TWO-STEP CLUSTER ANALYSIS FOR ENERGY PERFORMANCE INDICATORS COMPARISON

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Assessing energy performance indicators is important for understanding EU countries' progress toward achieving sustainability and climate goals, including reducing greenhouse gas emissions and increasing the share of renewable energy. This paper employs two-step cluster analysis (TSCA) using IBM SPSS 26.0 to classify EU member states based on six key energy indicators. The optimal number of clusters was determined using Schwarz's Bayesian Information Criterion (BIC), ensuring statistical robustness. Four distinct clusters were identified, revealing varying strengths and weaknesses. These insights provide important guidance for policymakers, enabling the development of targeted strategies for improving energy efficiency and sustainability across the EU.

Keywords*: Energy performance indicators, Two-step cluster analysis, Energy management, Sustainability*

1. Introduction

Monitoring and comparing the energy performance of EU countries is necessary to understand the progress made to meet the renewable energy and climate goals. The EU has set ambitious targets under its climate and energy frameworks, such as the goal of achieving a 32% share of renewable energy by 2030 and reducing greenhouse gas emissions by at least 55% by 2030, compared to 1990 levels [1,2]. These targets are part of the broader European Green Deal, which aims to make Europe the first climate-neutral continent by 2050. Energy performance indicators provide a quantifiable means of assessing how close EU countries are to achieving these objectives. Several indicators, such as primary energy consumption, energy productivity, and the share of renewable energy in transport, electricity, and heating, are regularly tracked by the EU and its member states through Eurostat [3]. Primary energy consumption reflects the total energy demand, while energy productivity measures the economic output per unit of energy consumed. The renewable energy indicators track the adoption of cleaner energy sources in industry sectors. These indicators are important for determining progress and ensuring that countries contribute equitably to the EU's collective climate targets. Despite common goals, there are significant variations in how EU member states perform across these indicators. Sweden and Denmark have already surpassed the 32% renewable energy target, largely due to their early investments in wind and biomass energy, whereas countries such as Luxembourg and Ireland are still far behind [3,4].

Clustering EU countries based on energy performance is significant to both policymakers and stakeholders. To identify the groups of countries with similar energy performance profiles, it becomes possible to design more targeted and effective energy policies. For instance, countries that lag in renewable energy adoption but have high energy consumption might benefit from policies that encourage renewable energy technologies, while those that already outperform in energy productivity may require strategies focused on maintaining energy efficiency [5]. But also, clustering allows policymakers to recognize best practices from high-performing clusters and encourage their adoption in lower-performing ones. Countries with high shares of renewable energy in electricity production, such as Portugal and Finland, can provide models for those relying heavily on fossil fuels for electricity generation [5-7]. This approach can encourage regional cooperation and transfer technologies among EU member states, with the alignment of national policies more closely with EU-wide climate objectives.

The primary aim of this paper is to group the EU member states into clusters based on six key energy performance indicators: primary energy consumption, energy productivity, renewable energy in transport, renewable energy in electricity, and renewable energy in heating and cooling. These indicators have been chosen for their relevance to the EU's overarching energy and climate goals and their ability to provide a view of each country's energy landscape. To achieve this objective, a two-step cluster analysis will be performed using IBM SPSS 26.0. This hybrid clustering technique is customized for the study because it can handle both continuous and categorical variables and automatically determine the optimal number of clusters using statistical criteria such as Schwarz's Bayesian Information Criterion – BIC [8]. The aim is to identify distinct clusters of EU member states that share similar characteristics in terms of their energy performance, allowing for a more structured comparison and policy evaluation.

