1782.405	25	1629.269	25

The analysis of Table 4 and Figure 1 shows that the United States and Norway can be considered the safest countries in terms of energy, which alternately took the first place in the IESRI rankings in the various analysed periods. The countries occupying the next high positions in the rankings, i.e., New Zealand (2, 3 place), Canada (3–5), Australia (4, 5) and Dania (5, 6) are slightly less energy-protected.

In the context of threats to energy security related to the dependence of many European countries on Russian energy sources, the Ukrainian–Russian conflict and the energy policy of the European Union, the assessments and forecasts of the energy security of European countries are interesting. Apart from Norway and Denmark, which are in the top rankings, Russia (7–11 places), the United Kingdom (8–12) and Poland (10–12) are the best in this respect. While the highest positions of Poland and the United Kingdom among European countries can be considered a good result, the position of Russia is relatively low, taking into account the energy resources at its disposal. The analysis of source data in the IESRI report (see Supplementary Materials) showed that the low position of Russia is mainly related to the following criteria: C12—Energy Expenditure Intensity, C17—Energy Expenditure Volatility, C20—Energy Consumption per Capita, C21—Energy Intensity, C22—Petroleum Intensity, C26—Transportation Energy Intensity, C28—Energy-Related Carbon Dioxide

Emissions per Capita, C29—Energy-Related Carbon Dioxide Emissions Intensity. In terms of the C12, C20, C26, and C28 criteria, Russia is usually ahead of 4–6 out of 25 countries surveyed. On the other hand, in terms of the C17, C21, and C29 criteria, Russia is usually ahead of only Ukraine, and for the C22 criterion, it is only better than Thailand. All these criteria relate to the internal aspects of energy security, in particular: the cost and volatility of energy prices, energy consumption and environmental impact. This observation explains the relatively low position of Russia, despite its extensive resources of fossil fuels for energy production.

