Article

Assessing the Performance of Sustainable Development Goals of EU Countries: Hard and Soft Data Integration

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Abstract: The European Union (EU) energy policy for sustainable development has been the topic of continuous debate, research, and analysis, which frequently focused on objectives and the evaluation of quantitative and qualitative performance. Different approaches can be used for the assessment of sustainable development goals. The authors of the article conducted a literature review of relevant research papers dated 2016–2020. The most common are quantitative methods based on hard data. Some qualitative studies based on soft data are also available but rare. This article proposes hybrid Rough Set Data Envelopment Analysis (DEA) and Rough Set Network DEA models that integrate both approaches. Also, the models allow the inclusion of uncertainty in the underlying data. The article uses hard data of the International Energy Agency (IEA) and the results of the EU survey regarding the influence of the socio-economic environment on CO₂ emissions in EU countries. The authors demonstrate that multifaceted and objective assessment is possible by merging concepts from the set theory and operational research.

Keywords: rough set; data envelopment analysis (DEA); network DEA; sustainability; EU countries; CO₂; qualitative (soft) data; quantitative (hard) data

1. Introduction

Energy is the main driver for economic growth; however, it is also the leading cause of CO₂ emissions [1]. A shift away from high-carbon energy sources resulted from depleting fossil fuels and the growing awareness of the negative impact made by economic development on the environment. There is a global consensus that energy needs to become eco-friendly [2]. Based on the United Nations Agenda 2030 [3], sustainable development is impossible without “access to affordable, reliable, sustainable, and modern energy for all”.

Many economies have set ambitious goals for their energy sectors, emphasizing safety, sustainability, environmental friendliness, resource-efficiency, and low-carbon dependency [4]. The European Union (EU) is especially active in introducing relevant regulatory framework and policies [5,6]. Policy instruments for the smarter and more sustainable electricity in the EU include a wide range of directives, strategies, and roadmaps with targets for a low-carbon economy, energy efficiency and renewable resources [4]. At the micro-level, European enterprises are also encouraged to innovate responsibly [7,8] and assess newly-developed technologies [9] considering the intended and unintended environmental and social impact.

Debates, research efforts, and analyses have been focusing on ways to measure and monitor the progress toward sustainability. Indicators commonly used for those purposes show the indivisibility of the relationship between energy and development. Instead of absolute values, the impact made

by economies on the natural environment is measured by the share of renewable energy in the total final energy consumption, energy intensity per unit of GDP [3], and CO₂ per unit of value-added [10]. However, other issues should also be considered. For example, energy sustainability is impossible without sufficient investments in energy efficiency, expressed as a percentage of GDP or direct investments in infrastructure and technology [3]. It is also important to compare the progress of countries considering many aspects of sustainable energy and development as well as find ways to aggregate the final assessment [11–13].

The review of the literature on the performance of sustainable development goals revealed many available approaches. The used methods range from a comparison of simple indicators via multivariate statistical analysis to an adaptation of multicriteria decision-making methods. In particular, the latter—the adaptation of multicriteria decision-making methods—is a rapidly growing research area [14]. However, most efforts are limited to the analysis of hard quantitative data that describe the progress of a country leaving out the context-dependency defined by the soft qualitative data.

Papers that use qualitative data either present it as an evaluation of policies and initiatives transformed into simple dummy variables [15,16], or consider it indirectly as various ranking scores [11]. In some instances, the data is presented as expert opinions [17] or importance weights determined by experts [18]. Qualitative data often contains more information. However, it is also ambiguous.

A dismissal or oversimplification of qualitative information means the rejection of a vast amount of knowledge. The success of a policy to reduce CO₂ emissions depends not only on economic prosperity measured by GDP per capita but also on priorities, set directly and indirectly by the public. The significance of both factors is evident in the midst of unprecedented challenges faced by societies, such as the expected recession and global changes resulting from the COVID-19 pandemic.

The suggestion to integrate soft and hard data on the socio-economic environment makes this article original. The proposal is to use different types of data, i.e., social authorization, the readiness for change, the standard of living, and efforts made toward the decoupling of economic growth and carbon emissions. The article offers to use hybrid models, i.e., Rough Set Data Envelopment Analysis (DEA) and Rough Set Network DEA, to deal with uncertainty in the underlying data used for assessing the performance of sustainable development goals in EU countries.

The article has the following structure. First, it provides a solid review of papers issued in 2016–2020 on monitoring and assessing efforts of EU countries toward energy sustainability. In this part, it also indicates methods and goals used as the background for a proposed approach. Next, Rough Set theory, DEA, and network DEA models are used to deal with uncertain data in the case of sustainable development assessment. Then, a case study is discussed, and results of the analysis are presented. The article finishes with conclusions.

2. Background Literature

Many research projects originated from the importance of sustainable development and free public access to EU data aggregated at a national level. Table 1 presents the results of the literature review conducted in the Scopus database. The analysis targeted relevant articles that focused on the EU and were published in 2016–2020. The summary below indicates the methods and aims of each research.

Based on the review, the interest in the problem of objective assessment is high and constant. Most papers focused on the results of multidirectional efforts toward sustainable development and the reduction of its negative impact on the environment. Some papers investigated the speed of changes taking place in this area, e.g., the transition to renewable energy sources.

Table 1. Summary of most relevant 30 papers.

Author	Methods and Main Indicators	Aims
Bigerna, Bollino, and Micheli (2016) [19]	Simulation model and general equilibrium model data: GDP, CO ₂ emission, RES development targets	To construct a model that identifies and estimates potential costs of non-compliance with RES targets in some counties; to present a simulation
D'Adamo and Rosa (2016) [20]	Growing steps structure of RE share and average values data: share of RE production and consumption per capita Macroeconomic models: NEMESIS and ASTRA with scenario simulation based on PRIMES	To assess the EC RES trajectory toward 2020 strategy
Duscha, Fougereyrollas, Nathani, Pfaff, Ragwitz, Resch, Schade, Breitschopf, and Walz (2016) [21]	data: CO ₂ reduction, consumption and import of fossil fuels, GDP, employment, RE deployment, costs related to RE deployment Markowitz portfolio theory data: cost and risk of RES technologies (e.g., production costs investment, GHG emissions, plant accident) from other studies K-means CA	To assess whether RES can positively contribute to the objectives of the European energy policy: combating climate change, improving the security of supply and resulting in economic benefits (job creation and economic growth)
deLlano-Paz, Fernandez, and Soares (2016) [22]		To analyze the EU policy framework goals, cost, risk, and security issues
Pacesila, Burcea, and Colesca (2016) [23]	data: renewables data (RES share, RES for heating and cooling, transport, energy dependence)	To analyze the RE sector in the EU
Cilinskis, Indzere, and Blumberga (2017) [24]	TOPSIS data: non-ETS emissions of GHG by different sectors	To introduce a methodology based on multi-criteria analysis TOPSIS to policy planning aimed at climate goals using a Latvian example
Momete (2017) [12]	Composite index of RE development based on aggregation data: production and consumption mix: fossil fuels oil, gas, coal, solid fuels, nuclear energy, and RES shares LEAP (Long-range Energy Alternatives Planning) and the MCDM AMS (the combination of three standard MCMs: AHP, MAUT and SMART)	To investigate the energy development in terms of RE in the Eastern Bloc of the EU
Nikolaev and Konidari (2017) [25]	data: structure of the final energy consumption by fuels, total contribution (capacity, electricity generation) of RES technologies, and policy packages assumptions PRIMES model that simulates energy consumption and the energy supply system data: GHG emissions, energy efficiency, RES, energy demand, with costs and required investments	To identify the most feasible level of ambition up to 2030 for the Bulgarian RE policy by simulating three scenarios aiming for different RES targets
Capros, Kannavou, Evangelopoulou, Petropoulos, Siskos, Tasios, Zazias, and DeVita (2018) [26]		To present a set of scenarios quantified by the PRIMES energy systems model

