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Article

Efficiency of Renewable Energy Potential Utilization in European Countries

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Abstract: The transition to renewable energy sources (RES) is crucial for achieving a low-carbon future and sustainable development. Reduction of greenhouse gas emissions is a priority goal in the European Union (EU) which actively promotes the development and use of renewable energy sources. This study evaluates the efficiency of EU countries in utilizing their geographical potential for wind and solar energy production. A two-stage radial network data envelopment analysis (NDEA) is proposed to estimate the efficiency of the utilisation of natural resources. The relationship between environmental potential and installed power capacity is evaluated in the first stage. In the second stage, the actual production from installed capacity is analysed. The efficiency trends over time are investigated. This approach offers a comprehensive assessment by considering both technical performance and environmental constraints. The results reveal that the development of alternative energy sources and the efficiency of the use of installed power capacity are not always in line with environmental conditions. The article's results highlight the necessity of a comprehensive approach to power capacity development basing on the renewable energy sources.

Keywords: renewables; RES; efficiency; network DEA; wind power; solar power; energy; EU; resources

1. Introduction

Today, global greenhouse gas emissions from energy (electricity, heat, and transport) are more than 73% [1]. For this reason, the 7th Sustainable Development Goal – which includes the issue of sustainable energy – has been of great interest for years. Many countries are making significant efforts to transition towards 100% renewable energy sources for their electricity needs. The European Union (EU) announced the European Green Deal in 2019, intending to become a net zero emitter of greenhouse gases by 2050. Transformation of the energy sector is the most critical element in the EU's net zero ambitions [2]. The development of renewable energy policies and strategies, as well as the current advancements in this field, are the subjects of extensive research and reporting. There has been a systematic increase in the number of articles and reports addressing this topic, which includes various comparative analyses between countries. Some opinions suggest that with current energy production and storage technologies, considering the energy and climate crisis alongside armed conflicts, we cannot meet energy demand without nuclear power or hydrogen. Nevertheless, wind and solar capacity have been growing the fastest in recent years. Analysing the data until 2023, the record was reached in 2022: 245 TWh of solar generation and 312 TWh of wind, which meant that these sources represented 12% of global electricity [3]. These sources are also believed to be the most environmentally neutral.

The development of energy production from renewable sources is determined by geographic, demographic, economic, and political factors. With limited resources, one of the challenges facing decision-makers is to choose the most beneficial technology in the long term from the available

alternatives. The evaluation of renewable energy sources could be carried out in four categories: economics, technology, environment, and society with the following criteria: cost (investment, maintenance, operation, and others), efficiency, environmental impact (pollution, land use, etc.), job creation, safety [4]. The country's renewable resources could be assessed based on capital investment, electricity generation, environmental performance index (EPI), and access to clean fuels and technologies for cooking [5]. According to Wind-energy potential in Europe 2020-2030 [6], the potential of energy source development can be distinguished among theoretical, technical, economic, and market. It has been emphasised that energy generation from a given source depends on the geographical location, but it is also influenced by macroeconomic factors, industry, and the structure of energy consumption [7].

In the case of solar and wind energy, geography strongly impacts the assessment of technology and its efficiency. The environmental conditions that prevail in the planned location are of great importance for the functioning of the future wind or photovoltaic farm. Nevertheless, considering theoretical potential, studies have shown that many countries are well positioned to take advantage of wind and solar energy despite different wind power fluctuation distributions or heterogeneity of global horizontal irradiance [8].

The purpose of the article is to evaluate the efficiency of the use of the location potential of European countries for sustainability and climate neutrality by comparing the theoretical wind resources and solar irradiation and the mix of energy production of the countries. The data envelopment analysis (DEA) is employed as the primary research method. DEA is an operational research method that solves a linear programming task to evaluate the relative efficiencies of elements from a set of objects called decision-making units (DMU). DEA has gained recognition and has been frequently used in studies on sustainability, eco-efficiency, and energy efficiency, including renewable sources. Reviews of articles on DEA applications in sustainability [9–11] have revealed a prevalent practice of juxtaposing regions or countries based on factors such as capital, labour force, and energy consumption on the one hand and GDP and CO₂ emissions + the other hand. These comparative analyses typically employ basic DEA models. Regarding energy generation efficiency, most studies on photovoltaic panels or wind turbine performance focus on micro-analysis and assess the power efficiency of individual farms.

This work adopts a two-stage radial network data envelopment analysis (NDEA) to estimate the efficiency of utilisation of natural resources at the country level. NDEA (also under the name multi-stage, multi-level, hierarchic) addresses the limitations of the conventional DEA that treats efficiency measurement as a 'black box' [12]. It is an extension of traditional DEA that considers the structure of the processes inside DMU and the intermediate products and sub-processes [13]. It provides information about the efficiency of subsystems within a given unit as well as its overall efficiency. The ability to capture the complexity and interconnections among processes and to ensure that each component of the system is operating efficiently is essential when intermediate products and byproducts impact the efficiency of the entire system [14]. NDEA contributes to a deeper understanding of the multifaceted nature of resource management efficiency and its implications for achieving sustainable development goals [15]. The two-stage system is the simplest network structure and divides DMU processes into two phases, assuming that the influence of some inputs on the outputs might be indirect. The exogenous inputs are utilised in the first phase to get the intermediate products (inputs) for the second phase to produce the final outputs [12]. The two-stage DEA model and its variants, as well as more advanced NDEA models, have been successfully applied in many energy and renewables studies. The review of the relevant research is summarised in the literature review section. However, the potential of NDEA appears to be still unexploited. In this work, two-stage DEA has been employed, firstly the relationship between environmental potential and installed power capacity has been evaluated, and then production from installed power has been analysed. The approach offers a more comprehensive and accurate evaluation of renewable energy investment efficiency, taking into account both the technical performance and the environmental constraints. The efficiency trends over time are also investigated.

The contribution of this article is three-fold. A methodological contribution is the proposal of a network DEA method framework for assessing the efficiency of using natural resources in the context of developing renewable energy technologies. The empirical contribution is the assessment of the compatibility of the development of renewable resources (RES) technology with the environmental potential of EU countries, indicating benchmarks and implications. The background to the analysis is an in-depth review of articles indicating recent advances in the DEA efficiency assessment of renewable energy sources.

The article is organised as follows. First, it presents the review of the papers on the assessment of countries in terms of energy transformation achievements by DEA and applications of the network DEA model in the literature on energy efficiency. Then, it introduces the DEA models used in this study. Next, the results of the computational analysis are presented. The article ends with conclusions, policy implications, and suggestions for future research directions.

2. Literature Review

The awareness of the necessity, but also the benefits of the development energy generation from renewables for long-term sustainability and circularity has been evoking huge interest from scientists and practitioners in recent decades [16]. Clean energy aspect has become a core element of every innovation aspiring to be seen as responsible and sustainable [17,18]. In energy efficiency analyses, DEA is commonly used as the primary performance assessment method. Scientists point to the applicability and adequacy of DEA in the energy sector, including renewable energy and environmental management or sustainability assessment in general. The review of DEA applications in the renewable energy source sector shows the variety of approaches and data considered. The purposes and scopes of the papers on energy efficiency by DEA make it possible to cluster them into several groups. Regarding the application areas, papers could be categorised into nine groups: environmental efficiency, economic and eco-efficiency, energy efficiency issues, renewable and sustainable energy, water efficiency, energy performance, energy saving, integrated energy efficiency, and others [19]. However, considering the object of the analysis, the following categories could be distinguished: (i) country/region-level performance analysis, (ii) sector/industry/enterprises-level analysis, (iii) efficiency of individual power farms, and (iv) others (e.g., renewable energy plans to be developed [20], supply chains [21]). The most popular division of approaches is to distinguish the objects of analysis: the eco-efficiency of countries and the technical efficiency of power plants [22].