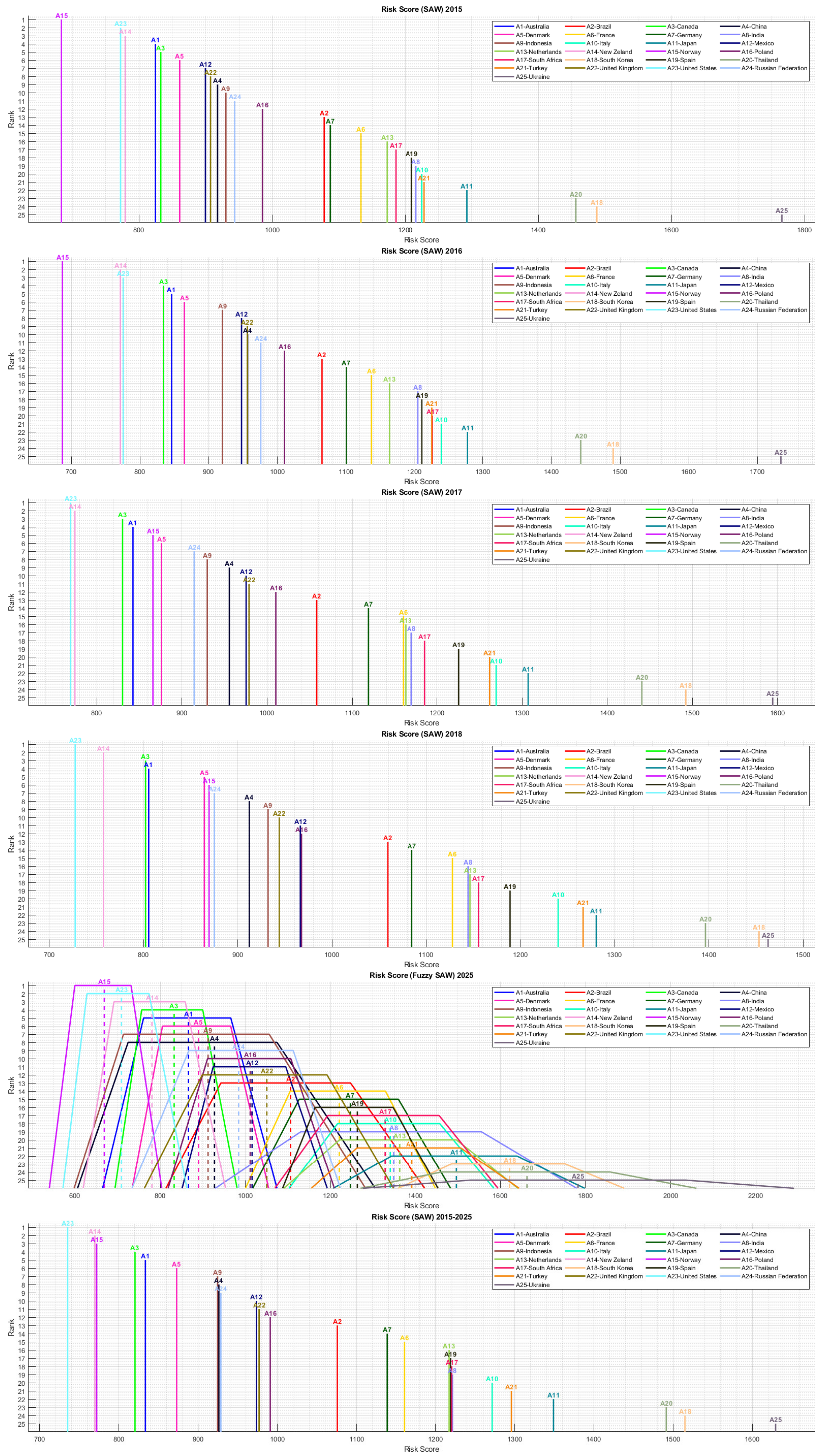

Figure 1. Energy security rankings in the periods 2015–2025 based on the SAW methodology.

The politically and economically dominant countries in the European Union, i.e., France and Germany, occupy positions 14, 15 in all rankings, while in 2015–2018 Germany was ranked 14, and France 15, and in the forecast for 2025, these countries changed places. These countries score low on the criteria C7—Petroleum Import Exposure, C8—Natural Gas Import Exposure, C10—Total Energy Import Exposure, and C25—Transportation Energy per Capita. Additionally, France has a low value of C9—Coal Import Exposure, and Germany has a very low rating in terms of C14—Retail Electricity Prices. In particular, the C7–C10 criteria show that these countries are highly dependent on fossil fuel imports. This problem is also clearly visible in the case of other European Union countries, i.e., the Netherlands (16–20 place), Spain (16–19), Italy (18–21), and Poland, which are similar in terms of the C7–C10 criteria, with isolated exceptions. For example, Poland and Germany, due to relatively large coal resources, perform well in terms of the C9 criterion. In addition, Italy scores the worst of all countries on the C14 criterion, and the Netherlands does poorly on the following criteria: C13—Energy Expenditures per Capita, C14, C20—Energy Consumption per Capita, C23—Electricity Diversity, C24—Non-CO_2 Emitting Share of Electricity Generation, and C28—Energy-Related Carbon Dioxide Emissions per Capita. In the case of Spain, the C14 criterion is assessed as very poor.

Among European countries, the problem of dependence on energy imports also applies to Turkey (19–21 place), and partially (criterion C9—Coal Import Exposure) also to Denmark and the United Kingdom. The only European country from among the analysed countries (apart from Russia), where the problem of dependence on energy imports appears to a very limited extent is Ukraine. On the other hand, it is Ukraine that occupies the last place in all sub-rankings and in the ranking aggregating all analysed periods of time. Ukraine's last place results primarily from the criteria: C12—Energy Expenditure Intensity, C17—Energy Expenditure Volatility, C19—GDP per Capita, C21—Energy Intensity, C22—Petroleum Intensity, C26—Transportation Energy Intensity, and C29—Energy-Related Carbon Dioxide Emissions Intensity.