2. Literature review

The energy performance indicators include primary energy consumption, energy productivity, and the share of renewable energy in transport, electricity, and heating/cooling. Each of these indicators is important in assessing the energy efficiency, sustainability, and overall energy transition of EU member states. Primary energy consumption refers to the total energy demand required to meet a country's energy needs, including production, transformation, and delivery losses [3,9,10]. It is an important metric for understanding the overall energy efficiency of a country, and it is directly linked to the EU's energy efficiency targets. Significant studies have examined the trends in primary energy consumption across the EU. The research found that between 2010 and 2019, primary energy consumption decreased by approximately 10% in the EU, which indicates efforts to decouple economic growth from energy use [11]. However, significant disparities exist between member states. Countries such as Germany and France account for a large proportion of the EU's primary energy consumption, while smaller nations like Malta and Cyprus contribute far less [3]. Research shows that many EU countries have managed to reduce their primary energy consumption through increased energy efficiency measures. The European Commission reports that countries such as Denmark and the Netherlands have implemented strong energy-saving policies, which have led to significant reductions in consumption [12]. However, the report also highlights those other countries, particularly in Eastern Europe, have struggled to meet the EU's targets for reducing primary energy consumption due to economic and infrastructural challenges [5]. Energy productivity is another important indicator, measuring the economic output generated per unit of energy consumed. High energy productivity indicates that a country is using energy efficiently to drive economic growth. In 2020, the average energy productivity in the EU was 8.0 euros per kilogram of oil equivalent, which is a significant improvement from previous years [3,13]. Studies show that countries such as Ireland, Denmark, and Luxembourg lead the EU in energy productivity, largely due to their service-based economies and lower reliance on energy-intensive industries [14]. On the other hand, Eastern European countries such as Poland and Bulgaria have lower energy productivity, which is partly due to their dependence on heavy industry and coal-based energy generation [5,15]. According to the European Environment Agency improvements in energy productivity will be important for meeting the EU's goal of reducing greenhouse gas emissions by 55% by 2030.

The third set of important critical indicators includes the share of renewable energy in three sectors: transport, electricity, and heating/cooling. The EU has set targets for increasing the share of renewable energy in these sectors as part of its Renewable Energy Directive. According to [3], the share of renewable energy in the EU's gross final energy consumption reached 22.1% in 2020, surpassing the 2020 target of 20%. However, the adoption of renewable energy varies significantly across sectors and member states. In the transport sector, the EU aims to achieve a 14% share of renewable energy by 2030. Currently, biofuels and renewable electricity are the main sources of renewable energy in transport. The share of renewable energy in transport across the EU stood at 10.2% in 2020, a slight improvement from previous years [3]. Countries such as Sweden, Finland, and the Netherlands are leading in renewable energy use for transport, thanks to their early investments in biofuels and electric vehicle infrastructure [5]. Conversely, countries like Hungary and Poland lag behind, due to their slower adoption of alternative fuels and electric mobility [5]. The electricity sector has seen the largest growth in the use of renewable energy. In 2020, renewable energy sources, including wind, solar, hydro, and biomass, account for 37.5% of the EU's electricity generation [3]. Several clustering techniques have been applied in energy performance analysis, including K-means, hierarchical clustering, and latent class analysis. K-means clustering is used due to its efficiency in handling large datasets; however, it assumes spherical cluster structures and requires the number of clusters to be predefined, which limits flexibility in exploratory studies [16]. Hierarchical clustering provides a detailed hierarchical structure but suffers from computational inefficiencies and sensitivity to outliers, making it unsuitable for large datasets with mixed data types [9,17]. Latent class analysis is another probabilistic approach but primarily focuses on categorical variables, limiting its application in datasets containing continuous energy indicators [18,19]. To address these limitations, two-step cluster analysis was chosen as it automatically determines the optimal number of clusters using Schwarz's Bayesian Criterion (BIC), reducing arbitrary cluster selection bias and also handles both continuous and categorical variables. In addition to clustering, multi-criteria decision-making (MCDM) methods are important for ranking energy performance among countries. Common MCDM approaches include Analytic Hierarchy Process (AHP), a structured technique for ranking criteria, but it requires extensive pairwise comparisons, making it impractical for large datasets [13]. Two-step cluster analysis represents a hybrid method that combines the strengths of both distance-based clustering and probabilistic modeling. The technique is used in cases when dealing with large datasets that include both continuous and categorical variables. Two-step cluster analysis has been used in energy research to study energy efficiency, renewable energy adoption, and greenhouse gas emissions. According to a study [19] two-step cluster analysis was used to categorize countries based on their energy efficiency performance and renewable energy use. The results showed clear differences between clusters of countries, with some clusters performing well in terms of renewable energy adoption but poorly in energy efficiency, and vice versa. One of the main advantages of two-step cluster analysis over K-means and hierarchical clustering is its ability to handle both categorical and continuous variables simultaneously. This makes it suitable for complex energy data, where variables such as energy consumption, renewable energy shares, and energy prices must all be considered. For instance, an analysis [20] used a two-step cluster analysis to examine energy-saving behaviors among EU households. The study found that households could be grouped into distinct clusters based on their energy consumption patterns and attitudes toward energy-saving technologies, helping to inform targeted policy interventions.