Considering the purpose of this paper (assessing European countries' efficiency of renewable energy potential utilisation by NDEA) the relevant works on renewable energy efficiency by DEA have been divided into 3 groups based on objects (DMU), DEA models, and variables under consideration into: (i) conventional DEA for energy and renewable energy sources in countries' comparisons, (ii) NDEA for energy and renewable energy research for geographical comparisons in a broader sense (countries, districts, provinces, regions etc.), and (iii) DEA (conventional and NDEA) for assessing the impact of geographical location. A review of recent works in distinguished groups is presented in the following sections: (2.1) DEA in cross-country analysis of energy efficiency, (2.2) NDEA in assessing energy efficiency, and (2.3) DEA in assessing the impact of geographical location on energy efficiency.

The period of analysis was selected according to the European Green Deal announcement in 2019 and ranges from a year before i.e. 2018 to 2024; the scope includes papers indexed in the Web of Science, Scopus and IEEE databases. The search query with obligation terms renewable(s) and DEA (data envelopment analysis) and energy or electricity or power and selected synonyms from the set: evaluation, assessment, analysis, effectiveness, efficiency, productivity, performance was employed.

2.1. DEA in Cross-Country Analysis of Energy Efficiency

Selected recent works on the renewable energy efficiency analysis of countries using the DEA method are summarised in Table 1. The objects of analysis, along with employed DEA models and variables under consideration, are indicated. The list excludes works that deal broadly with the

problem of country comparisons, where energy efficiency is one of the elements of countries' general sustainability assessment, e.g. [23], circular economy, e.g. [24], but also on the contrary, focused on a narrow aspect of assessment, e.g. electric vehicles [25].

Table 1. Works on cross-country renewable energy efficiency evaluation by DEA.

Title (Year)	DMU	DEA model	Analysis Criteria
Dynamic spillover effects of renewable energy efficiency in the European countries (2024) [26]	25 European countries from 2005 and 2020	two-stage: DEA and regression	Inputs: renewable energy consumption, capital labour Outputs: GDP Influencing factors: GDP, energy price, renewable energy consumption, information and communications technology, industrial value added
Evaluating renewable energy consumption efficiency and impact factors in Asia-pacific economic cooperation countries: A new approach of DEA with undesirable output model (2024) [27]	21 APEC member countries from 2011 to 2020	DEA with undesirable output	Inputs: foreign direct investment total energy consumption, total renewable energy capacity Outputs: GDP Undesirables: GHG
Evaluating solar photovoltaic power efficiency based on economic dimensions for 26 countries using a three-stage data envelopment analysis (2023) [28]	26 countries from 2000 to 2020	three-stage: DEA-SFA-DEA	Inputs: capital, labour, PV installed capacity, PV patents Output: PV generation Environment variables: proportion of the urban population, GDP per capita, CO ₂
Assessing Asian Economies Renewable Energy Consumption Efficiency Using DEA with Undesirable Output (2022) [29]	14 Asian countries in 2019	DEA with undesirable output	Inputs: labour, energy consumption, the share of renewable energy, and total renewable energy capacity Outputs: CO ₂ and GDP
Global renewable energy power generation efficiency evaluation and influencing factors analysis (2022) [7]	36 countries from 2009 to 2018	Super efficiency DEA, MI, and random forest regression model to analyse the influence of the selected factors	Inputs: five types of renewable energy installed capacity Outputs: renewable energy power generation Influencing factors: population size and density, economic level, urbanisation rate, production level, industrialisation level and structure, electricity and energy structure, carbon emissions, and technology level
Assessing Renewable Energy Production Capabilities Using DEA Window and Fuzzy TOPSIS Model [30] (2021)	42 countries 2010–2019	DEA window and FTOPSIS	Inputs: population, total energy consumption, and total renewable energy capacity Outputs: GDP, total energy production FTOPSIS: availability of resource, energy security, technological infrastructure, economic stability, social acceptance

Efficiency assessment of electricity generation from renewable and non-renewable energy sources using Data Envelopment Analysis (2021) [31]	126 countries from 2000 to 2016	BCC model	Inputs: renewable and non-renewable energy sources generation capacity Outputs: Power generation, CO ₂ emissions avoided
Environmental efficiency of disaggregated energy R&D expenditures in OECD: a bootstrap DEA approach (2021) [32]	26 OECD countries	Bootstrap IO CCR DEA	Inputs: six different energy R&D expenditure indicators in 2015 Outputs: CO ₂ emission per capita
Dual Efficiency and Productivity Analysis of Renewable Energy Alternatives of OECD Countries (2021) [5]	Selected OECD countries in 2012, 2014, and 2016	OO BCC model and MI	Inputs: investment in RE sources Outputs: electricity generation, EPI, the proportion of the population with access to clean fuels and technology for cooking
The efficiency of wind power companies in electricity generation (2021) [33]	78 wind power companies in 12 selected European countries in 2014	IO SBM VRS-DEA	Inputs: wind turbine power and number, fuel, tangible fixed assets, receivables and other assets, cash and cash equivalents Outputs: electricity production, EBITDA
A cross-European efficiency assessment of offshore wind farms: A DEA approach (2020) [34]	71 offshore wind farms across 5 countries in 2018	CCR DEA with sensitivity analysis	Inputs: number of turbines, cost, distance to shore, area Outputs: connectivity, generated electricity, water depth
Eco-efficiency assessment for some European countries using slacks-based measure data envelopment analysis (2020) [35]	17 European countries from 2013 to 2017	SBM DEA with undesirable outputs model and MI	Inputs: energy consumption, labour productivity, the share of renewable energy in energy consumption, gross capital formation productivity Outputs: GDP per capita, CO ₂ per capita
Eco-efficiency assessment of the electricity sector: evidence from 28 European Union countries (2020) [36]	28 EU countries 2010 and 2014.	DEA Directional Distance Function model	Inputs: labour, capital, GHG, acidifying gases, ozone Precursors Outputs: GVA
A global level analysis of environmental energy efficiency: an application of data envelopment analysis (2020) [37]	149 economies categorized into low-, middle- and high-income from 1993 to 2013	IO and OO DEA with and without undesirable output and directional distance function	Inputs: labour, capital, energy Outputs: GDP, CO ₂
Renewable Energy Utilization Analysis of Highly and Newly Industrialized Countries Using an Undesirable Output Model (2020) [38]	17 countries highly and newly industrialised from 2013 to 2018	DEA with undesirables preceded by Grey Prediction Model	Inputs: total renewable energy capacity, labour force, total energy consumption Outputs: CO ₂ , GDP
Across-country evaluation of energy efficiency from the	132 countries from 2007 to 2014	MinSum DEA	Inputs: GDP per unit of energy use, renewable energy consumption

sustainable development perspective (2019) [39]			Outputs: GDP, CO ₂ emissions per GDP
Cost-efficiency benchmarking of European renewable electricity support schemes (2018) [40]	25 EU member states and Norway from 2000 to 2015	CCR model	Inputs: PV fee, wind fee, LCOE PV, LCOE wind Outputs: PV share, Wind share, REs share
Renewable and sustainable energy efficiency: An analysis of Latin American countries (2018) [41]	156 Latin American countries from 1991 to 2013	SBM VRS DEA with window analysis	Inputs: labour, capital, energy consumption Outputs: GDP, CO ₂
Energy efficiency and its determinants: An empirical analysis (2018) [42]	20 of the largest producers of renewable energy from 2009 to 2013	BCC DEA and truncated regression	Input: primary energy consumption, capital, labour Output: GDP Regression: renewable energy consumption, GVA per capita, population density
Energy security and renewable energy efficiency in EU (2018) [43]	14 EU countries from 2004 to 2014	DEA and sequential Malmquist-Luenberger index	Input: deployed renewables Output: increase in the share of RE in total electricity generation Undesirable outputs: coal products, oil products and natural gas

Abbreviations: APEC – Asia-Pacific Economic Co-operation; BCC (VRS) – variable returns to scale DEA models; CCR – constant returns to scale; CEF – cost efficiency indicator; CO₂ – carbon dioxide emissions; DMU – decision-making unit; EPI – Environmental Performance Index; FTOPSIS – fuzzy technique for order of preference by similarity to ideal solution; GDP – gross domestic products; GHG – greenhouse gas emissions; IO – input-oriented; GVA – Gross Value Added; LCOE – levelized cost of electricity; MI – Malmquist Index; OO – output-oriented; PV – photovoltaics; RE, REs – renewable(s); SBM – slack based model; VRS (BCC) – variable returns to scale DEA models.