As far as non-European countries are concerned, the results of Brazil, China, India, Indonesia, Japan, Mexico, South Africa, South Korea and Thailand remain to be discussed, apart from the aforementioned United States, New Zealand, Canada and Australia. Brazil ranks 13th in all periods. Japan's position is similarly stable, ranking 22nd in all rankings. In turn, Thailand ranks 23rd in almost all periods, one position ahead of South Korea. The exception is the forecast for 2025, where South Korea ranks 23rd and is one place ahead of Thailand. China's energy security has been increasing in recent years because in the 2015 ranking it came 9th, in 2016 10th, and in 2017 and 2018, it was ranked 9th and 8th, respectively. The forecast for 2025 also points to the 8th position, as does the general ranking aggregating partial rankings. Indonesia ranks 7–10, and in most periods (2016, 2017, the forecast for 2025 and the overall ranking for 2015–2025) it is ahead of China. In 2015, Mexico was ranked 7th in the energy security ranking and was ahead of both China and Indonesia. However, over the next three years, it systematically fell to lower and lower positions in the ranking and in 2018 it was already in the 11th place. The same position is indicated by the forecast for 2025, and the ranking aggregating individual periods indicates the 10th position. As for India (16–19) and South Africa (17–20), in 2015, South Africa was ahead of India in terms of energy security; however, in the subsequent years, 2016–2018, India's security increased and it moved ahead of South Africa. In turn, the forecast for 2025 provides for an increase in India's energy risk and an increase in the security of South Africa. Similarly, the overall rankings for 2015–2025 indicate that over these years South Africa was characterized by a higher overall energy security than India.

The rankings in subsequent periods are relatively stable, and the positions of individual countries and their energy risk do not change substantially, as confirmed in Figure 2. Brazil (position 13), Japan (22) and Ukraine (25) are the most stable in the rankings. These countries occupy a stable position in all sub-rankings and in the ranking aggregating periods of time. The ranking of New Zealand, Australia, Denmark, France, Germany, South Korea and Thailand changes by at most one place in all time periods. On the other hand, Norway is characterized by the greatest volatility, occupying positions 1 to 6 in individual rankings. Russia and Mexico (7–11), the United Kingdom (8–12) and the Netherlands (16–20) also experience volatility with their positions in the rankings changing by 5 places. The stability chart of the rankings is shown in Figure 2.

