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Alina Cristina Nuta

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Article

The Significance of Economic Complexity and Renewable Energy for Decarbonization in Eastern European Countries

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Abstract: Emerging states' path to enhancing the welfare of their citizens has been strongly accompanied by environmental degradation; climate change effects often abrogate their economic results. This zero-sum game must change, and environmental concerns should be considered when the development of a country is discussed and assessed. In this sense, this study's objective is to analyze the impact of economic complexity and renewable energy consumption in the presence of economic growth and urbanization in selected emerging European countries from 1995 to 2021. We used a multiple-methodologic approach to highlight the supportive effects of economic complexity and renewable energy consumption in mitigating carbon emissions. Furthermore, the effects of economic growth and urbanization were emphasized by applying the cointegration regression (CCR), fully modified OLS, and dynamic OLS (FMOLS–DOLS) approaches. Additionally, we used Driscoll–Kraay estimation regression to test the robustness of our results. The results reveal the beneficial role of renewable energy consumption and economic complexity in the decarbonization process of selected countries. Furthermore, the study highlighted the detrimental influence of urbanization and economic growth, which were feasible considering the emerging status of the countries included in the panel.

Keywords: economic complexity; renewable energy; urbanization; environmental degradation

1. Introduction

1.1. Contextualization

National governments and international bodies struggle to find a compromise between social and economic issues and environmental sustainability [1–3]. Poverty, unemployment, and structural challenges are pushing the budgetary boundaries, challenging national economies and financial systems to address them while fighting against climate change effects [4–10]. Energy transition, greenhouse gas emissions, and biodiversity loss endanger humans' self-existence on Earth, with the vital risk being at the highest level so far in history as we know it [11].

Confronted with climate change pressure, the European Union has driven its targets to mitigate and adapt to climate risks, as stated by the Paris Agreement in 2015. Achieving climate neutrality by 2050 [12] will require a tremendous shift in development to become more sustainable and fairer for all. The European Green Deal highlights the EU strategy for a green and just transition path [13]. Transformations in economies, including industrial and productive structures, are required to organize their potential in a net-zero direction to enhance the economy–environment nexus and impact. An important aspect of this transition is linked to how emerging states and developing nations will be able to increase their resilience and capacity to develop within a framework that focuses on reducing greenhouse gas emissions. The task of cutting emissions by 55% by 2030 [13] will be implemented by adopting various instruments, such as regulations, climate-friendly innovation adoption, and sustainable finance. The aim of reducing greenhouse gas emissions is being progressively implemented, as seen in Figure 1, which shows the annual decrease in emissions from 1990 to 2022. Still, the EU-27 remains fourth among the top greenhouse gas emitters, according to Climate Watch [14].