Despite the use of clustering techniques in energy studies, existing research often focuses on either energy consumption patterns or renewable energy adoption in isolation. For example, K-means and hierarchical clustering have been used to group countries based on a single dimension, such as energy efficiency or renewable energy use. However, there is limited research that integrates multiple energy performance indicators, such as primary energy consumption, energy productivity, and renewable energy shares, into a unified analysis. This paper addresses this gap by applying two-step cluster analysis to examine a more complex set of indicators, to provide deeper insights into how EU member states compare across different dimensions of energy performance. The presented findings contribute to both policy development and academic understanding by identifying distinct clusters that reflect the complex interconnection between energy consumption, efficiency, and renewable energy adoption.

3. Methodology

The methodological framework is grounded on the five indicators that reflect the most recent data for the energy performance indicators of the members of the European Union make up the data set used in the current research. The dataset presented above is based on the most recent information available from the Eurostat database.

It is important to highlight that energy systems involve interdependent indicators such as primary energy consumption, energy productivity, and the share of renewable energy in different sectors. These indicators encompass both continuous variables (e.g., energy productivity measured in GDP per unit of energy) and categorical variables (e.g., classification of countries based on their renewable energy policies). Traditional clustering techniques, such as K-means and hierarchical clustering, struggle to handle both types of data effectively. Two-step cluster analysis (TSCA) offers an alternative by handling mixed data types. Unlike K-means clustering, which only supports continuous variables, TSCA can process both continuous (e.g., primary energy consumption) and categorical variables (e.g., whether a country has a high renewable energy policy commitment). But also the automatic selection of the optimal number of clusters. Hierarchical clustering methods require prior knowledge of the number of clusters, whereas TSCA determines the optimal number using the Schwarz Bayesian Criterion (SBC/BIC) and the Akaike Information Criterion (AIC), minimizing overfitting. The two-step cluster analysis follows the clustering optimization framework:

$$\arg\min \sum_{i=1}^{k} \sum_{x \in C_i} d(x, \mu_i)^2 + \lambda f(k) \tag{1}$$

Where: $C = \{C_1, C_2, \ldots, C_k\}$ represents the set of clusters, $d(x, \mu_i)$ is the distance function measuring similarity between data points and cluster centroids, $\lambda f(k)$ is a penalization term controlling for model complexity, regulated by BIC/AIC criteria.

Energy performance indicators presents nonlinear relationships and trade-offs. TSCA captures these dynamics through energy transition trade-offs. Countries with high energy consumption may belong to clusters with high GDP per capita, while countries with strong renewable energy shares may be grouped based on policy incentives rather than energy intensity alone. By considering multiple indicators simultaneously, TSCA prevents misleading conclusions from single-variable clustering approaches.

Using IBM SPSS 26.0, a two-step cluster analysis will be used to group the EU members. Using hierarchical techniques such as the agglomerative approach, two-step cluster analysis forms subclusters. The hybrid approach known as Two-Step cluster analysis first divides groups using a distance measure and then selects the best subgroup model using a probabilistic approach akin to latent class analysis [8]. The following indicators' energy performance indicator values are shown in Fig. 1 respectively, based on the findings of the descriptive statistics: Energy productivity, Primary energy consumption, Renewable energy in transport, Renewable energy sources in electricity, and Renewable energy sources in heating and cooling.