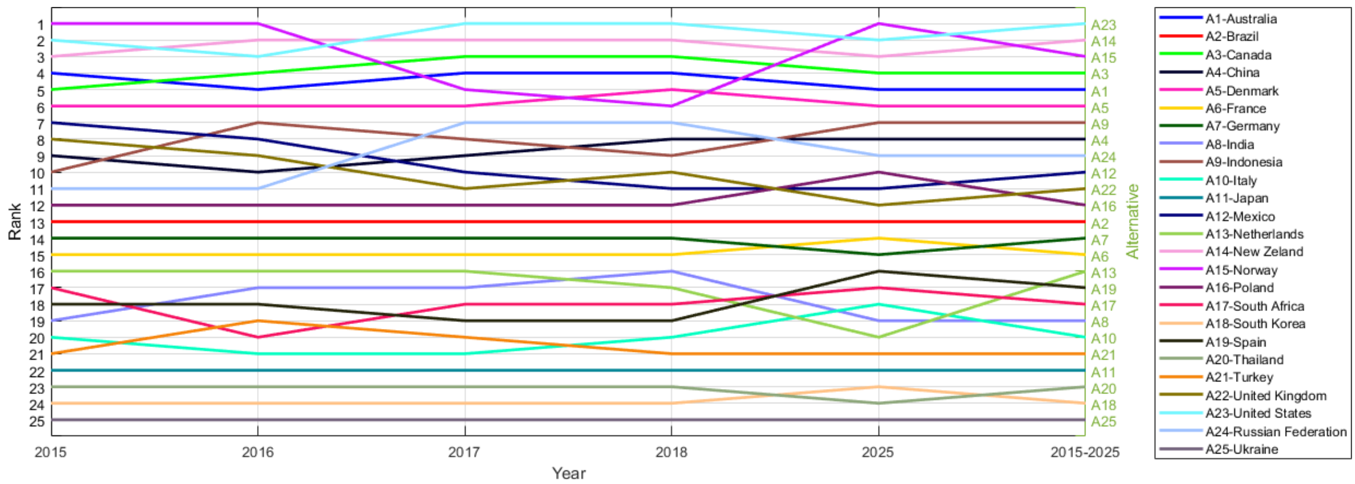

Figure 2. Volatility of SAW rankings in subsequent periods.

5. Discussion

It should be noted that there are studies in the literature which challenge the methodology included in the IESRI. The main disadvantage of the indicators included in this index is their varying degree of generality, i.e., one indicator is included in other indicators, but these dependencies are very difficult to determine [51]. As a result of such collinearity, the independent variables lose their independence and the entire index can be considered unreliable [52]. Therefore, researchers recommend revising the index and removing variables that do not contribute to its precision [51]. Taking into account these criticisms, it should be noted that from the perspective of the MCDM, these are important conclusions.

Firstly, in a situation where there are interdependencies between indicators (criteria), the SAW method should not be used, nor any other method based on utility theory that cannot capture the interdependence of the criteria. MCDM methods applying the utility theory should allow for modelling dependencies between criteria; otherwise, only independent criteria should be considered in the decision problem. In particular, the requirements that allow the use of the additive and multiplicative model of the utility function are additive independence and utility independence [53]. The SAW method is based on an additive utility function, so dependencies between criteria are unacceptable. However, in the case of methods based on outranking, criteria independence is recommended, but not required [54].

Secondly, the criteria included in the decision problem should create the so-called coherent criterion family [55]. This means that the set of criteria should be consistent $\left(\left(c_j(a_1) \geq c_j(a_2)\ \forall j = 1, \ldots, n\right) \wedge (\, a_2\, P\, a_3) \Rightarrow a_1\, P\, a_3\right)$ and complete $(c_j(a_1)\, I\, c_j(a_2)\ \forall j = 1, \ldots, n \Rightarrow a_1\, I\, a_2$, where I means indifference and P means preference), and the elimination of any criterion from the set would violate the principle of consistency or completeness [54]. Put simply, the coherent criterion family is a set of criteria that actually differentiate alternatives. Meanwhile, the analysis of IESRI indicators shows that the criteria C1–C6, C15, C16, and C18 do not differentiate between countries. Moreover, the analysis showed that the Holt model predicts different values of these criteria for Russia and Ukraine than for other countries, despite the fact that the values of the criteria for all countries are the same. The reason for this is the incompleteness of the data for Russia and Ukraine, because the values of the above-mentioned criteria for these countries have been given since 1995, while other countries have assigned values since 1980.

Taking into account the indicated problems regarding IESRI, the energy security study in the DMCDM model was repeated with two methodological modifications. Instead of using the SAW method, the NEAT F-PROMETHEE II fuzzy method was used. This method is based on outranking so it does not require independence between criteria. Additionally, when NEAT F-PROMETHEE II operates on crisp numbers, then it works exactly like the classic PROMETHEE II [56] method so there is no need to use different methods for certain (past and present) and uncertain (future forecast) data. Moreover, the study omitted the criteria C1–C6, C15, C16, and C18, meeting the recommendations for a coherent criteria family. In the NEAT F-PROMETHEE II method, a linear preference (V-shaped criterion) was used, and the value of the preference threshold was twice the standard deviation of the sample, determined on the basis of the value of alternatives for a given criterion in a given period of time. The results of energy security assessment obtained using the modified DMCDM approach are presented in Table 5 and Figure 3.