Conventional DEA models extended with an explanatory regression stage are the most popular approach to investigating energy efficiency. In addition to cross-country comparisons cited in Table 1, it is worth mentioning studies on the assessment of provinces or regions, the most numerous of which are represented by China [44–46] but also India, e.g. [47], Turkey, e.g. [48], Vietnam, e.g. [49].

Literature analysis, including broader review papers on sustainable development and eco-efficiency, i.e. [9–11,19,50], as well as cited in Table 1 papers with their summaries of input and output variables of previous research, allows the conclusion that in cross-country energy efficiency evaluation the most common comparison criteria are capital, labour force, total energy consumption on one hand and GDP and CO₂ emissions. Some studies analyse the productivity of installed capacity or the return on investment in RES. A significant group of papers include the financial perspective, considering the cost in relation to the achievements of the energy transformation. Variables taken into account highlight the relationship between innovations and R&D expenditures.

Concerning research methods following DEA models are mainly applied: (i) basic DEA, (ii) DEA with Malmquist index or window analysis to catch time changes, (iii) hybrid models combining DEA with other approaches (e.g., OLS regression/Tobit models, AHP, TOPSIS, artificial intelligence, fuzzy set), often referred to as two-stage.

2.2. NDEA in Assessing Energy Efficiency

Table 2 contains selected recent papers on energy efficiency and renewable energy sources by NDEA. The set includes papers on countries' energy efficiency but also regions, states, and provinces. The broader review results from the smaller number of works using network DEA models.

Table 2. Works on evaluation of energy from renewables by network DEA.

Title (Year)	DMU	DEA model	Analysis Criteria
A robust network DEA model for sustainability assessment: an application to Chinese provinces (2022) [51]	30 Chinese regions during 2000-2012	multiplicative two-stage relational NDEA	capital, labour, energy, GDP, CO ₂ , SO ₂
Policy, technical change, and environmental efficiency: Evidence of China's power system from dynamic and spatial perspective (2022) [52]	30 Chinese provinces from 2011 to 2020	DNSBM-DDF model and global MPI	feed-in tariff, renewable portfolio standard CO ₂ , SO ₂ , NO _x , and line loss
The dynamics of Indian energy mix: a two-phase analysis (2022) [47]	18 Indian states from 2008 to 2016	two phases consist of two stages serial NDEA and regression	renewable and conventional capacities, generation from RES and conventional sources, length of transmission lines, technical and commercial losses, agricultural-, residential-, and industrial consumption, state GDP per capita
Analysis of inter-temporal change in the energy and CO ₂ emissions efficiency of economies: a two divisional network DEA approach (2020) [53]	Iran's Electricity Distribution Network	two stage NDEA	labour, capital, energy consumption, GDP, CO ₂ , the total population
China's provincial eco-efficiency and its driving factors—based on network DEA and PLS-SEM Method (2020) [54]	30 Chinese regions in 1996 -2015	two-stage serial NDEA and PLS-SEM	labour, asset, energy consumption, land used, water, GDP, wastewater, exhaust, SO ₂ , investment in pollution control, solid waste utilization, wastewater treatment, greening rate
Developing a network DEA model for sustainability analysis of Iran's electricity distribution network (2020) [55]	Iran's electricity distribution network	serial and parallel NDEA	fuel, staff, import, export, sale to big industry, electricity generated, electricity distributed, loss in transmission, purchase, network length, service area, sale to customers
Dynamic linkages among economic development, energy consumption, environment, and health sustainable in EU and Non-EU Countries (2019) [56]	8 EU and 53 non-EU countries from 2010 to 2014	two-stage meta-frontier dynamic serial NDEA	labour, renewable and non-renewable energy consumption, assets, GDP, health expenditure, survival rate, tuberculosis rate, CO ₂ , PM2.5, mortality rates
Energy efficiency and health efficiency of old and new EU member states (2020) [57]	15 old and 13 new EU states from 2010 to 2014	two-stage meta-frontier dynamic serial NDEA	labour, renewable and non-renewable energy consumption, assets, GDP, health expenditure, survival rate, tuberculosis rate, CO ₂ , PM2.5, mortality rates
Environmental assessment of European Union countries (2019) [58]	28 EU countries 2006–2013	dynamic DEA	labour, capital, energy consumption, GHE, SO _x , GDP, GCF

Research on new and traditional energy sources in OECD countries (2019) [59]	35 OECD countries	dynamic SBM DEA	labour, energy consumption, new energy consumption, GDP, CO ₂ , PM2.5, fixed assets
Energy and CO ₂ emissions efficiency of major economies: a network DEA approach (2018) [60]	major economies	SBM two stages NDEA	energy resources, economic outputs, energy consumption, CO ₂
Economic and technical efficiency of the biomass industry in China: a network data envelopment analysis model involving externalities (2017) [61]	31 Chinese provinces in 2012	NDEA model with undesirable outputs	operational cost, forest residues, organic waste, rural power, fertilizers, agricultural machinery, commercial and residential power, agricultural production, rural power, pollutants, agricultural and straw residues

Abbreviations: DNSBM-DDF – dynamic slacks-based measure with network structure with directional distance function; MPI – Malmquist productivity index; PLS-SEM – partial least squares structural equation modelling; SBM – slacks-based measures; SO_x – sulfur oxides.

Network DEA is widely applicable to eco-energy efficiency and while the traditional DEA method evaluates the input-output process as a ‘black box’, NDEA allows it to look inside and assess the subprocess with additional inputs and outputs. It is believed to be a more appropriate approach to manage existing internal interactions. The works included in Table 2 extended the efficiency assessment of the transformation of resources such as labour, capital, and cost into energy production/consumption along with pollutants by considering additional variables describing the quality of life expressed by GDP or health indicators or transmission losses. Among the cited works there are analyses of transformations described by only a few main determinants (e.g., labour, capital, energy into GDP, and main pollutant CO₂), considering an extended collection of variables (e.g., health expenditure and survival rate, tuberculosis rate, PM2.5 air pollution, mortality rates) or presenting a technical perspective (e.g., RES and non-RES capacity into power from RES and non-RES, length of transmission lines, losses). It could be argued that the potential of the NDEA method seems to be unrecognised and underestimated.

2.3. DEA in Assessing the Impact of Geographical Location on Energy Efficiency

Considering the assessment of energy efficiency with limitations or benefits resulting from environmental conditions, including geographical location, most studies focus on micro-analysis of photovoltaic or wind turbine sites and assess the power efficiency of individual farms. Selected works from recent years are presented in Table 3.

Table 3. Works on DEA in assessing the impact of geographical location conditions on energy efficiency.