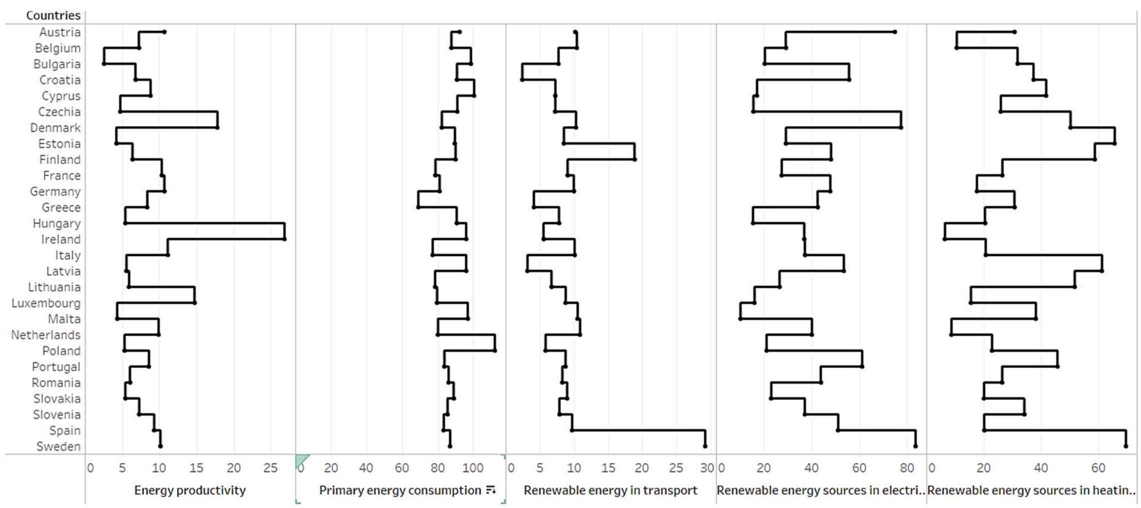

Figure 1. Descriptive statistics for analyzed indicators

In addition to the aforementioned cluster analysis, the paper will also rank the countries using the PROMETHEE method for multi-criteria decision-making using a modern software package (Visual PROMETHEE Academic) This part of the methodological framework should make it possible to see the leaders in the field of energy performance outside the created clusters. Energy performance indicators often involve a set of diverse and conflicting criteria, where PROMETHEE allows decision-makers to evaluate and compare multiple criteria simultaneously, facilitating a more holistic and comprehensive ranking of alternatives, provides a balanced view of alternatives. One of the key strengths of PROMETHEE is its ability to incorporate different types of preference functions and flexibility, which allows it to handle various types of data associated with energy performance indicators. The decision maker in this analysis chooses a preference function for each criterion Ri, which is why a fuzzy preference relation is formed where Si (a,b) implies preferences of intensity a in relation to preference b:

$$S_i: AxA \rightarrow [0,1]; S_i(a,b) = P_i\big(f_i(a) - f_i(b)\big) = P_i(d) \tag{2}$$

Outranking PROMETHEE concept is valuable in energy performance evaluation ranking alternatives according to their abilities being better or worse in certain aspects. Clear ranking and identifying possible discrepancies in energy- related decisions promote PROMETHEE as a crucial energy performances MCDM method especially in conducting analysis under different assumptions. By combining these analyses, it is possible to determine a benchmark in the area of energy performance of member countries and, based on that, determine guidelines for further improvement and development. The method used to determine the number of clusters is summed up in the Auto-clustering table. For each possible number of clusters, the clustering criteria are calculated. The Schwarz Bayesian Criterion (SBC), also known as the Bayesian Information Criterion (BIC), is a criterion used to assess the goodness of fit of a statistical model while accounting for its complexity. In the context of two-step cluster analysis, it is used to determine the optimal number of clusters. Smaller BIC values indicate better models, while in this case, the "best" cluster solution has the least BIC. A big ratio of distance measures and a moderately large ratio of BIC changes are characteristics of a successful solution. The authors assign the number of clusters automatically. As a result, 4 is the ideal number of clusters, since this cluster solution has the lowest Swarz's Bayesian Criterion value and the largest Ratio of Distance Measures value (Table 1).

Table 1. The ratio of distance measures and the lowest value of Swarz's Bayesian Criterion

Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change[a]	Ratio of BIC Changes[b]	Ratio of Distance Measures[c]
1	387,67			
2	453,54	65,86	1,00	1,48
3	536,69	83,15	1,26	1,53
4	**632,17**	**95,47**	**1,45**	**1,09**
5	729,68	97,51	1,48	1,27
6	831,79	102,11	1,55	1,11
7	935,59	103,79	1,57	1,19
8	1041,79	106,20	1,61	1,39
9	1151,48	109,69	1,66	1,07
10	1261,78	110,29	1,67	1,17

a. The changes are from the previous number of clusters in the table.

b. The ratios of changes are relative to the change for the two cluster solutions.

c. The ratios of distance measures are based on the current number of clusters against the previous number of clusters.

4. Results and discussion

The validity of the cluster analysis and the set model was proven through the Silhouette measure of cohesion and separation which is over 0.5 which is very good. Descriptive statistics between clusters, especially the mean value of the analyzed indicators, have been used to demonstrate the conditions in the energy performance clusters of the EU members. Therefore, the second cluster has the highest mean value for Primary energy consumption while the third cluster has the highest value for the three indicators: Renewable energy in transport, Renewable energy sources in electricity, and Renewable energy sources in heating and cooling (Table 2).