Table 5. The results of energy security assessment with the use of a coherent family of criteria and the NEAT F-PROMETHEE II method.

Country (Alternative)	k = 1 (2015)		k = 2 (2016)		k = 3 (2017)		k = 4 (2018)		k = 5 (2025)		2015–2025	
	ϕ_{net}	Rank	ϕ_{net}	Rank	ϕ_{net}	Rank	ϕ_{net}	Rank	ϕ_{net}	Rank	ϕ_{net}	Rank
A1-Australia	0.0297	11	0.0162	12	0.0191	11	0.0282	10	0.0277	12	0.0261	11
A2-Brazil	0.0329	10	0.0313	11	0.0317	10	0.0161	12	0.0783	7	0.0395	10
A3-Canada	0.0649	8	0.0649	8	0.0607	9	0.0617	8	0.0498	10	0.0587	9
A4-China	0.1026	4	0.0985	5	0.0989	5	0.1099	5	0.1289	3	0.1127	4
A5-Denmark	0.1360	2	0.1343	1	0.1412	1	0.1362	2	0.1464	1	0.1396	1
A6-France	0.0571	9	0.0632	9	0.0691	7	0.0788	7	0.0553	9	0.0671	7
A7-Germany	−0.0050	14	−0.0038	14	0.0021	14	0.0102	13	−0.0404	17	−0.0087	15
A8-India	−0.0438	19	−0.0332	18	−0.0195	17	−0.0292	18	−0.0440	18	−0.0345	18
A9-Indonesia	0.0246	12	0.0361	10	0.0166	12	−0.0057	15	0.0628	8	0.0243	12
A10-Italy	−0.0189	17	−0.0197	17	−0.0190	16	−0.0106	16	−0.0138	15	−0.0141	16
A11-Japan	−0.0717	20	−0.0586	20	−0.0628	20	−0.0621	20	−0.1244	20	−0.0815	20
A12-Mexico	0.0958	6	0.0707	7	0.0638	8	0.0611	9	0.0485	11	0.0620	8
A13-Netherlands	−0.0994	21	−0.0948	21	−0.0864	21	−0.0832	21	−0.1339	21	−0.1015	21
A14-New Zealand	0.1026	5	0.1068	4	0.1099	4	0.1071	6	0.1061	6	0.1066	6
A15-Norway	0.1295	3	0.1317	2	0.1194	3	0.1267	3	0.1344	2	0.1290	3
A16-Poland	−0.0186	16	−0.0170	16	−0.0133	15	−0.0033	14	0.0088	13	−0.0036	14
A17-South Africa	−0.1188	22	−0.1369	22	−0.1361	22	−0.1439	22	−0.1532	22	−0.1427	22
A18-South Korea	−0.1616	23	−0.1592	23	−0.1517	23	−0.1603	23	−0.1631	23	−0.1603	23
A19-Spain	−0.0019	13	0.0079	13	0.0098	13	0.0191	11	0.0058	14	0.0110	13
A20-Thailand	−0.1756	24	−0.1638	24	−0.1876	24	−0.2040	24	−0.1638	24	−0.1834	24
A21-Turkey	−0.0128	15	−0.0049	15	−0.0281	18	−0.0602	19	−0.0466	19	−0.0427	19
A22-United Kingdom	0.1379	1	0.1288	3	0.1361	2	0.1458	1	0.1108	5	0.1319	2
A23-United States	0.0858	7	0.0907	6	0.0978	6	0.1135	4	0.1173	4	0.1080	5
A24-Russian Federation	−0.0283	18	−0.0475	19	−0.0349	19	−0.0243	17	−0.0142	16	−0.0250	17
A25-Ukraine	−0.2429	25	−0.2417	25	−0.2366	25	−0.2276	25	−0.1836	25	−0.2183	25