Title	DMU	DEA model	Analysis Criteria
A novel two-stage multicriteria decision-making approach for selecting solar farm sites: A case study (2024) [62]	39 potential cities in the Baltic region	DEA and TOPSIS	temperature, wind speed, humidity, precipitation, and air pressure as inputs and sunshine hours, elevation, and irradiation and six evaluation criteria to prioritize the locations
Benchmarking performance of photovoltaic power plants	3 PV power plants in	multi-period DEA	solar insolation, daily sun-hours, temperature,

in multiple periods (2023) [63] Analysis of dynamic renewable energy generation efficiency and its influencing factors considering cooperation and competition between decision-making units: a case study of China [64]	multiple periods China's provinces	DEA cross-efficiency	installation cost, installed capacity cumulative installed capacity, annual equipment utilisation hours, electricity consumption of power generation companies, electricity generation
New approach to prioritize wind farm sites by data envelopment analysis method: A case study (2023) [65] A two-stage approach of DEA and AHP in selecting optimal wind power plants (2023) [66]	14 offshore sites of the Moroccan seas for 2016–2020 12 locations in Vietnam	DEAM (super-efficiency DEA model) DEA (CCR-I, CCR-O, BCC-I, BCC-O, SBM-I-O, SMB-O-C) and AHP	water depth, distance to coast, accessibility, maximum wave height, maximum wind speed, wind power density DEA: frequency of natural disasters, land cost, wind blow, population, quantity of proper geological and topographical area AHP: location characteristic, technical, economic, social, environmental
A novel integrated approach for ranking solar energy location planning: a case study (2021) [67]	10 provinces in Canada	hybrid approach composed of data (DEA), balanced scorecard (BSC) and game theory (GT)	cost of construction, income, electricity generated by the plant and electricity generated by the panel, amount of pollution
Techno-enviro assessment and ranking of Turkey for use of home-scale solar water heaters (2021) [68]	2 types of solar water heaters for 45 stations in Turkey	BCC and additive DEA model	total annual irradiation, diffuse radiation percentage, cold water temperature, total solar fraction, solar contribution to heating, CO ₂ emissions avoided, boiler energy to heating and to DHW
A two-stage multiple criteria decision making for site selection of solar photovoltaic (pv) power plant: a case study in Taiwan (2021) [69]	20 potential cities and counties of Taiwan	DEA (CCR-I, CCR-O, BCC-I, BCC-O, SBM-I-O, SMB-O-C) and AHP	DEA: temperature, wind speed, humidity, precipitation, air pressure, sunshine hours, insolation AHP: site characteristics, technical, economic, social, environmental
Performance evaluation of solar PV power plants in Taiwan using data envelopment analysis (2021) [70]	solar PV power plants in Taiwan.	epsilon-based DEA	surface area, number of modules, ambient temperature, plant capacity, PV module temperature, irradiation, generated energy

Location optimization of wind plants using DEA and fuzzy multi-criteria decision making: a case study in Vietnam (2021) [71]	20 potential provinces in Vietnam	DEA, FAHP, FWASPAS	DEA: land cost, intensity of natural disasters occurrence, wind power density, quantity of proper geological areas, population FAHP: technical, economic, social/political, environmental
Factors affecting the efficiency of wind power in the European Union countries (2019) [22]	27 EU countries	two-stage bias-corrected DEA	installed wind power capacity, average wind power density, wind-generated electricity, and additional aspects: environmental, economic and energy security
A novel multi-period double frontier network DEA to sustainable location optimization of hybrid wind-photovoltaic power plant with real application (2018) [72]	22 Iran provinces	double frontier (optimistic and pessimistic) parallel single- and multi-period NDEA	land cost, HDI, distance to high consumptions province, wind speed, population, electricity consumptions, sunny hours, above sea level

Abbreviations: AHP – Analytic Hierarchy Process; DEAM – Data Envelopment Analysis Modified, DHW – Domestic hot water, FAHP – Fuzzy Analytic Hierarchy Process; FWASPAS – Fuzzy Weighted Aggregated Sum-Product Assessment; HDI – Human Development Index.

The works cited in Table 3 indicate the successful application of the DEA method to assess the location in a country or region. The list of common criteria used in reviewed relevant studies included the data resulting directly from the geographical location (e.g., wind speed, probability of natural disasters, irradiance, accessibility, water depth), social aspects (e.g., electricity demand, population), and technical criteria (e.g., cost of construction, generated energy, avoided CO₂, distance to transmission lines, losses).

The presented review does not exhaust the possibilities of categorizing works in the field of application of the DEA method to assess the change towards zero-emission economies. It is also worth mentioning the emerging postulates to enhance the robustness of the overall assessment by hybrid models that integrate DEA and AI algorithms and leveraging advantage of the methods: the interpretability and transparency with the capabilities of detecting patterns, self-learning, and handling large data sets.

3. Research Methods and Data

Data envelopment analysis was developed by the A. Charnes, W.W. Cooper and E. Rhodes [73], who extended M.J. Farrell's [74] concept of the *best practice frontier*. DEA is an operational research method widely used in management science to measure the relative efficiency of n units called decision-making units (DMUs) from a homogenous set of comparable entities. It is a technique that assesses the process of transforming multiple inputs (x_{ij} , $i = 1, \dots, m$) into multiple outputs (y_{rj} , $r = 1, \dots, s$) (Figure 1a) solving linear programming tasks for each DMU ($j = 1, \dots, n$), where λ_j represents the weights and indicates the benchmarks and φ is the radial efficiency score of j th DMU:

$$\max \varphi, \quad (1)$$

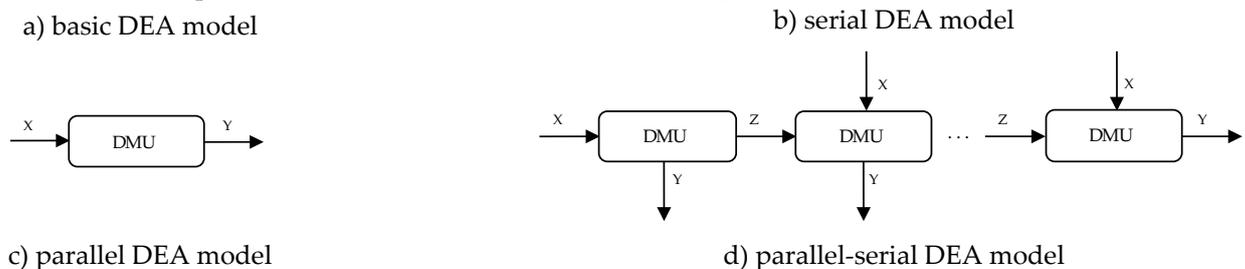
$$\begin{aligned}\sum_{j=1}^n \lambda_j x_{ij} &\leq x_{ij0}, i = 1, \dots, m, \\ \sum_{j=1}^n \lambda_j y_{rj} &\geq \varphi y_{rj0}, r = 1, \dots, s, \\ \lambda_j &\geq 0, j = 1, \dots, n.\end{aligned}$$

Network DEA is an extension of the traditional DEA approach, permitting the consideration of the internal process structure and the examination of intermediate products and subprocesses [13]. The enhancement of network DEA is attributed to R. Färe and S. Grosskopf [75,76], who introduced the term and developed the concept in the context of analysing complex systems [77]. However, the idea of the division of a production system had been discussed in the literature earlier in the 1980s and 1990s e.g., in studying the performance of US Army recruitment [78] or in measurement of the efficiency of a two-stage agricultural production system with intermediate products [79].

Network systems can have various structures. It is important to gain information about the efficiency of selected areas within a given unit as well as its overall efficiency. The ability to capture the complexity and interconnections within production processes and ensure that each system component is operating efficiently is essential when intermediate products and by-products impact the efficiency of the entire system. Network DEA helps to identify where resources can be reallocated within the system to improve efficiency, as it might highlight underperforming or over-utilised stages of the production process.