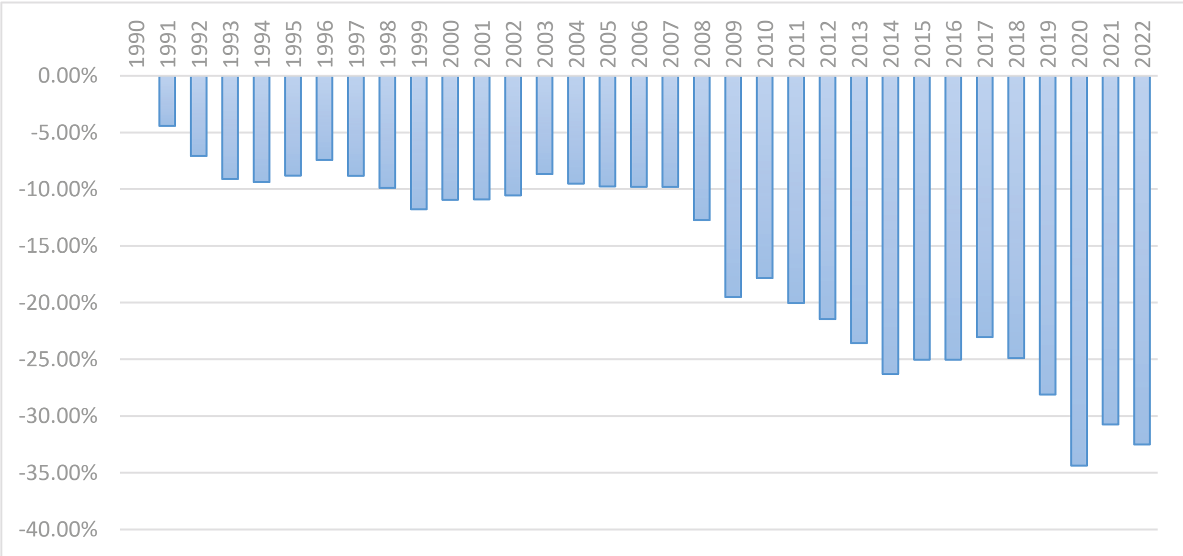

Figure 1. EU−27 total net emissions (UNFCCC) kt CO_2 eq (all greenhouse gases). Scheme 2024. (https://www.eea.europa.eu/data-and-maps/data/data-viewers/greenhouse-gases-viewer (accessed on 7 July 2024)).

All countries must intensify their efforts to diminish their emissions. Moreover, the energy sector is liable for a large share of greenhouse gas emissions (75%, according to [15]). In this sense, one highly appreciated and evaluated driver is renewable energy consumption [16–20]. Additionally, ref. [21] stated that the structure of energy consumption can be optimized by technological innovation. A positive impact of green energy on sustainable development was also found by [22] when they analyzed a panel of 53 emerging economies. Ref. [23] highlighted the relevance of energy resilience policies in the context of geopolitical instability for European Union countries, analyzing the perception of their citizens.

Thus, the European Union's share of renewable energy represents 23% of total consumption (Figure 2), and current targets recognize the need to increase the share of renewables in the mix to 42.5% by 2030.

Moreover, as important as urbanization is considered for the development of states, the more pronounced the adverse effects have become regarding the environmental impact.

The Industrial Revolution is often related to environmental damage, assuming a sudden increase in energy consumption, especially from fossil fuels, and the structural transformations in sectors that became drivers of pollution, including the large-scale use of natural resources. On the other hand, progress has also generated the development of green technologies that are friendly to the environment, contributing to the reduction of pollution, while simultaneously increasing the potential to eliminate or reduce the effects of climate change [24–26].

Additionally, a country's economic complexity describes its capability to produce and transition a complex and diverse range of goods based on its know-how and innovation potential. Economic complexity is a broader indicator of a country's development that requires investments, innovation, knowledge, and skills [27,28]. In this sense, the economic complexity index ranks countries according to their export baskets [29]. A more complex product structure based on knowledge-intensive and technology-intensive processes can determine a robust relationship with the environment [24].