Table 1. Cont.

Author	Methods and Main Indicators	Aims
Cirstea, Moldovan-Teslios, Cirstea, Turcu, and Darab (2018) [11]	Index construction based on weighting and aggregation data: RE mix shares, indicators from sustainability dimensions of the energy system (environmental, e.g., quality of the natural environment, renewable energy consumption; institutional, e.g., transparency of policymaking; GDP per capita; social, e.g., availability of latest technology, spending on R&D; economic, e.g., production of RE, inflation rate). The index uses other rankings scores.	To design a composite index: RE Sustainability Index and use it to examine European countries
Holma, Leskinen, Myllyviita, Manninen, Sokka, Sinkko, and Pasanen (2018) [17]	Qualitative expert judgment methods data: share of energy from RES LARS (least angle regression), PCA data: the share of RES in RE mix; indicators from 4 dimensions: environmental, e.g., CO ₂ emissions per capita; security, e.g., energy import; economic, e.g., GDP per capita, energy consumption per capita and per GDP, cost of energy; political (dummy variables)	To discuss expert assessment of the impacts and risks of RE production in Finland
Papież, Śmiech, and Frodyma (2018) [15]	Preliminary (yes/no) analysis of the existing initiatives data: an overview of the national adaptation policies: National Adaptation Strategy and National Action Plan	To identify factors which determine energy policy in EU countries on the basis on the share of RES in the RE mix
Pietrapertosa, Khokhlov, Salvia, and Cosmi (2018) [16]	Co-integration tests and OLS panel regression data: Selected Europe 2020 strategy ratios, e.g., GDP, R&D expenses, employment rate, energy consumption, GHG emission etc.	To overview adaptation initiatives undertaken in 11 south-east European countries with reference to the policies and measures promoted by the EU National Adaptation Strategy and National Action plan
Radulescu, Fedajev, Sinisi, Popescu, and Iacob (2018) [27]	Linear regression models, panel data techniques data: GDP, energy consumption from RES Hierarchical CA, convergence analysis panel data model (regression)	To determine the most important ratios in the “Europe 2020 Strategy” for sustainable and inclusive growth
Soava, Mehedintu, Sterpu, and Raduteanu (2018) [28]	data: energy consumption shares of energy consumption for different RES and many variables for CA defining levels of R&D, human capital, and demographic features	To examine the causal relationship between economic growth and RE consumption
Arbolino, Boffardi, and Ioppolo (2019) [29]	Descriptive statistic and CA data: share of RE in heating cooling and transport	To propose an approach for ex-post monitoring of the actions implemented in Italian regions
Bórawski, Bėldycka-Bórawska, Szymańska, Jankowski, Dubis, and Dunn (2019) [30]		To assess RE market development with regard to biofuels in the EU

Table 1. Cont.

Author	Methods and Main Indicators	Aims
Brożyna, Mentel, Ivanová, and Sorokin (2019) [31]	Hierarchical CA data: indicators of RE	To distinguish countries among the new EU MSs that increased their electrical capacity from RES
Cirstea, Tiron-Tudor, Nistor, Cirstea, and Fulop (2019) [32]	Multidimensional scaling data reduction method and CA data: energy indicators, e.g., energy imports, energy use, energy production, capacity, the share of RES, GHG	To measure the differences between the countries in the Eastern European region in terms of RE and economic development
Lindberg and Markard (2019) [6]	Transition pathway (semi-coherent pattern of major changes) analysis data: list of key EU electricity policies and their key industry actors	To assess the EU electricity policy mix supporting different transition pathways
Lyeonov, Pimonenko, Bilan, Štreimikienė, and Mentel (2019) [33]	Modified OLS data: GDP per capita and GHG emissions, RE consumption, green investment	To analyze the linkages between GDP per capita, GHG and RE in the total final energy consumption and green investments in the EU
Malinauskaite, Jouhara, Ahmad, Milani, Montorsi, and Venturelli (2019) [5]	Descriptive statistics analysis data: energy consumption trends, sources and sectors, energy savings	To review EU strategies and policies on energy efficiency; to present national case studies for Italy and the UK
Mikalauskiene, Štreimikis, Mikalauskas, Stankūnienė, and Dapkus (2019) [34]	Descriptive statistics analysis data: GHG emissions and removals by sector, a set of indicators for the assessment of energy intensity, the structure of consumption, dependency, shares of RES in sectors	To assess GHG emission trends and climate change mitigation policies in the fuel combustion sector of Lithuania and Bulgaria
Neofytou, Karakosta, and Gómez (2019) [18]	Promethee II data: 12 indicators from 4 dimension: environmental impacts, e.g., GHG reduction, energy-saving; social impact, e.g., employment; economic impacts, e.g., GDP; energy systems impacts, e.g., import, intensity	To assess alternative climate and energy policy scenarios and their socioeconomic, environmental, and energy impacts
Pach-Gurgul and Ulbrych (2019) [35]	Hellwig's multidimensional comparative analysis data: energy consumption, the share of RE in energy consumption	To empirically verify progress made implementing the provisions of the EU Energy Package by the V4 countries
Siksnielyte and Zavadskas (2019) [4]	MCDM, TOPSIS data: indicators for monitoring the progress (electricity interconnection, market concentration, electricity prices, retail electricity markets share of RES in final electricity consumption), indicators for the assessment of sustainability: economic (e.g., prices), environmental (e.g., share of RES, distribution losses) security (import)	To monitor the progress of the electricity sector toward EU objectives; assess the sector sustainability

Table 1. Cont.