Network DEA models are known by several different names in the literature, depending on the structure of the model and the research goals, reflecting their development history. Two-stage DEA is one of the simplest and is used to model processes that can be divided into two stages, where the outputs from the first stage are used as inputs to the second stage. Multi-stage (multi-level, serial) DEA is a generalisation of the two-stage approach, encompassing several sequential stages that are connected in a network. Parallel DEA enables the consideration of the combined impact of parallel subprocesses that operate simultaneously and independently on the DMU efficiency. Hierarchical DEA is used in situations where the DMU's subprocesses have a hierarchy structure [77]. Supply Chain DEA is a specific case of Network DEA, focused on the analysis of performance within the supply chain. It takes into account the flows of materials, information and resources between different entities, which is crucial for assessing the efficiency of the entire chain [80]. Suppliers, manufacturers, distributors and retailers can also be analysed in terms of their performance and impact on other units in the chain. Dynamic NDEA is used to analyse the efficiency over time [81]. It models the DMU as a system consisting of many internal subprocesses but also considers time-varying data and the transfer of resources from one period to the next.

Selected examples of network structures are illustrated in Figure 1 (serial, parallel, parallel-serial, hierarchical, with feedback, dynamic NDEA, mixed DEA model). Just like the basic DEA models, network models are constantly evolving, and new techniques and applications are being developed to improve analysis accuracy. There are network DEA models with undesirable factors [82], and stochastic network DEA that could handle uncertainty in the data [83]. To deal with uncertain data fuzzy [84] or rough [85] network DEA models have been developed. The other extensions are multi-period network DEA models with feedback [86].



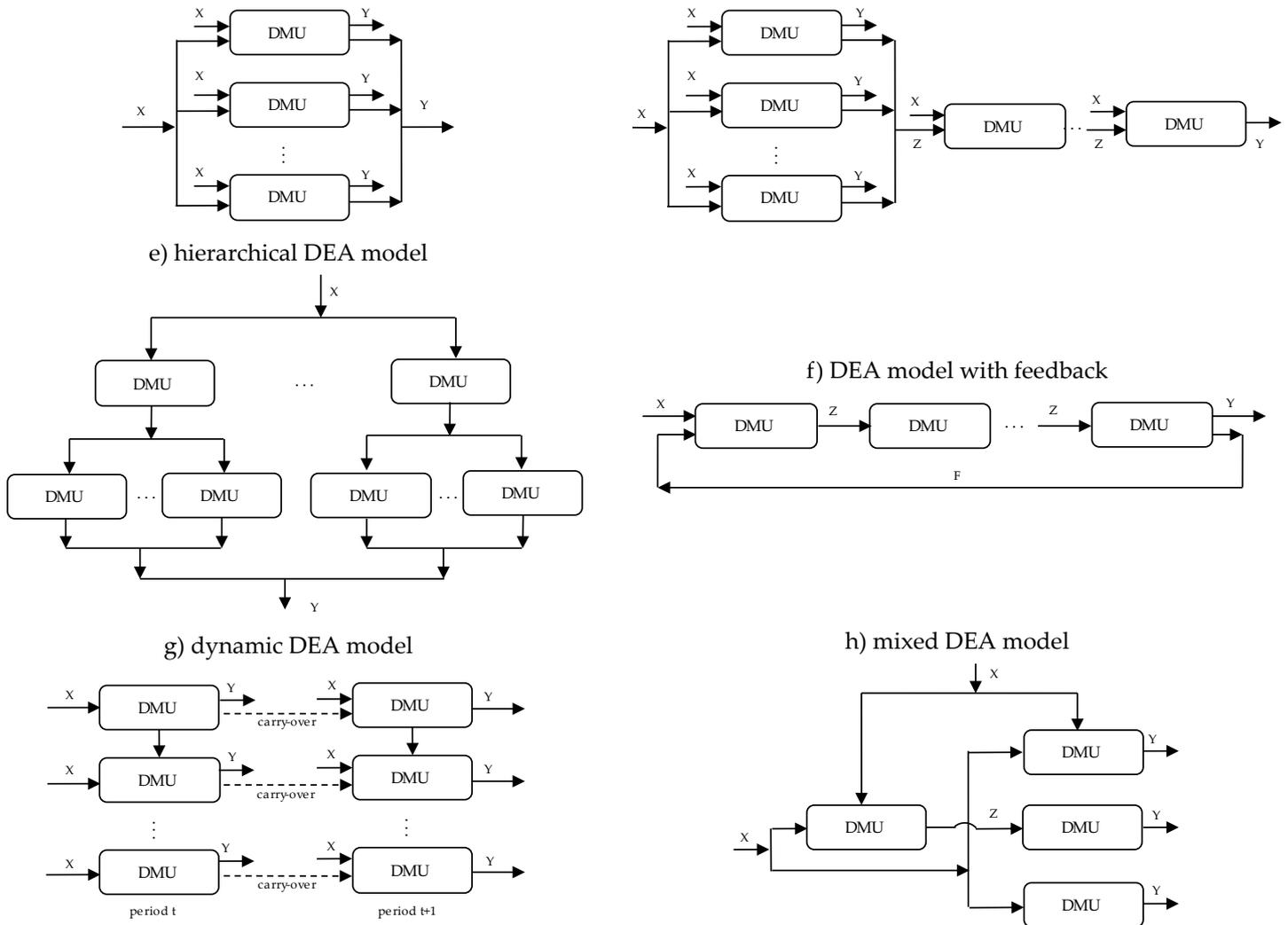


Figure 1. Network DEA models (a) basic DEA model; (b) serial DEA model; (c) parallel DEA model; (d) parallel-serial DEA model; (e) hierarchical DEA model; (f) DEA model with feedback; (g) dynamic DEA model; (h) mixed DEA model. Source: Own elaboration based on [12,13,87,88].

In the article, the environmental potential of renewable energy in the country was decomposed into two aspects: capacity in relation to natural resources and energy production in relation to capacity. It makes the simplest two-stage structure of network systems can be employed, where the outputs from the first stage are intermediate products and in the second stage are used to produce the final outputs of the system. The model engaged is an output-oriented adaptation of [89] with solution by (Emrouznejad & Amin, 2009) to ratio data as follows:

$$\begin{aligned}
 & \max \sum_{r=1}^s \varphi_r / s, \\
 & \sum_{j=1}^n \lambda_j x_{ij} \leq x_{ij0}, i = 1, \dots, m, \\
 & \sum_{j=1}^n \lambda_j z_{kj} = \sigma_k z_{kj0}, k = 1, \dots, d, \\
 & \sum_{j=1}^n \lambda_j z_{kj} \geq \sum_{j=1}^n \mu_j z_{kj}, k = 1, \dots, d, \\
 & \sum_{j=1}^n \mu_j z_{kj} = \omega_k z_{kj0}, k = 1, \dots, d, \\
 & \sum_{j=1}^n \mu_j y_{rj} \geq \varphi_r y_{rj0}, r = 1, \dots, s, \\
 & \lambda_j \geq 0, j = 1, \dots, n,
 \end{aligned} \tag{2}$$

$$\begin{aligned}\mu_j &\geq 0, j = 1, \dots, n, \\ \omega_k &\geq 0, k = 1, \dots, d, \\ \sigma_k &\geq 0, k = 1, \dots, d, \\ \varphi_r &\geq \tau, r = 1, \dots, s, \\ \sum_{j=1}^n \mu_j &= \tau, \\ \sum_{j=1}^n \lambda_j &= \tau.\end{aligned}$$

The x_{ij} is i th input, z_{kj} is k th intermediate, and y_{rj} is r th output of DMU j for $j = 1, \dots, n$. To account for variable returns to scale τ set to 1.

To take into consideration the diversity of countries and the unequal needs (e.g., the number of citizens), an assessment of both capacity and production per capita was studied. However, to meet the convexity assumption, absolute values were used, and additional inputs (area, population) were introduced into the model to include indicators in the form of ratios.