Table 2. Descriptive statistics among clusters

	Primary energy consumption		Energy productivity		Renewable energy in transport		Renewable energy sources in electricity		Renewable energy sources in heating and cooling	
	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.
Cluster	86,68	3,51	6,98	2,06	8,74	1,15	32,76	14,14	21,78	6,97
	101,90	6,88	5,22	2,62	7,78	1,95	17,08	4,95	33,48	8,25
	88,53	5,78	6,47	1,98	11,44	10,49	49,27	20,71	57,18	11,52
	82,00	8,02	13,10	5,95	8,58	2,29	45,81	20,87	26,00	15,15

Fig. 2 depicts the cluster structure and number of countries as well as cluster size and dominance. The most significant cluster share and size has the fourth cluster 33,3% with nine countries. Lithuania, Latvia, Estonia, Croatia, Finland and Sweden has the lower cluster share but the mean of the Renewable energy in transport, Renewable energy sources in electricity, and Renewable energy sources in heating and cooling indicators is the highest one. The results of the two-step cluster analysis revealed significant insights into the energy performance of EU member states. The identified clusters highlight varying strengths and weaknesses among countries, with some clusters excelling in renewable energy adoption while others demonstrate higher levels of primary energy consumption. The clear distinction in the mean values of the indicators across clusters indicates that different policy strategies are needed to address these disparities. These results demonstrate the uneven progress toward EU energy targets, highlighting the need for customized policy measures to address each cluster's specific strengths and weaknesses.