Author	Methods and Main Indicators	Aims
Siksnelyte, Zavadskas, Bausys, and Streimikiene (2019) [36]	MCDM MULTIMOORA optimization based on Ratio Analysis technique data: indicators for monitoring the progress of energy import dependency and energy security (e.g., import, supplier concentration), indicators for monitoring the progress of decarbonization (e.g., energy consumption, GHG emission), national energy targets and their implementation, set of EISD indicators to comparative assessment of sustainable: social (e.g., affordability of electricity), economic (e.g., energy use and productivity), and environmental (e.g., GHG emissions) Efficiency index based on normalization, weighting, and aggregation and PCA	To present the EU energy policy context; to analyze trends in energy development in eight Baltic Sea Region countries
Arbolino, Boffardi, Simone, and Ioppolo (2020) [13]	data: indicators from dimension: sectoral trends (e.g., GDP, energy intensity per capita, RE production per capita, energy consumption), interaction with the environment (e.g., CO ₂ emissions), economic and policy aspects (e.g., Tax, R&D Expenditure)	To propose an approach for achieving increased efficiency energy; to present the test on a sample of 20 Italian provinces
Fedajev, Stanujkic, Karabašević, Brauers, and Zavadskas (2020) [37]	MCDM MULTIMOORA: The Ratio System, the Reference Point, and the Full Multiplicative Form data: indicators grouped into dimensions: employment, R&D, climate change and energy, education, poverty, and social exclusion: employment rate, GDP expenditure on R&D, GHG, the share of RE, energy consumption per capita, education leavers, attainment of tertiary education, people at risk of poverty System of equations based on the OLS model	To classify and rank the EU countries according to the progress in the implementation of the EU strategy “Europe 2020”
Swain and Karimu (2020) [38]	data: electricity price, RE demand, non-RE demand, GDP, heating, and cooling	To examine the RE synergy effect on selected SDGs based on electricity prices in EU countries

Abbreviations: AHP—analytical hierarchy process; CA—cluster analysis; EISD—Energy Indicators for Sustainable Development; ETS—emissions trading system; EU—European Union; GDP—gross domestic product; GHG—greenhouse gas; MAUT—multi-attribute utility theory; MCDM—multi-objective decision-making, multi-criteria decision-making; MCM—multi-criteria method; MS—member state; OLS—ordinary least square; PCA—principal component analysis; R&D—research and development; RE—renewable electricity, renewable energy; RES—renewable energy sources; SDG—sustainable development goals; SMART—simple multi-attribute ranking technique.

Calculations and analyses were based on various indicators. Among the most commonly used were renewable energy shares/amount as indicators of energy sustainability [4,5,11–13,15,17–20,22,23,25–35,37,38] and the associated greenhouse gas emission [13,15,18,19,21,22,24,26,27,32–34,36,37].

Monitoring, rankings, and ratings of sustainability were made using various methods:

- qualitative descriptions or expert knowledge analysis [6,16–18];
- descriptive statistics analysis [5,20,34];
- utilization of equations describing relations [22];
- scenario simulations [19,21,26];
- aggregation of data to the index [11–13,35];
- regression models [15,27,28,33,38];
- cluster analysis and principal component analysis methods [13,15,23,29–32];
- multidimensional statistical analysis [4,24,25,35–37].

The regression models could be divided into simple equations [28,33,38] and extended, multiple variables [15,27]. Some authors created rankings based on several indicators [12] or their set that described different dimensions [4,11,13,36,37]. Policy and strategy studies were mostly a yes/no analysis of documents [16] or dependencies between them [6]. The portfolio of methods is extensive and still open for suggestions.

The main advantage of the DEA method is a comparative analysis of multiple variables. The method was applied empirically in many areas [39]. DEA-based assessment of sustainable development goals allows for the relativization of performance based on the underlying relationship between the weighted sum of results and the weighted sum of cost [40]. The issues of weighting are solved using objective linear programming. Table 2 presents examples of DEA applications for the assessment of sustainability in EU countries. In this case, the inputs and outputs are given as a reference to previous studies and practice.

Table 2. Example of papers relevant to Data Envelopment Analysis (DEA) and EU sustainability.

Authors	DEA Models	Aims	Variables
Grochová and Myšková (2016) [41]	Standard DEA BCC model with slacks	To assess the ability of EU countries to achieve the objectives of Strategy 2020	Input: electricity production from RES, alternative and nuclear energy, fossil fuel energy, adjusted savings of CO ₂ damage Output: unemployment, GDP per capita
Ifthikhar, He, and Wang (2016) [42]	SBM DEA model with an undesirable output	To analyze energy and CO ₂ emission efficiency (ECEE) of major economies (including the EU)	Input: labor, capital, energy Output: GDP Undesirable output: CO ₂
Madaleno Moutinho, and Robaina (2016) [43]	Standard CCR and BCC DEA models	To estimate and compare the efficiency	Input: capital, labor, fossil fuel, RE or GDP per labor, GDP per capita, fossil fuel per GDP Output: GDP per GHG
Sanz, Yñiguez, and Velasco (2016) [44]	DEA with a desirable and undesirable output and MI	To analyze the efficiency of EU countries, focusing on Spain	Input: gross capital formation (GCF), energy consumption, RE consumption, Output: GDP Undesirable output: GHG

Table 2. Cont.

Authors	DEA Models	Aims	Variables
Moutinho, Madaleno, and Robaina (2017) [45]	DEA and regression analysis	To estimate the efficiency	Inputs: labor and capital productivity, the weight of fossil energy and the share of RE in GDP Output: GDP per GHG emissions Regression analysis: environmental tax revenues, resources productivity, and domestic material consumption Input: the deployed renewables Output: an increase in the share of RE in the total electricity generation
Gökgöz and Güvercin (2018) [46]	super-efficiency DEA and MI	To benchmark the RE performance of countries under different energy regime settings	Undesirable outputs: the imports of coal products, oil products, and natural gas Input: cost (efficiency indicator based on support in technology price and electricity consumption), LCOE index (cost level for producing electricity from the RES) Output: the share of assessed RE technology compared to the electricity consumption level (generated electricity/electricity consumption)
Mezősi, Szabó, and Szabó (2018) [47]	DEA	To assess the cost-efficiency of RE support schemes	Input: labor, capital, EC (energy consumption) Output: GDP, sulfur oxide SO _x , GCF (gross capital formation) Input: labor, capital, energy Output: GDP Undesirable output: CO ₂ Input: fossil fuel depletion, total land occupation, water depletion, the annualized cost of electricity Output: climate change (GWP100), human toxicity, ozone depletion, total job-years, electricity generated (data from: [51])
Hsieh, Lu, Li, Chiu, and Xu (2019) [48]	SBM dynamic DEA	To measure the environmental efficiency of energy	
Teng, Lu, and Chiu (2019) [49]	DEA type meta-frontier non-radial directional distance function	To evaluate the efficiency of energy and CO ₂ emission	
Zurano-Cervello, Pozo, Mateo-Sanz, Jimenez, and Guillen-Gosalbez (2019) [50]	Lifecycle and DEA	To assess the sustainability level of the power sector	

Abbreviations: BCC—introduced by Banker, Charnes and Cooper [52] DEA model; CCR—Charnes, Cooper and Rhodes [53] basic DEA model; DEA—Data Envelopment Analysis; MI—Malmquist index; SBM—slacks-based measure; EU—European Union; GDP—gross domestic product; GHG—greenhouse gas; RE—renewable electricity, renewable energy; RES—renewable energy sources.