In the model, the average expansion rate of outputs is calculated $\sum_{r=1}^s \varphi_r/s$. The efficiency for the first and second stage and the overall efficiency are defined as follows:

$$\begin{aligned}\psi_1^* &= \sum_{i=1}^m (1/m) / \sum_{k=1}^d (\omega_k^*/d), \\ \psi_2^* &= \sum_{k=1}^d (\omega_k^*/d) / \sum_{r=1}^s (\varphi_r^*/s), \\ \psi^* &= \psi_1^* \times \psi_2^*.\end{aligned}\quad (3)$$

To measure changes over time, in periods 1 and 2, the Malmquist index was calculated. Malmquist index decomposes changes in efficiency into frontier-shift (covered efficiency in period 2 with respect to period 1 frontier $\psi_{t_2j_0}^{*t_1}$, efficiency in period 2 with respect to period 2 frontier $\psi_{t_2j_0}^{*t_2}$, efficiency in period 1 with respect to period 1 frontier $\psi_{t_1j_0}^{*t_1}$, and efficiency in period 1 with respect to period 2 frontier $\psi_{t_1j_0}^{*t_2}$) and catch-up effect (efficiency in period 2 with respect to period 2 frontier $\psi_{t_2j_0}^{*t_2}$ and efficiency in period 1 with respect to period 1 frontier $\psi_{t_1j_0}^{*t_1}$). A value greater than 1 indicates progress in total factor productivity, and less than 1 indicates a decrease. The Malmquist index is calculated using the following formula:

$$M_{j_0}^* = \left(\psi_{t_2j_0}^{*t_2} / \psi_{t_1j_0}^{*t_1} \right) \left(\sqrt{\left(\psi_{t_2j_0}^{*t_1} / \psi_{t_2j_0}^{*t_2} \right) \left(\psi_{t_1j_0}^{*t_2} / \psi_{t_1j_0}^{*t_1} \right)} \right).\quad (4)$$

Figure 2 presents the structure of the adapted network system. To determine the potential wind power, the mean wind speed in 10% windiest areas (x_1) was considered since the power of the flowing air is directly proportional to the air density – ρ , the area covered by the rotor blades – A , and the cube of the wind speed – v : $P = 1/2 \rho A v^3$. The photovoltaic power potential (x_2) was expressed in Wh/m² by Global Horizontal Irradiance (GHI). To include the information on the size of the country: population (x_3) and land area (x_4) are included. Intermediate effects represent wind capacity (z_1) and PV capacity (z_2). The results are wind energy generation (y_1) and solar power generation (y_2). The efficiency trends over time in periods $t = 2018$ and 2022 are investigated. Information on the basic and auxiliary data used in the NDEA model is presented in Table 4.

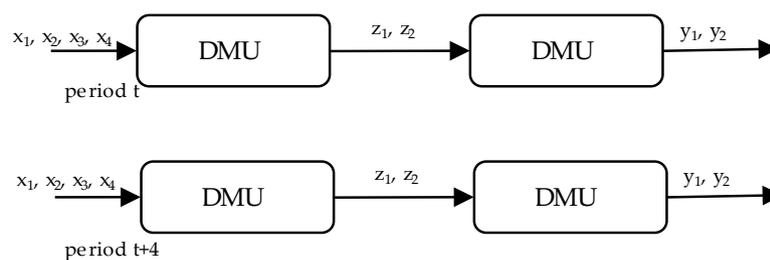


Figure 2. Model structure Source: Own elaboration.

Table 4. Data set.

Variable	Description, source	Unit, year	Source
x1	Mean wind speed	m/s (data for 10% windiest area)	[90]
x2	GHI	kWh/m ² /day	[91]*
x3	Population	million people, 2018-2022	[92,93]
x4	Land area	square thousand km, 2021	[94]
z1	Wind energy capacity	MW, 2018, 2022	[95]
z2	Solar PV capacity	MW, 2018-2022	[95]
y1	Wind energy generation	GWh per year, 2018-2022	[96]
y2	Solar power generation	TWh per year, 2018-2022	[97]
v1	Wind capacity per capita	W	
v2	PV capacity per capita	W	
v3	Wind energy generation per capita	kW	
v4	Solar power generation per capita	kW	

*Data from Finland based on publications [98].

The study covers 32 countries from 2018 to 2022. In the last 5 years, there has been significant progress in the development of solar energy and a moderate increase in wind energy. Taking 2018 as the base value, the average power value of PV installations in the analysed set in 2022 is 468%, and 145% for wind power. Table 5 shows the correlations of variables in 2022, and Table 6 presents basic statistics.

Table 5. Correlations of variables.

	Populat ion	Land area	Mean Wind Speed	GHI	Wind capacit y per capita	Solar PV capacit y	Wind energy generat ion per capita	Wind energy generat ion per capita	Wind capacit y	Solar PV capacit y	Wind energy generat ion
Population	1.000										
Land area	0.683	1.000									
Mean Wind Speed	0.203	0.154	1.000								
GHI	0.029	-0.027	-0.593	1.000							
Wind capacity per capita	0.078	0.283	0.633	-0.340	1.000						
Solar PV capacity per capita	0.260	-0.104	0.114	0.047	0.139	1.000					
Wind energy generation per capita	0.029	0.242	0.678	-0.361	0.985	0.089	1.000				
Solar power generation per capita	0.334	-0.005	0.006	0.283	0.121	0.920	0.064	1.000			
Wind capacity	0.823	0.508	0.328	-0.063	0.398	0.374	0.327	0.431	1.000		
Solar PV capacity	0.826	0.416	0.168	0.008	0.187	0.573	0.108	0.584	0.910	1.000	
Wind energy generation	0.819	0.494	0.406	-0.098	0.428	0.346	0.372	0.403	0.985	0.856	1.000
Solar power generation	0.853	0.484	0.134	0.112	0.185	0.521	0.105	0.603	0.914	0.973	0.865

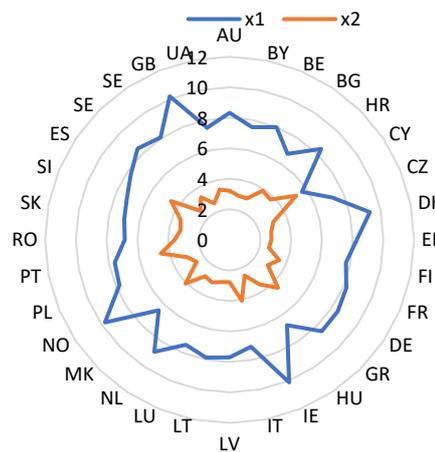
The development of renewable energy sources is consistent with the size of the country measured by population, and to a lesser extent with area. It can be observed that solar and wind conditions are inversely related. The lack of wind conditions is often associated with favourable sunny conditions and vice versa. Moreover, it can be seen that both wind farms and solar farms have high-capacity utilization rates, although wind farms outperform solar farms. While the development of renewable energy sources is more compatible with wind conditions, it is not as dependent on solar conditions. The absolute values of photovoltaic and wind power as well as solar and wind energy generation are correlated, but when relative values (per inhabitant) are considered, there are no such relationships.

Table 6. Basic statistic for 2022.