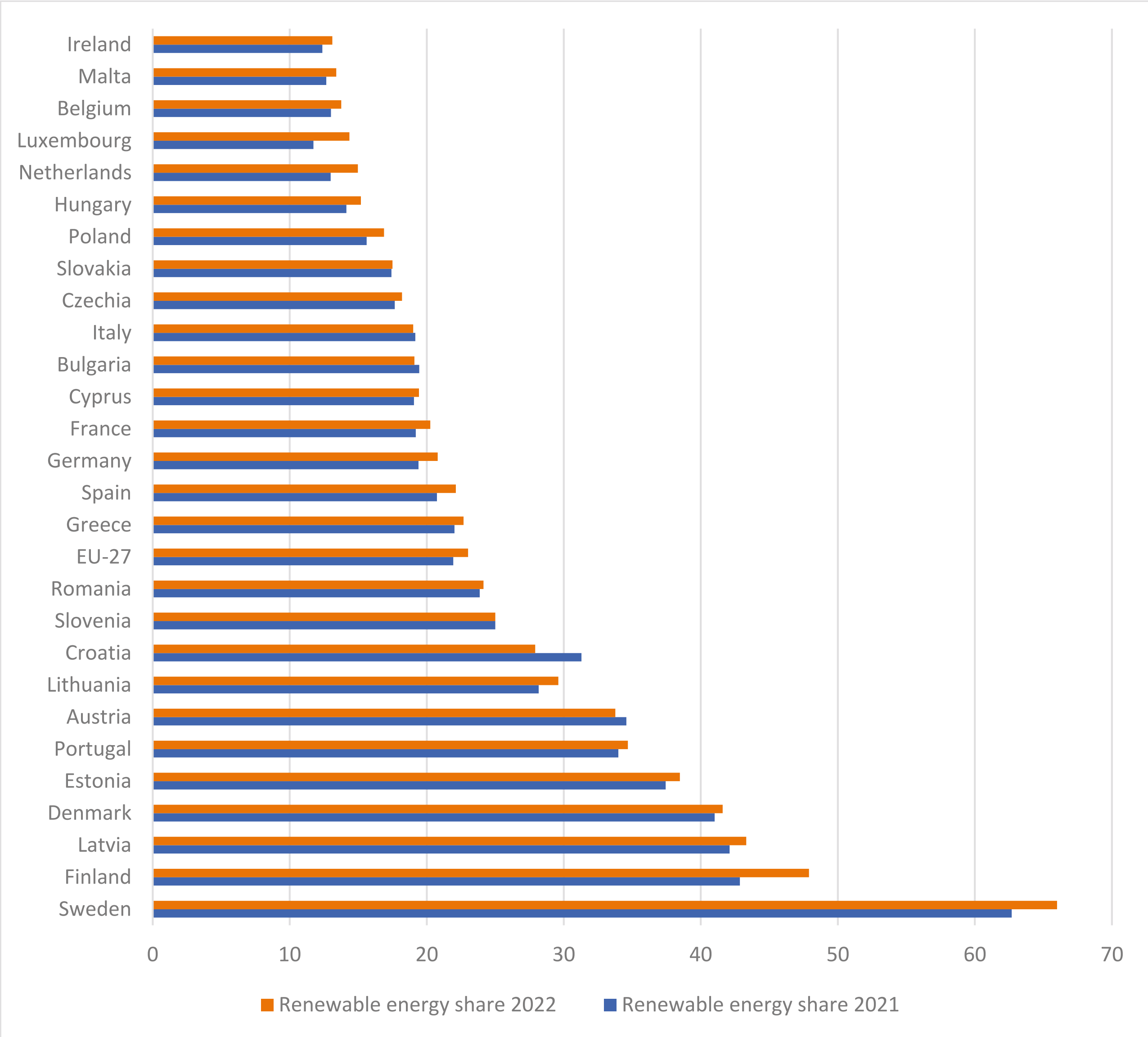

Figure 2. Renewable energy consumption in EU−27, 2021–2022. Source: Eurostat, https://ec.europa.eu/eurostat/databrowser/view/NRG_IND_REN/default/table?lang=en (accessed on 11 July 2024).

Furthermore, Europe's exports are highlighted in Figure 3. The economic complexity of selected European countries is presented in Table 1. When a country's commercial transactions are based on primary commodities and raw materials used as input goods by different buyers, the added value is lower, and the potential to pollute is higher [28]. By contrast, exports based on complex and innovative products are more desirable for rapid and greener development [30].

Though various and valuable, the existing literature often remains trapped in topic-oriented silos. While the literature reflecting renewable energy consumption's impact on environmental quality is quite advanced, the emphasis on economic complexity impact remains limited, especially regarding emerging countries with a former communist background. Consequently, the current paper seeks to contribute to the existing literature in several ways.