Hence, DEA-based approaches to the assessment of sustainability in different countries were used for various purposes. In some instances, the focus was placed on efficiency while transforming hard data on labor, capital, and energy into GDP. Other papers considered the associated production of pollutants (mainly greenhouse gas emissions) [45,48,49] and renewables [45–47]. Changing trends of RE amounts [46,48,49] was another popular area of assessment.

Papers in Tables 1 and 2 provide references that are mainly notes and documents published by EU institutions, primarily the European Commission (EC). The popular references were: *A policy framework for climate and energy in the period from 2020 to 2030* [54] in [12,16,18,20,22,36]; *Energy Roadmap 2050* [55] in [4,5,16,18,21,22,26,36]; and *EU Energy 2020—A Strategy for Competitive, Sustainable and Secure Energy* [56] in [4,12,20,22,36]. Just as frequent were *Clean Energy for All Europeans—unlocking Europe’s growth potential* [57] in [4,5,26,30,36], *Guidelines on State aid for environmental protection and energy, 2014–2020* [58] in [6,47]; *Climate Action—Paris Agreement* [59] in [44]; and *2030 Climate and Energy Goals for a Competitive, Secure and Low-carbon EU Economy* [60] in [25]. In some instances,

references were made to a set of documents related to energy, e.g., *Energy Strategy and Energy Union* [61] in [32]. Some documents were issued by the Council of the European Union, e.g., *EU Response to the 2030 Agenda for Sustainable Development a Sustainable European* [62] in [30]. The United Nations (UN) outlines in *Sustainable development goals* [3,63] were the most popular reference in documents issued by international agencies, cited in [4,11,24,32,33,38]. Another important reference was reports of the International Atomic Energy Agency (IAEA), such as *Energy Indicators for Sustainable Development: Guidelines and Methodologies* [64], used in [4,11–13,34,36].

To sum up, data was mainly taken from the EU statistical office Eurostat [65] in [4,15,19,20,22,23,28,30–38,41,43,44] or the European Environmental Agency (EEA) [66] in [5,18,23,29,30,33,38,43,50]. Also, EU documents and websites were used, such as EC Europe 2020 Targets: Statistics and Indicators at the EU Level [67] in [27]. The indicated reliable data and reports were also provided by the International Energy Agency [10] in [1,4,11,13,21–23,28,29,34–36,38,46,48,50]. Other popular data sources were the World Bank Open Data [68] mentioned in [12,32,33,41,42,46], World Energy Council [69] cited in [12,13,23] or the estimation of the European Investment Bank [70] in [22]. In the case of individual country analysis, the local data sources were used, e.g., the Italian National Institute of Statistic, the Italian company GSE [13,29] or the Latvian Ministry of Environmental and Regional Development [24]. The data sources were also reports of independent research and consulting firms, such as Enerdata, Global Energy Statistical Yearbook [71] in [42]. This article used the International Energy Agency (IEA) data [72] and the soft data on social authorization for moving toward a low-carbon economy from an EC survey *Europeans' attitudes on energy policy* [73].

The cited papers assumed that the data underlying the assumption were solid and reliable. Most of them analyzed absolute energy sustainability indicators from statistical databases. The few cases that used qualitative data treated it in the same way: the transformation into numerical variables was a conversion to zero—one values [15,16]. Also, it was used directly as expert opinions [17,18]. Conversion of qualitative data into quantitative data without considering the subjectivity and the resulting uncertainty was associated with the loss of information, shallow conclusions, and misinterpretation.

There are many approaches to incorporation of uncertainty into the DEA, e.g., chance-constrained DEA model [74]. In the context of sustainability assessment, uncertainty in data is mainly modeled using concepts derived from Fuzzy Sets [75,76]. For example, DEA and fuzzy best and worst methods were combined and used to prioritize renewable energy sources [77]. Fuzzy numbers were used to describe the ambiguity of a qualitative index used to assess an RE technical plan [78]. This article proposes a hybrid model that integrates the Rough Set theory and DEA to model the vagueness of data. Rough Sets, although different with some origin assumptions, by some authors are treated as an approach derived from Fuzzy Sets [79,80]. The merging of concepts from the set theory and operational research address the need for multifaceted and objective assessment as it proved to be effective in the case of technology prioritization [81]. Fuzzy sets in non-empty space are based on the membership function. Using the membership function relates to the basic problem of choosing the method of its construction. The Rough Set theory, which does not require special assumptions as to data and probability distribution, characterized by mathematical simplicity, has found many applications. However, the combination of Rough Sets with the DEA method is unpopular and relatively rarely used.

3. Methods

Data Envelopment Analysis (DEA) is a linear programming technique that allows evaluating the relative efficiency of Decision-Making Units (DMUs). The method was initiated by Charnes, Cooper, and Rhodes (1978) [53] based on a paper by Farrell (1957) [82] and his concept of the best practice frontier. The DEA method uses the idea of technical efficiency. It evaluates the performances of the units, considering the relationship of outputs and inputs in connection to the value of this relationship in other DMUs covered by the study (Figure 1).

Figure 1. DEA concept.

Considering n DMUs where each DMU_j , $j \in J = \{1, \dots, n\}$ uses m inputs $x_j = (x_{1j}, x_{2j}, \dots, x_{ij}, \dots, x_{mj})$, $i \in I = \{1, \dots, m\}$, and produces s outputs $y_j = (y_{1j}, y_{2j}, \dots, y_{rj}, \dots, y_{sj})$, $r \in O = \{1, \dots, s\}$, the standard BCC-O DEA model (the output oriented Banker, Charnes, and Cooper model [52], applicable to technologies characterized by variable returns to scale) can be written as follows:

$$\begin{aligned} & \max \phi, \\ & \sum_{j=1}^n \lambda_j x_{ij} \leq x_{i0}, i = 1, \dots, m, \\ & \sum_{j=1}^n \lambda_j y_{rj} \geq \phi y_{r0}, r = 1, \dots, s, \\ & \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0. \end{aligned} \quad (1)$$

The score ϕ , specified in Equation (1) ranges from 0 for the worst performing units, to 100%, for the best ones. The symbol λ_j represents the weight of DMU_j .