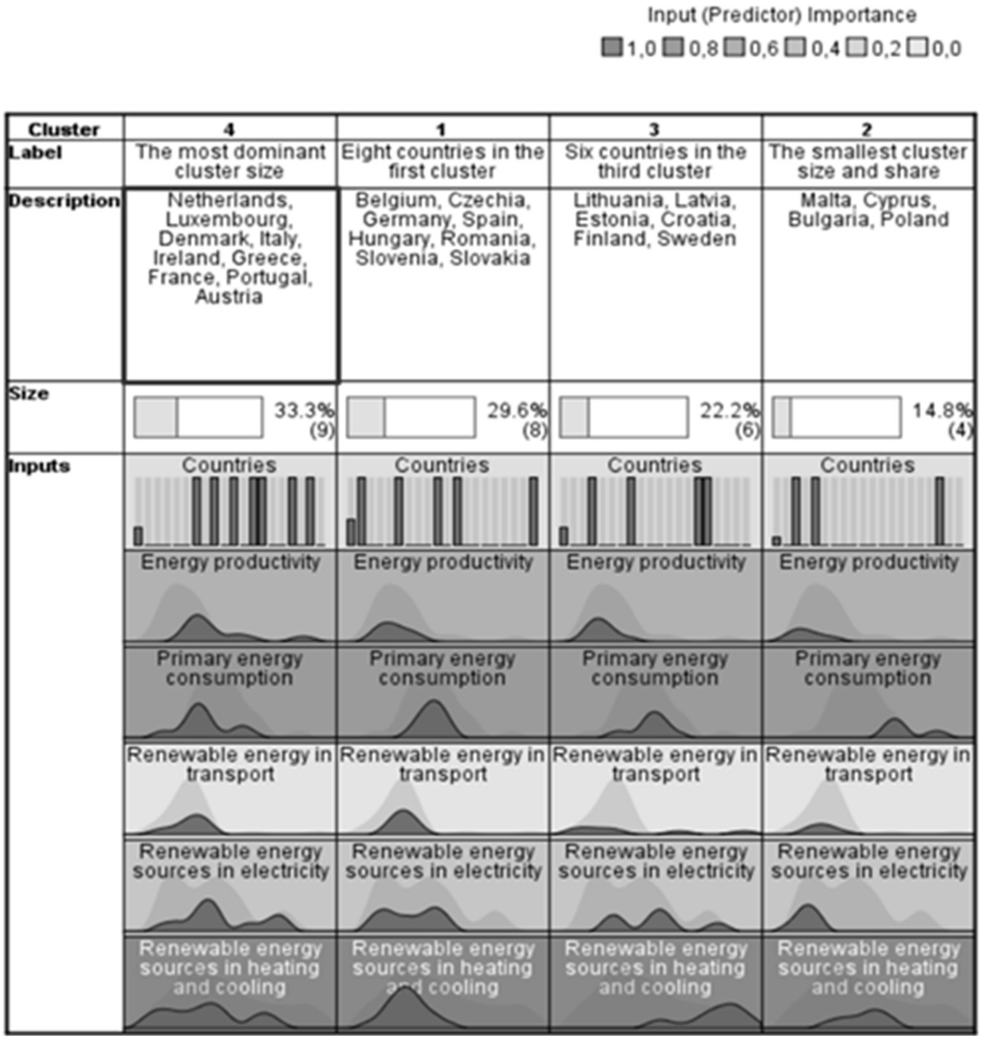

Figure 2. Cluster structure

The findings contribute to more informed decision-making in the development of energy policies, with the focus on how to balance consumption, productivity, and renewable energy transition across the EU. The second part of the implemented methodology relates to multi-criteria decision-making output. The first most significant decision- making output is GAIA analysis, a statistical method used in Visual PROMETHEE Academic, categorizes alternatives into small clusters based on the dominant criteria for each alternative's data. The effectiveness of this analysis depends on the quality of the model, which is determined by selecting appropriate criteria and options for ranking [21]. If the model's quality exceeds 60%, it can be considered to address the relevant questions adequately. In the example of the EU27 ranking, the model quality is 67.5% (Fig. 4). In the context of multi-criteria decision-making for energy performances, distinct groups or clusters of alternatives emerge. The first cluster, located in the first quadrant (quadrants in the matrix are numbered counterclockwise), includes Lithuania, Slovenia, Croatia, and others, which stand out due to factors such as Primary energy consumption and Renewable energy sources in heating and cooling. Alternatives like Bulgaria and Malta are identified in the fourth quadrant, while Hungary for example is positioned in the fourth quadrant, without clearly belonging to any specific group. The significant distance between Slovenia and Romania from the groups and their position near the coordinate origin suggests that their energy performances are not at an adequate level. Sweden, Finland, Denmark, Austria, and Portugal, located in the second quadrant have the leading position for analyzed indicators especially for Renewable energy sources in electricity and Renewable energy in transport marked by "bold- black stick".

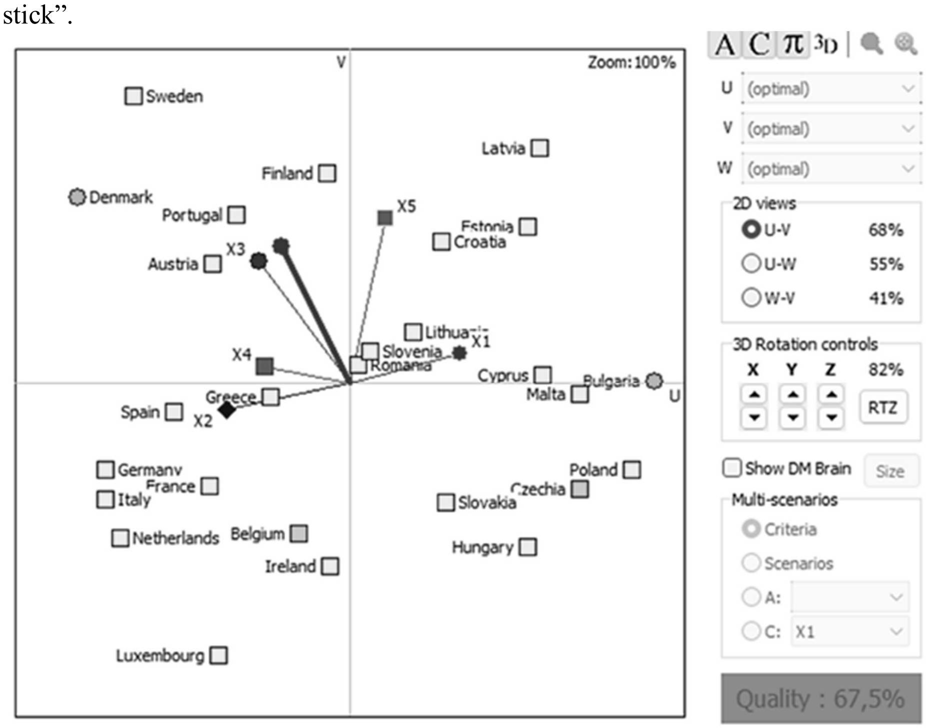

Figure 4. GAIA

*X1-Primary energy consumption; X2- Energy productivity; X3- Renewable energy sources in electricity; X4- Renewable energy in transport; X5- Renewable energy sources in heating and cooling.

PROMETHEE network view depicts the most significant conjunctures between EU members according to Phi coefficient. In PROMETHEE, the Phi coefficient is typically used in the flow model to express the overall performance of each alternative. The flow model is designed to give a preference ranking to each alternative based on how it performs concerning the other alternatives across various criteria. The idea is to calculate the **positive flow** (how much an alternative is preferred over others) and the negative flow (how much it is less preferred). These flows are then combined into a single score for each alternative, and the alternatives are ranked based on this score. Based on this, it can be concluded that Sweden and Denmark especially stand out as optimal alternatives (Fig. 5). Sweden has the highest positive Phi coefficient.The Phi coefficient essentially quantifies the net preference an alternative has over other alternatives. It is a value between -1 and 1, where the value close to 1 means the alternative is strongly preferred compared to others.

$$\varphi = \varphi^{+} - \varphi^{-} \tag{3}$$

Where φ^{+} is positive and φ^{-} is negative flow and the φ is overall Phi coefficient.