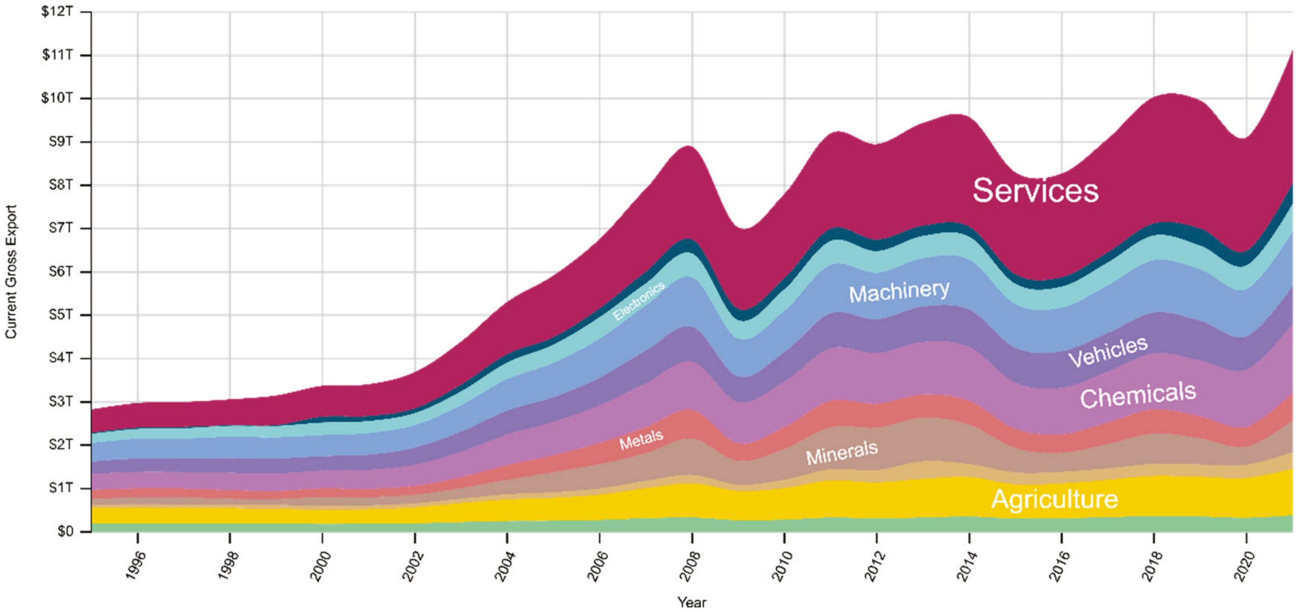

Figure 3. Europe product exports, 1995–2021. Source: downloaded from https://atlas.cid.harvard.edu/explore/stack?country=4&year=2021&queryLevel=group&startYear=1995&productClass=HS&product=undefined&target=Product&partner=undefined (accessed on 11 July 2024).

Table 1. Economic complexity index in selected European countries.

	2021	Position	2020
Bulgaria	0.62	39	0.56
Poland	1.02	25	0.98
Romania	1.23	19	1.22
Hungary	1.52	11	1.52
Czech Republic	1.75	6	1.82

Source: https://atlas.cid.harvard.edu/rankings (accessed on 11 July 2024).

First, based on the above remarks, to fill the literature gap, the purpose of this research is to determine the impact of the independent variables (economic complexity, renewable energy consumption, economic growth, urbanization) on the dependent variable, environmental degradation (measured by carbon emissions), in selected European emerging countries (Bulgaria, Czech Republic, Hungary, Poland, and Romania) from 1995 to 2021. Second, we chose this panel of countries due to their homogeneous aspects reflected by their historical and economic evolution. Thus, the analysis will bring relevant findings and policy directions for the countries' stakeholders to motivate their path to decarbonization and energy transition.

Third, the methodological approach represents another important new element of this study. This research uses three models to test the impact: cointegration regression (CCR), fully modified OLS, and dynamic OLS (FMOLS–DOLS) approaches as primary models. Moreover, we used Driscoll–Kraay estimation regression to test the robustness of the results. By combining multiple modeling methodologies, the relevance of the findings of this study is provided.

1.2. Literature and Research Questions

Moving towards an energy mix dominated by renewable sources is seen as an appropriate option for lowering the ecological footprint and a path towards a healthier ecological environment with fewer emissions [22,31–34]. Reconsidering the energy mix should support a just transition and involve care for social aspects during the process [35], with renewable energy and clean technologies being essential for diminishing carbon emissions in OECD countries [36].

Ref. [37] proved that excessive natural resource exploitation exacerbates environmental degradation while economic growth targets demand increased energy consumption. Under these circumstances, national governments should target an extended share of renewable energy sources to compensate for the energy demand without increasing environmental degradation. Decision-makers, especially in emerging and developing countries, are reluctant to put growth policies under scrutiny for ecological quality, even if, according to [38], renewable energy consumption reduces air pollution in China in an analysis of China's current five-year plan.

Nevertheless, recent studies have shown that economic growth is not affected by environmentally friendly policies and renewable energy [39]. As the relationship between economic growth and renewable energy expansion is not linear, previous studies concluded that simply expanding the share of such energy sources is insufficient to ensure sustainable growth [40], with efficiency being critical under these circumstances.

A recent paper [31] discovered a reducing effect of renewable energy on carbon emissions in 30 top-emitting countries. Moreover, a positive relationship between economic growth and environmental degradation was found across all quantiles. Similarly, [41] confirms a negative association between renewable energy and carbon emissions, affirming that economic growth creates ecological damage. On the other hand, [42] discovered no causality between carbon emissions and renewable energy, while economic growth increases environmental damage in a selection of emerging economies. Unlike these previous studies, in this research, we added economic complexity besides traditional economic growth to express development rather than simply growth.