In the case of sustainability assessment and comparisons, data (x_j, y_j) are often presented and interpreted in the form of ratios rather than in absolute numbers (e.g., GDP per capita, or CO₂ per GDP). On the other hand, subjects of decision are numerators ($\bar{x}_j, \bar{y}_j$) and denominators ($\underline{x}_j, \underline{y}_j$) of these fractions (x_j, y_j) . The basic standard CCR model (Charnes, Cooper, and Rhodes [20] DEA model) is technically incorrect when data is used in the form of ratios [83–86]. Assuming $I^R \subseteq I$ and $O^R \subseteq O$ represent, respectively, ratio inputs and ratio outputs, and $I^A = I \setminus I^R$ and $O^A = O \setminus O^R$ represent absolute (non-relative) inputs and outputs and, furthermore, $x_{ij} = \frac{\bar{x}_{ij}}{\underline{x}_{ij}}$, for each $i \in I^R$ and $y_{rj} = \frac{\bar{y}_{rj}}{\underline{y}_{rj}}$, for each $r \in O^R$, the BCC model Equation (1) can be deployed [83] or the nonlinear solution [84,85] Equation (2):

$$\begin{aligned} & \max \phi, \\ & \sum_{j=1}^n \lambda_j x_{ij} \leq x_{i0}, i \in I^A, \\ & \sum_{j=1}^n \lambda_j y_{rj} \geq \phi y_{r0}, r \in O^A, \\ & \sum_{j=1}^n \lambda_j (\bar{x}_{ij} - x_{i0} \underline{x}_{ij}) \leq 0, i \in I^R, \\ & \sum_{j=1}^n \lambda_j \bar{y}_{rj} - \phi y_{r0} \sum_{j=1}^n \lambda_j \underline{y}_{rj} \geq 0, r \in O^R, \\ & \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0. \end{aligned} \quad (2)$$

Symbols used as in Equation (1).

This paper proposes to integrate DEA and Rough Set methods to deal with data uncertainty [87]. The Rough Set theory, introduced by Pawlak (1982) [88], is a mathematical approach to vagueness and uncertainty. The uncertainty modelling with the concept of rough variables of inputs and outputs [89]: $[x_{ij}^a, x_{ij}^b], [x_{ij}^c, x_{ij}^d], [y_{rj}^a, y_{rj}^b], [y_{rj}^c, y_{rj}^d]$, where: $x_{ij}^c \leq x_{ij}^a < x_{ij}^b \leq x_{ij}^d$, $y_{rj}^c \leq y_{rj}^a < y_{rj}^b \leq y_{rj}^d$, $i = 1, \dots, m$, and $r = 1, \dots, s$ is presented in Figure 2. The ranges $[x_{ij}^a, x_{ij}^b]$ and $[y_{rj}^a, y_{rj}^b]$ represent lower approximations, $[x_{ij}^c, x_{ij}^d]$ and $[y_{rj}^c, y_{rj}^d]$ upper approximations (boundaries) of the unknown real values of input x_{ij} and output y_{rj} , respectively.

Figure 2. Concept of rough input-output variables.

Using the concept of trust in rough variables and assuming the level α , such as $0.5 \leq \alpha \leq 1$, α -optimistic and α -pessimistic values can be calculated for each rough variable and each DMU: $[x_{ij}^{inf(\alpha)}, x_{ij}^{sup(\alpha)}], [y_{rj}^{inf(\alpha)}, y_{rj}^{sup(\alpha)}]$ [89]. The following Equations (3)–(6) formulas can be used:

$$x_{ij}^{sup(\alpha)} = \begin{cases} (1 - 2\alpha)x_{ij}^d + 2\alpha x_{ij}^c, & \text{if } 0 \leq \alpha \leq \frac{x_{ij}^d - x_{ij}^b}{2(x_{ij}^d - x_{ij}^c)} \\ 2(1 - \alpha)x_{ij}^d + (2\alpha - 1)x_{ij}^c, & \text{if } \frac{2d - x_{ij}^a - x_{ij}^c}{2(x_{ij}^d - x_{ij}^c)} \leq \alpha \leq 1, \\ \frac{x_{ij}^d(x_{ij}^b - x_{ij}^a) + x_{ij}^b(x_{ij}^d - x_{ij}^c) - 2\alpha(x_{ij}^b - x_{ij}^a)(x_{ij}^d - x_{ij}^c)}{(x_{ij}^b - x_{ij}^a) + (x_{ij}^d - x_{ij}^c)}, & \text{otherwise} \end{cases} \quad (3)$$

$$x_{ij}^{inf(\alpha)} = \begin{cases} (1 - 2\alpha)x_{ij}^c + 2\alpha x_{ij}^d, & \text{if } 0 \leq \alpha \leq \frac{x_{ij}^d - x_{ij}^c}{2(x_{ij}^d - x_{ij}^c)} \\ 2(1 - \alpha)x_{ij}^c + (2\alpha - 1)x_{ij}^d, & \text{if } \frac{x_{ij}^b + x_{ij}^d - 2x_{ij}^c}{2(x_{ij}^d - x_{ij}^c)} \leq \alpha \leq 1, \\ \frac{x_{ij}^c(x_{ij}^b - x_{ij}^a) + x_{ij}^a(x_{ij}^d - x_{ij}^c) - 2\alpha(x_{ij}^b - x_{ij}^a)(x_{ij}^d - x_{ij}^c)}{(x_{ij}^b - x_{ij}^a) + (x_{ij}^d - x_{ij}^c)}, & \text{otherwise} \end{cases} \quad (4)$$

$$y_{rj}^{sup(\alpha)} = \begin{cases} (1 - 2\alpha)y_{rj}^d + 2\alpha y_{rj}^c, & \text{if } 0 \leq \alpha \leq \frac{y_{rj}^d - y_{rj}^b}{2(y_{rj}^d - y_{rj}^c)} \\ 2(1 - \alpha)y_{rj}^d + (2\alpha - 1)y_{rj}^c, & \text{if } \frac{2y_{rj}^d - y_{rj}^a - y_{rj}^c}{2(y_{rj}^d - y_{rj}^c)} \leq \alpha \leq 1, \\ \frac{d(y_{rj}^b - y_{rj}^a) + y_{rj}^b(y_{rj}^d - y_{rj}^c) - 2\alpha(y_{rj}^b - y_{rj}^a)(y_{rj}^d - y_{rj}^c)}{(y_{rj}^b - y_{rj}^a) + (y_{rj}^d - y_{rj}^c)}, & \text{otherwise} \end{cases} \quad (5)$$

$$y_{rj}^{inf(\alpha)} = \begin{cases} (1-2\alpha)y_{rj}^c + 2\alpha y_{rj}^d, & \text{if } 0 \leq \alpha \leq \frac{y_{rj}^a - y_{rj}^c}{2(y_{rj}^d - y_{rj}^c)} \\ 2(1-\alpha)y_{rj}^c + (2\alpha-1)y_{rj}^d, & \text{if } \frac{y_{rj}^b + y_{rj}^d - 2y_{rj}^c}{2(y_{rj}^d - y_{rj}^c)} \leq \alpha \leq 1, \\ \frac{y_{rj}^c(y_{rj}^b - y_{rj}^a) + y_{rj}^a(y_{rj}^d - y_{rj}^c) - 2\alpha(y_{rj}^b - y_{rj}^a)(y_{rj}^d - y_{rj}^c)}{(y_{rj}^b - y_{rj}^a) + (y_{rj}^d - y_{rj}^c)}, & \text{otherwise} \end{cases} \quad (6)$$