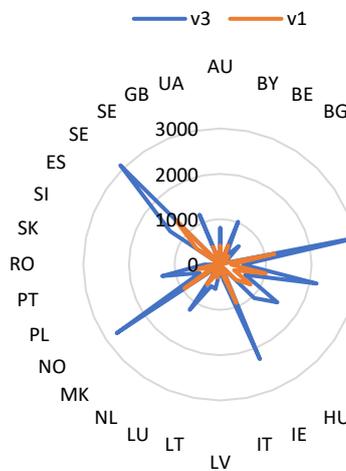
	Min	Max	Mean	Std. dev.
x1	5.66	10.18	7.90	1.01
x2	2.53	5.21	3.33	0.68
x3	0.65	83.37	18.12	22.32
x4	2.57	579.40	170.30	166.59
z1	3.00	66315.00	7490.81	13064.71
z2	56.00	66554.00	7101.69	12782.09
y1	5.00	125287.00	16167.99	26724.79
y2	0.01	58.98	7.05	12.34
v1	0.71	1379.90	377.42	372.40
v2	26.88	1286.15	310.56	254.56
v3	0.89	3230.37	860.08	916.97
v4	5.40	958.21	292.85	233.90

Based on the analysis of the minimum, maximum, and standard deviation values, it can be concluded that countries share similar environmental conditions. However, their utilisation varies. Wind energy potential and the amount of wind energy produced per capita are the most diverse. These variations are depicted in Figure 3, highlighting the differences between countries.

a) geographical characteristics



b) wind power per capita



c) solar power per capita

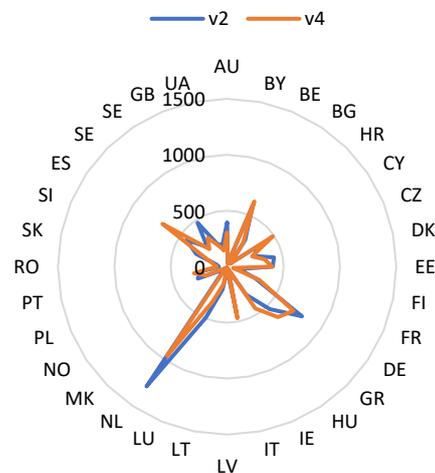


Figure 3. Countries characteristics: (a) geographical characteristics; (b) wind power per capita; (c) solar power per capita.

The leaders in wind energy are the northern countries: Denmark, and Sweden, but also Norway, and Finland. Considering solar power: Netherlands Germany, Spain, Greece, and Belgium.

4. Results

Table 7 displays the efficiency scores estimated by traditional one-stage DEA and two-stage DEA.

Table 7. Final efficiency score.

Country		Two-stage NDEA 2018				Two-stage NDEA 2022			Malmquist index			
		One stage DEA 2018	One stage DEA 2022	First stage	Second stage	Overall	First stage	Second stage	Overall	catch-up	frontier-shift	index
AU	Austria	41.6%	43.1%	39.2%	78.2%	30.7%	48.5%	63.6%	30.9%	1.01	1.57	1.58
BY	Belarus	4.7%	5.5%	2.3%	50.5%	1.2%	2.2%	63.8%	1.4%	1.20	1.54	1.84
BE	Belgium	100.0%	97.3%	97.3%	86.7%	84.3%	77.0%	96.0%	74.0%	0.88	1.64	1.44
BG	Bulgaria	43.2%	40.2%	22.7%	84.1%	19.1%	21.5%	75.5%	16.2%	0.85	1.44	1.22
HR	Croatia	14.2%	18.9%	5.7%	73.4%	4.2%	7.1%	60.5%	4.3%	1.03	2.12	2.18
CY	Cyprus	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	79.6%	79.6%	0.80	1.12	0.89
CZ	Czechia	100.0%	100.0%	100.0%	100.0%	100.0%	49.9%	68.6%	34.2%	0.34	2.87	0.98
DK	Denmark	100.0%	100.0%	100.0%	70.1%	70.1%	100.0%	75.8%	75.8%	1.08	1.49	1.61
EE	Estonia	100.0%	100.0%	100.0%	71.8%	71.8%	100.0%	75.8%	75.8%	1.06	0.86	0.91
FI	Finland	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	50.7%	52.8%	0.53	0.91	0.48
FR	France	33.2%	43.1%	30.1%	100.0%	32.1%	37.2%	100.0%	37.2%	1.16	1.34	1.55
DE	Germany	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	1.00	1.00	1.00
GR	Greece	70.2%	73.1%	43.1%	96.6%	41.7%	58.9%	89.5%	52.7%	1.26	1.42	1.80
HU	Hungary	100.0%	100.0%	100.0%	71.1%	71.1%	100.0%	100.0%	100.0%	1.41	1.01	1.42
IE	Ireland	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	1.00	1.00	1.00
IT	Italy	97.8%	87.8%	47.6%	86.5%	41.2%	50.0%	80.4%	40.2%	0.98	1.74	1.70
LV	Latvia	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	1.00	0.45	0.45
LT	Lithuania	36.1%	39.8%	14.5%	76.7%	11.1%	39.3%	56.9%	22.4%	2.01	2.04	4.09
LU	Luxembourg	100.0%	100.0%	100.0%	75.7%	75.7%	100.0%	65.6%	65.6%	0.87	0.86	0.74
NL	Netherlands	100.0%	100.0%	100.0%	83.1%	83.1%	100.0%	100.0%	100.0%	1.20	1.16	1.39
North												
MK	Macedonia	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	1.00	1.00	1.00
NO	Norway	39.7%	100.0%	100.0%	59.8%	59.8%	50.0%	50.0%	25.0%	0.25	73.09	18.28
PL	Poland	27.9%	36.0%	5.4%	48.7%	2.6%	33.4%	83.7%	27.9%	10.62	1.47	15.63
PT	Portugal	78.9%	64.6%	21.1%	100.0%	21.1%	36.3%	99.3%	36.0%	1.71	1.73	2.96
RO	Romania	61.0%	59.7%	38.5%	95.4%	36.7%	24.7%	96.4%	23.8%	0.65	1.60	1.04
SK	Slovakia	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	1.00	1.00	1.00
SI	Slovenia	28.5%	27.0%	0.5%	69.5%	0.3%	0.4%	66.2%	0.3%	0.77	1.23	0.95
ES	Spain	81.4%	95.2%	40.0%	100.0%	40.0%	64.3%	100.0%	64.3%	1.60	1.37	2.20
SE	Sweden	100.0%	100.0%	18.9%	85.2%	16.1%	74.1%	79.9%	59.2%	3.68	2.02	7.46
SE	Switzerland	45.5%	33.1%	2.3%	60.6%	1.4%	2.4%	61.7%	1.5%	1.03	1.20	1.24
GB	UK	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	1.00	1.00	1.00
UA	Ukraine	5.3%	22.0%	3.7%	75.5%	2.8%	10.7%	32.2%	3.4%	1.24	1.23	1.53
Average		72.2%	74.6%	60.4%	84.4%	53.7%	63.7%	81.9%	55.6%			

The DEA method has an advantage in that it considers all the results obtained and input data simultaneously. In other words, it selects the units that perform the best based on a given criterion. On average, the first stage of the DEA method, which evaluates the potential of the environment, has a lower effectiveness of 0.6 compared to the second stage's 0.8 effectiveness. When considering the NDEA in 2018, the following leaders were indicated: Cyprus, Czechia, Finland, Germany, Ireland,

Slovakia, and the United Kingdom. In 2022, the group of countries that scored 100% were: Germany, Hungary, Ireland, Latvia Netherlands, North Macedonia, Norway, Slovakia, United Kingdom. It can be noted that many countries, including Germany, Ireland, Latvia, North Macedonia, Norway, Slovakia, and the United Kingdom were rated as fully effective in both periods. Considering changes in time, in most cases, there was an increase in relative efficiency.