The analysis of Table 5 and Figure 3 shows that the rankings obtained using the NEAT F-PROMETHEE II method and the reduced set of 20 criteria differ significantly from the rankings obtained using the 29 criteria and SAW method used in IESRI. In all periods, lower ratings for energy security can be noted for countries such as Australia (from 4, 5 to 10–12), Canada (from 3–5 to 8–10), Indonesia (7–10 to 8–15), the Netherlands (from 16–20 to 21), New Zealand (from 2, 3 to 4–6), Poland (from 10–12 to 13–16), South Africa (from 17–20 to 22), the United States (from 1–3 to 4–7) and Russia (from 7–11 to 16–19). On the other hand, many countries improved their rankings, and the greatest benefits from the methodological changes were achieved by China (from 8–10 to 3–5), Denmark (from 5, 6 to 1, 2), France (from 14, 15 to 7–9) and the United Kingdom (from 8–12 to 1–5). The position was slightly less improved for Brazil (from 13 to 7–12), Italy (from 18–21 to 15–17), Japan (from 22 to 20), Spain (from 16–19 to 11–14) and Turkey (from 19–21 to 15–19). In the case of the remaining countries, there were very little or no changes in their positions held.

Despite the above-mentioned differences between the SAW and NEAT F-PROMETHEE II rankings, the top two rankings include New Zealand, Norway, Denmark and the United States. Since the high ranks of the energy security of these countries are confirmed in all periods and by both methodologies, it should be assumed that these countries are indeed characterized by the lowest energy risk. In turn, the least secure in terms of energy, according to both methodologies, are Ukraine, Thailand and South Korea.