The Rough Set DEA model results in the range of efficiency indicators for the assumed level of α : $[\phi^{inf(\alpha)}, \phi^{sup(\alpha)}]$ [81,89]:

$$\begin{aligned} & \max \phi^{sup(\alpha)} \\ & \sum_{j=1, j \neq j_0}^n \lambda_j x_{ij}^{sup(\alpha)} + \lambda_{j_0} x_{ij_0}^{inf(\alpha)} \leq x_{ij_0}^{inf(\alpha)}, i = 1, \dots, m, \\ & \sum_{j=1, j \neq j_0}^n \lambda_j y_{rj}^{inf(\alpha)} + \lambda_{j_0} y_{rj_0}^{sup(\alpha)} \geq \phi^{sup(\alpha)} y_{rj_0}^{sup(\alpha)}, r = 1, \dots, s, \\ & \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0, j = 1, \dots, n; \end{aligned} \quad (7)$$

$$\begin{aligned} & \max \phi^{inf(\alpha)}, \\ & \sum_{j=1, j \neq j_0}^n \lambda_j x_{ij}^{inf(\alpha)} + \lambda_{j_0} x_{ij_0}^{sup(\alpha)} \leq x_{ij_0}^{sup(\alpha)}, i = 1, \dots, m, \\ & \sum_{j=1, j \neq j_0}^n \lambda_j y_{rj}^{sup(\alpha)} + \lambda_{j_0} y_{rj_0}^{inf(\alpha)} \geq \phi^{inf(\alpha)} y_{rj_0}^{inf(\alpha)}, r = 1, \dots, s, \\ & \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0, j = 1, \dots, n. \end{aligned} \quad (8)$$

Achievement of sustainability goals is the effect of many consecutive stages (subprocesses). Network DEA models are multistage. They allow examining the efficiency of DMUs that have internal network structures and provide measures for the components that make up the DMUs [90]. Presented below is a general two-stage process, where the first stage uses inputs $x_j = (x_{1j}, x_{2j}, \dots, x_{ij}, \dots, x_{mj})$ $i \in I = \{1, \dots, m\}$ to produce outputs $z_j = (z_{1j}, z_{2j}, \dots, z_{dj}, \dots, z_{Dj})$ $d \in D = \{1, \dots, D\}$, and then, these z_j are used as inputs of the second stage to produce outputs $y_j = (y_{1j}, y_{2j}, \dots, y_{rj}, \dots, y_{sj})$ $r \in O = \{1, \dots, s\}$, where $\sim$ represents unknown decision variables. Assuming w_1 and w_2 are weights that are specified by users and reflect the user preference [91]:

$$\begin{aligned} & \min w_1 \phi_1 - w_2 \phi_2, \\ & \sum_{j=1}^n \lambda_j x_{ij} \leq \phi_1 x_{ij_0}, i = 1, \dots, m, \\ & \sum_{j=1}^n \lambda_j z_{dj} \geq \tilde{z}_{dj_0}, d = 1, \dots, D, \\ & \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0, \\ & \sum_{j=1}^n \mu_j z_{dj} \leq \tilde{z}_{dj_0}, d = 1, \dots, D, \\ & \sum_{j=1}^n \mu_j y_{rj} \geq \phi_2 y_{rj_0}, r = 1, \dots, s, \\ & \sum_{j=1}^n \mu_j = 1, \mu_j \geq 0. \end{aligned} \quad (9)$$

In the case of a rough variable, for example z from the range: $[z_{dj}^a, z_{dj}^b]$, where: $z_{dj}^a < z_{dj}^b$, $d \in D = \{1, \dots, D\}$ formulas Equations (3)–(6) reduce to:

$$\begin{aligned} z_{dj}^{inf(\alpha)} &= \alpha z_{dj}^a + (1-\alpha) z_{dj}^b, \\ z_{dj}^{sup(\alpha)} &= (1-\alpha) z_{dj}^a + \alpha z_{dj}^b. \end{aligned} \quad (10)$$

For $\alpha = 0.5$ $[z_{dj}^{inf(\alpha)}, z_{dj}^{sup(\alpha)}]$ reduces to mean: $[(z_{dj}^a + z_{dj}^b)/2, (z_{dj}^a + z_{dj}^b)/2]$, and for $\alpha = 1.0$ to origin range: $[z_{dj}^a, z_{dj}^b]$.

The presented models and their combinations can be used to assess the level of development of EU countries from the perspective of sustainability. The main advantages of Rough DEA include

the simple interpretation of both the level of trust: the higher the wider the efficiency range, and the relations: to obtain the maximum score the best characteristics of the evaluated DMU is compared with the worst of others and vice versa while forming the lower bounds.

4. Results

4.1. Discussion of Data and Models

In the literature the conventional data for productivity analysis by DEA are labor and capital as inputs and economic growth measured by GDP as an output. In the case of sustainability development assessment, the volume of energy is considered as the main input of GDP. It is used in the form of, e.g., the share of RE, resource depletion, and GHG emissions (Table 2).

Data on sustainable development are processed by many institutions, e.g., the World Bank, the European Environment Agency (EEA), and Eurostat. Differences in collection and aggregation methodologies often imply a certain inconsistency in the published data. In this study, hard data: GDP (in billion US dollars using 2010 exchange rates), population (in millions), and CO₂ emissions (in millions of tons of CO₂) in 2017 were taken from IEA (2019), *CO₂ Emissions from Fuel Combustion* [72].

The soft data is based on the survey *Europeans' Attitudes on Energy Policy* [73], which was conducted in 28 EU member states. The survey revealed a high consensus and positive attitude toward the current energy policy. For example, about 60% of respondents totally agreed, and 30% tended to agree with statements “it should be the EU’s responsibility to encourage more investment in renewable energy” and “it should be the EU’s responsibility to encourage more investment in energy research and innovation”. The percentages of agreements were correlated between countries. The Pearson’s correlation coefficient for the statements was 0.9. The most frequent answer regarding the priorities for the next five years was investments in clean energy technology and their development. Respondents had less enthusiasm about the reduction of the impact made by energy on climate change and the reduction of the overall energy consumption in the EU.