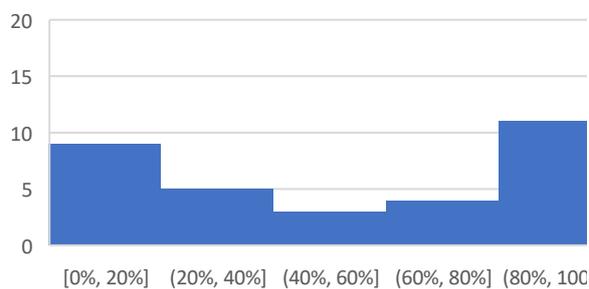
Table 8 shows the correlations between scores obtained by NDEA models and standard DEA models in 2018 and 2022.

Table 8. Correlations of results.

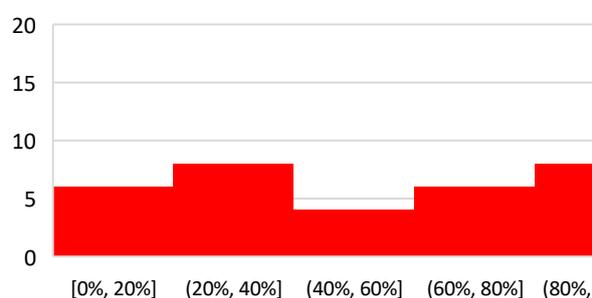
	Overall NDEA 2018 ($X \rightarrow Z \rightarrow Y$)	Overall NDEA 2022 ($X \rightarrow Z \rightarrow Y$)	DEA 2022 ($X \rightarrow Y$)
DEA 2018 ($X \rightarrow Y$)	82.7%		93.4%
DEA 2022 ($X \rightarrow Y$)		83.9%	
Overall NDEA 2018 ($X \rightarrow Z \rightarrow Y$)		84.6%	
	First stage NDEA 2018 ($X \rightarrow Z \rightarrow Y$)	First stage NDEA 2022 ($X \rightarrow Z \rightarrow Y$)	DEA 2022 ($X \rightarrow Z$)
DEA 2018 ($X \rightarrow Z$)	84.3%		94.8%
DEA 2022 ($X \rightarrow Z$)		92.4%	
First stage NDEA 2018 ($X \rightarrow Z \rightarrow Y$)		89.0%	
	Second stage NDEA 2018 ($X \rightarrow Z \rightarrow Y$)	Second stage NDEA 2022 ($X \rightarrow Z \rightarrow Y$)	DEA 2022 ($Z \rightarrow Y$)
DEA 2018 ($Z \rightarrow Y$)	49.8%		54.0%
DEA 2022 ($Z \rightarrow Y$)		51.8%	
Second stage NDEA 2018 ($X \rightarrow Z \rightarrow Y$)		54.1%	

A high correlation was observed in the results in 2022 and 2018 of total efficiency, but also of the first stage in relation to classic DEA. Additional conditions cause the efficiency calculated by network DEA to be lower. The correlation indicates that there is no consistency in the assessment of the efficiency of the second stage in 2018, and there are no proportional changes in energy production from panels and turbines (second stage) between 2018 and 2022. A histogram of the results of individual stages is shown in Figure 4.

a) Overall NDEA 2018



b) Overall NDEA 2022



c) First stage NDEA 2018

d) First stage NDEA 2022

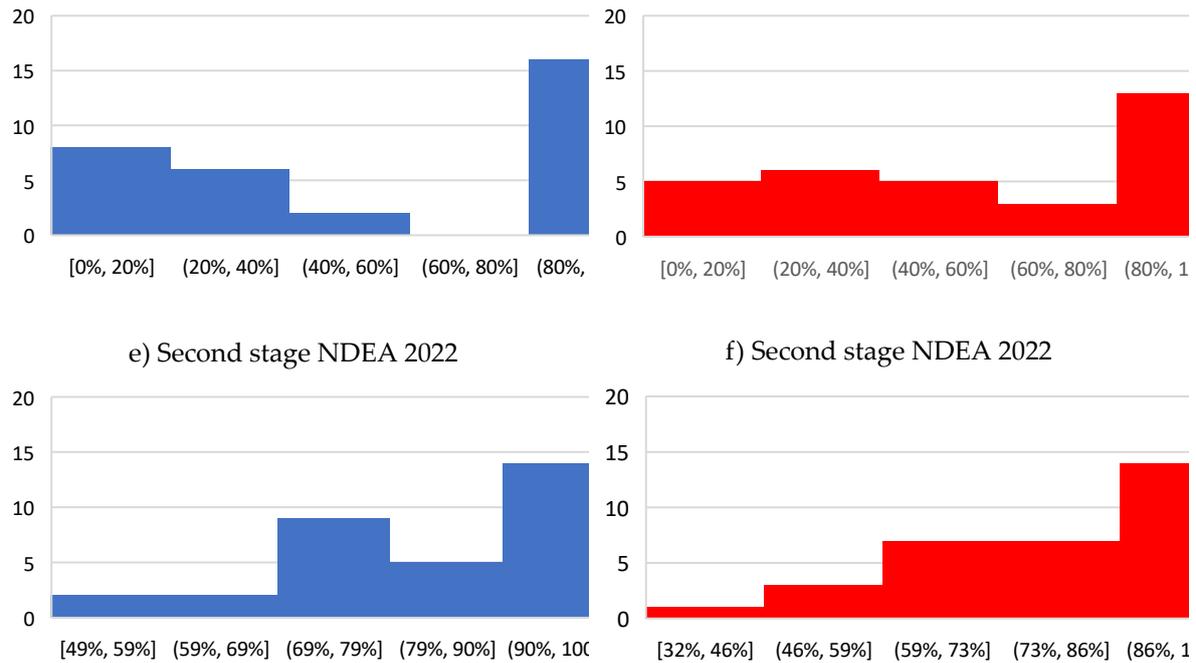


Figure 4. Histograms of efficiency scores by NDEA: (a) overall 2018; (b) overall 2022; (c) first stage NDEA 018; (d) first stage NDEA 2022; (e) second stage NDEA 2018; (f) second stage NDEA 2022.

5. Discussion and Conclusions

The article proposes an assessment of the location of countries for the development of solar and wind technologies and the level of their use by the NDEA. As a result, energy production was evaluated in relation to installed capacity and geographic location, which is expressed in wind density and irradiation. The need for clean energy has been taken for granted. Therefore, policies and laws or distance to transmission lines were excluded from the analysis as it was assumed that each country should adapt them to future needs.

The issue of sustainable energy is a growing concern, and achieving carbon neutrality requires a proper strategy. By taking location-related factors into account, we can broaden our perspective and develop sustainable progress. Multi-stage DEA has advantages over conventional DEA as it assesses both potential development and actual implementation. This study proposes a network DEA model that utilises geographic location potential and assesses wind and solar potential and energy production in European countries. The combined assessment of wind and solar potential is compatible with bidirectional development, including hybrid solar power plants that compensate for the lack of solar energy in winter months with wind energy. It is important to note that this study doesn't refer to hydropower due to its controversial nature and limitations.

Presented study has important policy implications. It shows that EU green energy policies may be tailored to the specific situation and the potential of each member state, based on the objective study of their relative efficiency and progress. By focusing on the most suitable strategies for each country, the overall EU transition to green energy can be faster, more efficient, and more equitable than in the case of one-size-fits-all approach. Regular monitoring and evaluation of countries' performance with methods such as NDEA allow for evidence-based policy adjustments that respond to the often fast changing environmental, economic, and technological circumstances.

Systematic evaluation of countries is crucial as renewable energy sources have high dynamics of changes. Future studies should consider the complex internal structure of the network DEA model. While DEA is generally viewed as an objective method, as shown, the final ranking of efficiency is influenced by the adopted model. Additionally, extending the analysis to developing countries is worth considering as they need better policies and support for sustainable progress. Interesting

direction of future development is to combine DEA with machine learning methods to exploit big data sets for advanced forecasting.

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Data Availability Statement: Publicly available datasets were analysed in this study.

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

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