A result of 0.82 for the Phi coefficient signifies that the alternative in question is highly preferred, suggesting that it is a strong contender in the decision-making process and outperforms most of the other alternatives based on the criteria considered. This can guide decision-makers toward making a final choice with confidence. In decision-making, a Phi of 0.82 represents a clear winner in terms of overall desirability based on the weighted criteria considered in the analysis, promoting Sweden as a favorable benchmark in energy performance evaluation.

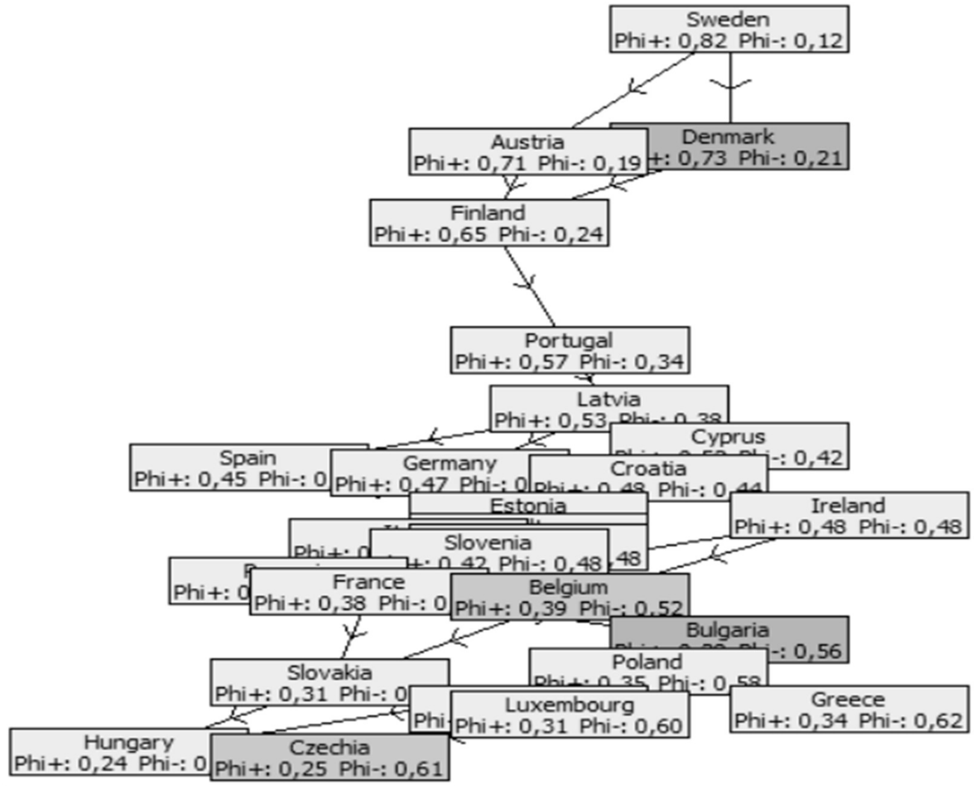

Figure 5. PROMETHEE network view

Additionally, the "spider" diagrams depict the countries' leaders in the analyzed area. A positive orientation is present for the majority of energy performance indicators.