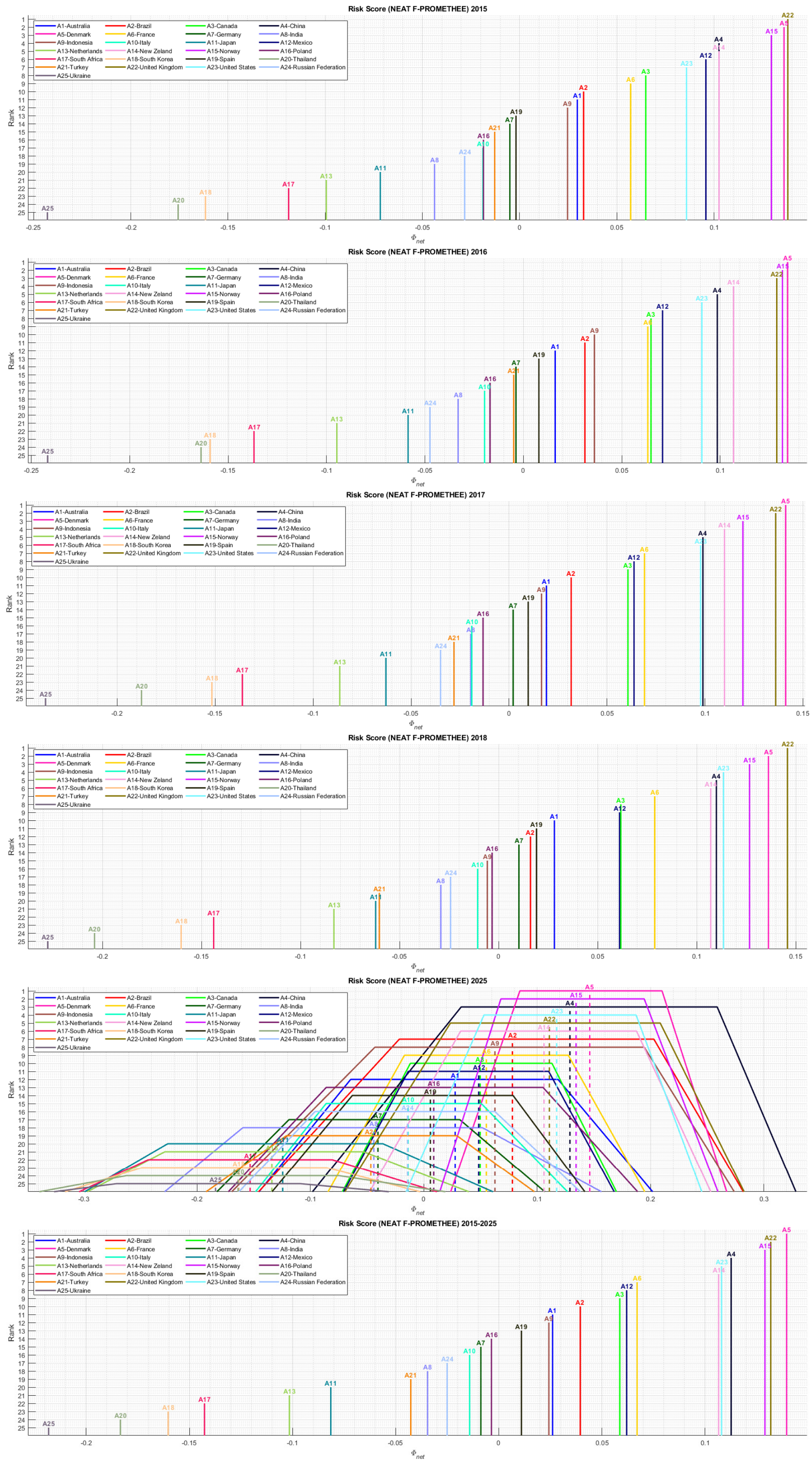

Figure 3. Energy security rankings obtained using a coherent criteria family and the NEAT F-PROMETHEE II method.

Figure 4 shows the variability of the NEAT F-PROMETHEE II rankings obtained in subsequent periods and the ranking aggregating partial rankings. When observing Figure 4, it can be noticed that the individual rankings do not change for countries occupying positions 20–25 (Japan, the Netherlands, South Africa, South Korea, Thailand, and Ukraine). As for the other countries, the positions of Denmark (1, 2), Norway (2, 3), China (3–5), New Zealand (4–6), France (7–9), Canada (8–10), Australia (10–12), Italy (15–17) and India (17–19) are stable. The position of other countries in the rankings changes to a greater extent.