The agreement to the statement that “it should be the EU’s responsibility to encourage more investment in renewable energy” was chosen to reflect the social authorization and readiness for change. The following relationship was assumed: the socio-economic environment (the social agreement to investments and robust data on a country’s standard of living measured by GDP per capita) influences CO₂ emissions. A simple DEA model was used for total agreements only (Figure 3a), and Rough DEA—for total agreements and tendencies to agree, thus creating a rough variable (Figure 3b).

Figure 3. Cont.

Figure 3. Tested model: (a) BCC DEA and Ratio DEA; (b) Rough DEA; (c) Rough network DEA.

The network Rough DEA model was also used to assess efficiencies of investments in low-carbon development. The authors analyzed the transformation of agreement with investments and the standard of living into the value of investments in energy (the first stage) and the value of investments in low-carbon development (the second stage) (Figure 3c).

Referring to the equations of the models presented in the Methods section, as x_1 was taken attitude to policy, as x_2 GDP per capita, as y_1 GDP per CO₂ emission in DEA and Rough DEA model. In network Rough DEA model, x_1 represented attitude to policy, x_2 GDP per capita, z_j total public energy for research, development and deployment (RD&D) budget, y_1 GDP per CO₂ emission. Equal weights w_1 and w_2 was assumed, and $\alpha = 0.6$, and $\alpha = 0.8$.

The data on the total public budget (in millions US dollars) allocated for research, development and deployment (RD&D) of energy technologies in 2017 was taken from IEA [10]. Not all data was available. For this reason, network Rough DEA analysis was performed on a smaller data set. Due to the limitation of the DEA model assuming a positive relationship between inputs and outputs, the degree of low-carbon economies was measured by the inverse of the classical CO₂ value per GDP. The summaries of data covered by the analysis are presented in Tables 3–5 and Figures 4 and 5.

Table 3. Descriptive statistics of data.

	GDP [B US \$]	Population [M]	CO ₂ in [M T]	Total Public Energy RD&D Budget [M US \$]	EU Should Encourage Investments in Energy [%] Totally Agree	Tend to and Totally Agree
Avg.	672.39	18.30	114.62	310.80	61.18	91.18
Std. dev.	1018.72	23.76	161.28	420.21	10.60	4.85

Abbreviations: RD&D—research, development and deployment.

Table 4. Data correlations (absolute variables).

	GDP	CO ₂
CO ₂	0.932	
Population	0.962	0.946

Table 5. Data correlations (ratio variables).

	GDP per Capita	GDP per CO ₂	EU Should Encourage Investments: Totally Agree
GDP/CO ₂	0.680		
RD&D budget per capita	0.593	0.443	
EU should encourage investments: totally agree	0.248 ¹	0.433	
tend to agree and totally agree	0.213 ¹	0.244 ¹	0.646

¹ Statistically insignificant with $p < 0.05$. **Figure 4.** GDP per CO₂ with relation to GDP per capita and the percentage of respondents who totally agreed with the statement about the EU's responsibility.

Figure 5. GDP per CO₂ with relation to GDP per capita and RD&D budget per capita.

Apart from an obvious linear relationship between CO₂, population and GDP, a small but statistically significant relationship was found between GDP per CO₂ and the total agreement to encourage more investment in energy research and innovation. This relationship justifies the consideration of the opinion in the evaluation of a low-carbon economy. Also, there is a noticeable correlation between GDP per capita and RD&D per capita, which indicates that higher spending in wealthier states could achieve lower emissions per GDP.

The charts in Figures 4 and 5 visualize the relationships between considered variables of EU states. In both figures, SE positively stands out: high social awareness and the above-average standard of living are reflected in a low-carbon economy. However, LU demonstrates that GDP per capita does not always determine the level of GDP per CO₂. FR shows that high GDP per CO₂ can be reached having a moderate social agreement. MT demonstrates that the same can be done with a below-average GDP per capita. ES, CY, and SI are examples indicating that eco-awareness can precede the results of actions aimed at low CO₂ emissions. At the other end are the countries of Central and Eastern Europe (PL, RO, CZ, SK) with a low agreement to the need for investment, low GDP per capita, and high current CO₂ emissions per GDP. Figure 5 depicts the general relationship, i.e., the higher GDP per capita, the higher is RD&D expenditure. However, it also indicates that the current RD&D budget does not always directly relate to achievements (in the case of FI).

4.2. Data Analysis

The results of applied DEA models are presented in Tables 6 and 7 and Figures 6 and 7. BCC-O corresponds to model (1), Ratio DEA—(2), Rough BCC DEA—(7, 8), and Network Rough BCC DEA—(9) with the rough concept (7, 8). DEA model scores based on only hard data GDP per capita and GDP per CO₂ without a qualitative variable was also presented (Ratio DEA only hard data).

Table 6. Progress of the EU toward achieving sustainable development goals—DEA and Rough DEA models.

Country	Ratio DEA only Hard Data	BCC-O	Ratio DEA Model (non-Linear)	Rough BCC DEA Model $\alpha = 0.6$		Rough BCC DEA Model $\alpha = 0.8$	
	ϕ	ϕ	ϕ	$\phi^{inf(\alpha)}$	$\phi^{sup(\alpha)}$	$\phi^{inf(\alpha)}$	$\phi^{sup(\alpha)}$
AT Austria	49.1%	63.6%	69.8%	54.0%	99.7%	49.7%	100.0%
BE Belgium	44.9%	77.3%	64.0%	47.7%	100.0%	45.6%	100.0%
BG Bulgaria	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
CY Cyprus	44.4%	44.9%	44.4%	44.9%	45.4%	44.9%	48.8%
CZ Czechia	34.7%	52.6%	43.1%	37.2%	100.0%	34.4%	100.0%
DE Germany	41.2%	45.3%	43.8%	42.0%	53.9%	41.9%	100.0%
DK Denmark	76.0%	87.0%	83.9%	77.7%	100.0%	76.0%	100.0%
EE Estonia	27.9%	30.8%	31.0%	27.6%	38.7%	27.6%	100.0%
EL Greece	56.6%	56.1%	56.6%	56.1%	56.1%	56.1%	62.7%
ES Spain	61.5%	62.4%	61.5%	62.4%	62.4%	62.4%	65.8%
FI Finland	46.5%	76.9%	66.9%	51.0%	100.0%	47.2%	100.0%
FR France	77.1%	100.0%	100.0%	82.5%	100.0%	78.6%	100.0%
HR Croatia	87.9%	87.6%	87.9%	87.6%	87.6%	87.6%	100.0%
HU Hungary	73.5%	73.3%	75.6%	73.3%	73.3%	73.3%	100.0%
IE Ireland	66.3%	88.8%	94.9%	68.5%	100.0%	66.3%	100.0%
IT Italy	63.8%	100.0%	82.7%	69.6%	100.0%	65.0%	100.0%
LT Lithuania	89.3%	88.7%	89.3%	88.7%	88.7%	88.7%	93.1%
LU Luxembourg	48.7%	63.6%	67.4%	51.4%	79.3%	48.7%	100.0%
LV Latvia	63.5%	99.7%	100.0%	99.7%	99.7%	99.7%	100.0%
MT Malta	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
NL The Netherlands	40.7%	53.8%	58.1%	45.6%	77.8%	40.9%	100.0%
PL Poland	43.2%	58.5%	56.7%	43.1%	100.0%	43.1%	100.0%
PT Portugal	67.4%	74.1%	76.9%	66.9%	73.3%	66.9%	100.0%
RO Romania	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
SE Sweden	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
SI Slovenia	50.6%	50.4%	50.6%	50.4%	50.4%	50.4%	54.4%
SK Slovakia	57.0%	100.0%	100.0%	56.8%	100.0%	56.4%	100.0%
UK United Kingdom	64.7%	74.2%	77.6%	67.5%	98.4%	66.0%	100.0%

Table 7. Progress of the EU toward achieving sustainable development goals—Network DEA model.