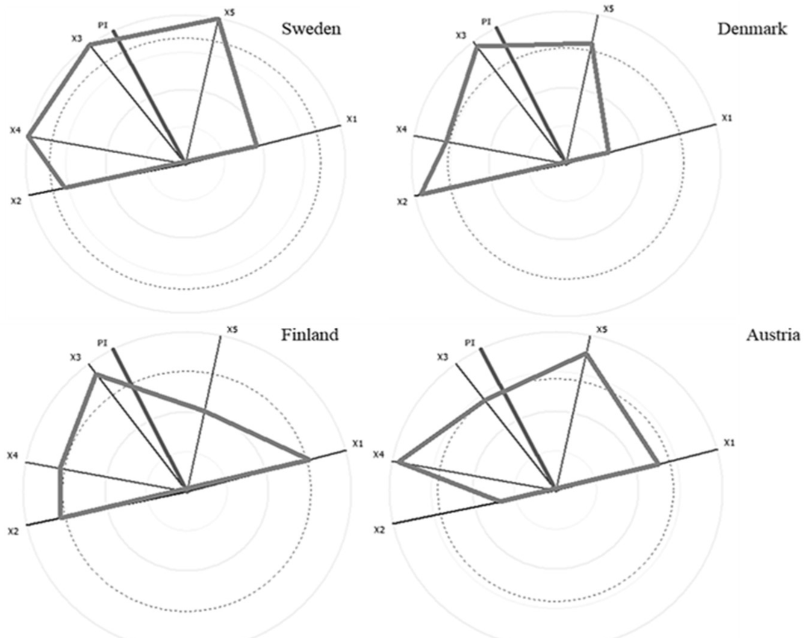

Figure 6. Spider charts for energy performance leaders among EU members

The analysis identified four distinct clusters of EU member states, each with unique energy performance characteristics. Cluster 2 showed the highest primary energy consumption, with a mean of 101.90 units, while Cluster 3 led in renewable energy adoption, particularly in transport (11.44%), electricity (49.27%), and heating and cooling (57.18%). These findings show the diverse energy profiles within the EU, with some countries excelling in renewable energy while others lag in consumption efficiency. This clustering offers policymakers valuable insights into designing targeted energy strategies. Countries in Cluster 2, for example, could benefit from policies that prioritize reducing energy consumption, whereas Cluster 3 countries might focus on maintaining their renewable energy advancements. Policymakers can use these profiles to set differentiated energy targets that reflect each cluster's specific needs and capabilities, facilitating more efficient resource allocation. However, the study has limitations. The analysis relies solely on the latest available Eurostat data, making it a real-time snapshot rather than reflecting long-term trends. Additionally, the study does not account for socio-economic factors that may influence energy performance, such as economic growth rates or industrial structures, which could further refine the clustering.

In recent years, Sweden, Denmark, Finland, and Austria have made notable progress in improving their energy performance, particularly in advancing renewable energy. Their efforts have not only supported their own national energy objectives but also influenced the European Union's renewable energy policies. Sweden has become a leader in renewable energy in Europe, with nearly 60% of its energy derived from renewable sources such as hydropower, wind, and biomass. The country's commitment to reducing carbon emissions and phasing out fossil fuels has had a substantial impact on the EU’s climate goals. Sweden aims to achieve net-zero emissions by 2045 and advocates for more ambitious EU-wide renewable energy targets. Denmark, known for its bold wind energy strategy, has become a global leader in wind turbine production and offshore wind energy. Wind power now accounts for around 50% of Denmark’s electricity consumption, and the country aims to achieve fossil fuel independence by 2050. Denmark’s successful integration of wind energy into its grid has served as a model for the EU, promoting further investments in offshore wind as part of the Green Deal. Denmark has also played a key role in pushing for stronger renewable energy targets and energy efficiency measures within the EU. Finland has made significant progress in diversifying its energy mix by increasing its use of bioenergy, wind, and solar power. The country plans to phase out coal by 2030 and increase its renewable energy share. Finland’s sustainability efforts align with the EU's renewable energy directives, and its focus on bioenergy and forest-based solutions has influenced EU policies on sustainable biomass use and carbon-neutral solutions. Austria has been highly successful in integrating renewable energy, especially hydropower and biomass, into its energy system. Over 70% of Austria's electricity is generated from renewable sources, and the country has committed to achieving carbon neutrality by 2040. Austria has been an active advocate for stronger EU climate policies, including increased funding for renewable energy technologies and carbon pricing. Its emphasis on hydropower and renewable heating systems has contributed to EU strategies for sustainable energy production and energy efficiency.

5. Conclusion

This study applied a two-step cluster analysis to classify EU member states based on key energy performance indicators. The results revealed four distinct clusters, demonstrating differences in primary energy consumption, energy productivity, and renewable energy adoption. Countries in

Cluster 3 excelled in renewable energy integration, while Cluster 2 had the highest energy consumption, highlighting the need for tailored energy transition strategies. The insights gained from this clustering analysis provide recommendations for countries with lower energy efficiency and renewable energy adoption, such as Serbia and Bosnia and Herzegovina. These nations, which face challenges in transitioning away from fossil fuels, can use best practices from higher-performing EU member states, particularly those in Cluster 3, which have successfully integrated renewable energy into their national grids.

The clustering insights provide valuable guidance for policymakers by identifying countries that require targeted energy transition policies. High energy-consuming countries should prioritize efficiency improvements and investment in renewables, while nations with advanced renewable adoption can serve as models for technology and policy diffusion. Aligning national policies with EU energy transition goals is essential for achieving the Green Deal objectives. Future research should extend this clustering approach by incorporating socio-economic and industrial indicators to refine energy transition strategies. Additionally, applying this methodology over multiple years would help track progress toward EU climate goals and identify emerging trends in energy efficiency and sustainability.

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