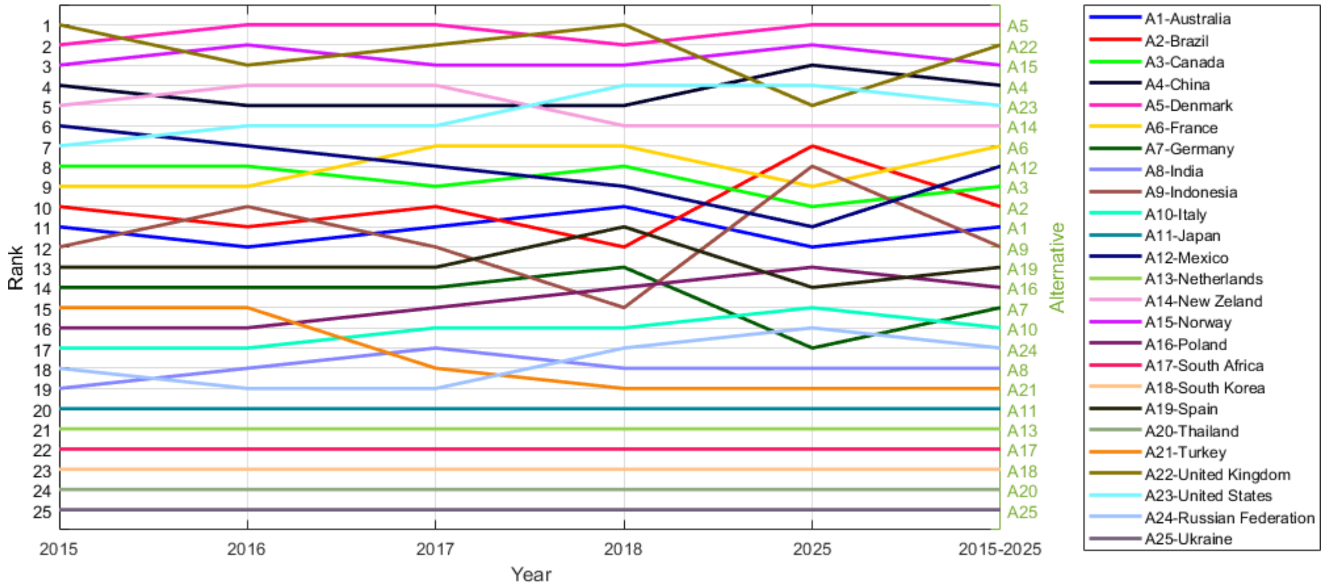

Figure 4. Variability of NEAT F-PROMETHEE II rankings in subsequent periods.

6. Conclusions

This article deals with methodological and practical aspects related to energy security and multi-criteria assessment. The methodological contribution of the article was the development of a framework for the dynamic assessment of energy security. In line with the research objective, the developed framework allows for the assessment of energy security in the past, present (based on certain data) and future (based on uncertain forecasts). The framework is based on the MCDM methodology in terms of dynamics, allowing for:

- Aggregation of assessments from various periods of time into one global assessment;
- Defining any strategies for aggregating periods of time;
- Capture of data from the past, present and forecasts of the future;
- Consideration of changes in the sets of alternatives and criteria;
- Consideration of variable weights of criteria;
- Consideration of the trend of changes in the value of alternatives over time.

These features are the main novel contributions and advantages of the proposed framework compared with other DMCDM-based approaches used in the literature. These features undoubtedly testify to the innovativeness of the framework because other DMCDM implementations do not provide all the listed possibilities in a single implementation (see Section 2). It is worth noting that, contrary to the purpose of the research, the developed framework is not limited to the dynamic assessment of energy security but could also find application in many completely different fields where it is required to capture trends and changes over time. This universality of the framework increases its practical value because it can be used in any decision-making problems that require capturing the dynamics of a decision-making situation.

Against the background of methodological research, a practical contribution was also made to the assessment of the energy security of countries in the period 2015–2025, based on the MCDM methodology and the proposed dynamic approach. The study was carried out using the SAW/Fuzzy SAW and NEAT F-PROMETHEE II methods, which are significantly different from each other in the calculation procedures used. The study showed that the differences between these methods result in large differences in the assessment of energy security of countries. However, using both methods, it was possible to identify countries that are characterized by a high or low level of energy security. Norway, Denmark, the United States and New Zealand are among the safest countries in terms of energy resources. In turn, Thailand, South Korea and Ukraine are the most exposed to energy risk.

Referring to the research limitations, it should be noted that in the case of the practical study presented in Sections 4 and 5, there was no need to modify the weights of the criteria. There were also no changes to the collections of alternatives and criteria. For these reasons, this theoretical possibility of the framework has not been presented in practice. Moreover, the practical study was based on the IESRI, which has been accused of methodological errors in the scientific literature. Therefore, one can try to challenge the results obtained in Section 4. However, the most significant errors of the IESRI were eliminated in the study presented in Section 5, which makes the results presented in this section reliable. In the course of further work, the use of other data sources for the assessment of energy security may be considered. It is also worth practically verifying the aforementioned possibility of dynamically modifying sets of criteria, alternatives and criteria weights.

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Data Availability Statement: Data are contained within the article and Supplementary Material.

Conflicts of Interest: The authors declare no conflict of interest.

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