Country	Network Rough BCC DEA Model			
	$\phi_1^{inf(\alpha)}$	$\phi_1^{sup(\alpha)}$	$\phi_2^{inf(\alpha)}$	$\phi_2^{sup(\alpha)}$
AT Austria	82.2%	98.8%	44.1%	44.1%
BE Belgium	81.8%	100.0%	38.5%	39.6%
CZ Czechia	100.0%	100.0%	17.7%	28.9%
DE Germany	77.0%	91.4%	35.7%	35.7%
DK Denmark	76.4%	89.8%	76.0%	76.0%
ES Spain	77.0%	82.7%	39.4%	39.4%
FI Finland	85.5%	99.4%	40.7%	40.7%
FR France	83.3%	99.6%	62.1%	62.1%
HU Hungary	100.0%	100.0%	42.6%	63.7%
IE Ireland	76.8%	92.8%	66.3%	66.3%
IT Italy	86.7%	100.0%	43.6%	61.9%
NL	80.8%	96.7%	39.3%	39.3%
The Netherlands				
PL Poland	100.0%	100.0%	25.1%	25.1%
PT Portugal	100.0%	100.0%	34.3%	36.7%
SE Sweden	72.9%	84.4%	100.0%	100.0%
SK Slovakia	100.0%	100.0%	30.1%	100.0%
UK United Kingdom	80.3%	95.9%	51.9%	51.9%

Figure 6. Visualization of the scores—DEA and Rough DEA ($\alpha = 0.6$).

Figure 7. Visualization of the scores—Rough network DEA ($\alpha = 0.6$).

Including additional variables in DEA increase or leave the rating unchanged. Assessment with both quantitative and qualitative variables is less strict. It is worth noting that the assessment based only on quantitative data is close to the pessimistic estimation from the Rough BCC DEA model integrating soft and hard data for $\alpha = 0.8$.

Differences between nonlinear and traditional BCC approaches are insubstantial. The highest scores by these models (1) and (2) are obtained by representatives of various groups of countries:

- SE—the leader, which obtains the high score despite high social awareness and the high GDP per capita;
- FR and IT—with above average GDP per capita and under average agreement;
- RO, BG, and SK—where the score is due to low GDP per capita and low agreement;
- MT—despite a high agreement with average GDP per capita;
- LV—with an average agreement but low GDP per capita.

The incorporation of inconsistency in opinions broadens the range of scores. The 100% effective countries may also be countries, which by models (1) or (2) achieved high nearly 100% result, i.e., (i) IE or DK, but also those having average results, namely, (ii) BE and FI, or even low results, i.e., (iii) CZ or PL. It is significant that in the case of groups (i) and (ii), the dispersion between optimistic and pessimistic results is large, around 50%.

The two-stage network evaluation shows a relatively high efficiency of the first stage—the transformation of GDP per capita and public awareness into the RD&D budget. Results of the second stage indicate the need for much improvement in expenditure efficiency. However, these conclusions should be made with caution as financial expenses often have an effect in the long term.

The provided example of assessing the performance of sustainable development of EU countries indicates that depending on the assumed interpretation of qualitative data, varying scores can sometimes be obtained. Four groups of EU countries can be distinguished based on the Rough BCC DEA model:

- with stabile, equal pessimistic, and optimistic results: BG, CY, EL, ES, HR, HU, LT, LV, MT, RO, SE, SI, PT;
- with small, less than 0.2, differences: DE, EE, FR;

- with average, from 0.2 to 0.4, differences: DK, IE, IT, LU, NL, UK;
- with extreme, over 0.4, differences: AT, BE, CZ, FI, PL, SK.

The final assessment may consist of an average score with a range of possible results. The width of the assessment range represents its sensitivity to changes in data interpretation.

5. Discussion

The contribution of the article is two-fold. First, it presented a new hybrid model based on a combination of Rough Sets and DEA. The model is intended for the integration of hard and soft data in the object ranking task. It enables the inclusion of uncertainty in the underlying data. Second, the article demonstrated the use of the Rough DEA model by assessing EU countries in terms of their progress toward sustainable development objectives. It allows the assessment of physical data and socio-economic data and permits for a more multi-faceted and objective evaluation. The paper is also significant because both quantitative and qualitative data were used to appraise the performance of countries in the field of sustainable development.

Sustainable development goals address many global challenges, including those related to poverty and social inequalities [3], exploitation of natural resources, growing global population, and energy needs [92], and the aging society in the EU [93]. The article refers to the monitoring of clean energy goals considering investments in technology development and modernization at a given level of economic growth and social support.

The article is particularly relevant under the present circumstances. The period chosen for the analysis precedes the anticipated global economic crisis, which will hit many countries that were most affected by COVID-19. In their efforts to reduce CO₂ emissions, government-level decision-makers will have to focus more on the economic opportunities of individual countries and public opinion.

The assessment of the EU's progress toward sustainable development goals was based on hard and soft data integration. It can be treated as a preliminary stage of quantitative considerations regarding the need to increase ecological awareness, shaping the sense of responsibility and readiness to bear the costs of eco-development. The used approach allows broadening the perspective and provides more reliable sustainability rankings. The presented studies did not fully explore the broad research topics of the subject. In future research, it is worth designing a dedicated survey for the measurement of the degree of social readiness to incur expenses of transformation into a low-carbon economy. However, the most important extension of the presented models is the inclusion of a time delay between expenditure, social readiness, and quantitative indicators of sustainability. This task should comprise an adequate aggregation of data according to the schedule of research and investment processes.

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Abbreviations

AT	Austria
BE	Belgium
BG	Bulgaria
CY	Cyprus
CZ	Czechia
DE	Germany
DK	Denmark

EE	Estonia
EL	Greece
ES	Spain
FI	Finland
FR	France
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LV	Latvia
LU	Luxembourg
MT	Malta
NL	The Netherlands
PT	Portugal
PL	Poland
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia
UK	United Kingdom

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