The bidirectional causality between renewable energy and non-renewable consumption should also be considered, according to [43], due to lower prices of dirty energy, especially during economic decline.

Ref. [44] studied the specific asymmetries between economic growth and carbon emissions, with numerous policy recommendations for a low-carbon transition.

After confirming the EKC hypothesis, [45] showed that carbon emissions increased in the presence of multiple factors, such as resource abundance, high economic growth, and major direct investment flows, which generate specific attention from decision-makers to find a sustainable path for developing economies by using cleaner technologies.

Ref. [46] examined China's path in the renewable energy era in the context of economic potential maximization, underlining the still important role of fossil fuels and a traditional industrial approach.

A causality analysis revealed the role of renewable energy in enhancing growth through the new jobs that will be created in the context of economic restructuring [47].

Fast-growing developing economies are characterized by increasing urbanization, population density, and standard of living, all contributing to a higher level of environmental degradation [48,49]. Under these circumstances, renewable energy solutions are vital for ensuring future development and improving environmental quality [50].

Analyzing government-driven urbanization in China, [51] found that GDU reduces CO_2 emissions intensity. They revealed the relevance of an urban energy transition, in which urbanization must be approached more rationally. Controlling urban carbon emissions was identified as a key tool in reaching net-zero emissions in China's cities according to [52], especially when the industrial structure lacks upgraded features. Furthermore, [53] evaluated the potential of municipal solid waste as a renewable energy source, thus covering an essential aspect of sustainable development based on circular economy capacity in reducing emissions by adopting innovative waste management strategies.

The effect of economic complexity on environmental quality remains inconclusive in the literature. In this sense, a positive impact has been highlighted by [54], while a negative impact of economic complexity was found by [24,39].

A study on OECD countries from 1998 to 2017 [54] found that economic complexity exerts a mitigation effect on carbon emissions, even if the direct effect on emissions is positive in selected countries. Moreover, when using the Method of Moment Quantile regression, the results found a statistically significant and negative effect of economic complexity on environmental degradation in all quantiles, which adds to the power of ECI in reducing environmental degradation. Furthermore, another study on OECD countries found a positive relationship between ECI and environmental degradation, measured by ecological footprint. However, the harmful effect is discontinued by the human capital index.

An inverted U-shaped curve between economic complexity and environmental degradation was found by [55] in a study covering emerging countries from 1984 to 2017. The results reveal the beneficial effect of higher economic complexity levels on environmental quality. An increase in environmental performance at higher levels of economic complexity was also underlined by [24].

Under these circumstances, this study will consider the following research questions:

- What is the potential of renewable energy consumption in the decarbonization of emerging European countries?
- Will economic complexity be a beneficial factor for environmental quality?
- Will the results of the analysis confirm the detrimental role of urbanization?

2. Data and Methodology

2.1. Data

This study used four independent variables (including control): renewable energy consumption, urbanization, economic growth, and the economic complexity index to test the impact on European carbon emissions. Carbon emissions were used to measure pollution and environmental damage levels in the assessed countries. Renewable energy consumption was chosen as the main indicator of environmentally friendly behavior and is one of the most relevant targets of the European Green Deal for sustainable development. Additionally, a country's innovative and technological development is reflected by its economic complexity level. Furthermore, as the control variable, the study used urbanization (acknowledged in the literature as having an important impact on the environment) and economic growth (appreciated as being directly linked to a state's economic potential). All variables are presented in Table 2. Figure 4 highlights the evolution of analyzed variables over time. It can be observed that the countries included in the panel have comparable evolutions, being a homogeneous group with similar characteristics.

Table 2. Data definitions and data sources.

Variables	Abbrs.	Def.	Sources
Carbon emissions	CO_2	Carbon dioxide emissions stemming from the burning of fossil fuels and the manufacture of cement	OWD [56]
Renewable energy consumption	REN	Renewable energy consumption (% of total final energy consumption)	WBI [57]
Economic complexity index	ECI	Economic complexity index of a country	Harvard's Growth Lab [58]
Urbanization	URB	Urban population	WBI [59]
Economic growth	GDP	GDP per capita (constant 2015 USD)	WBI [60]

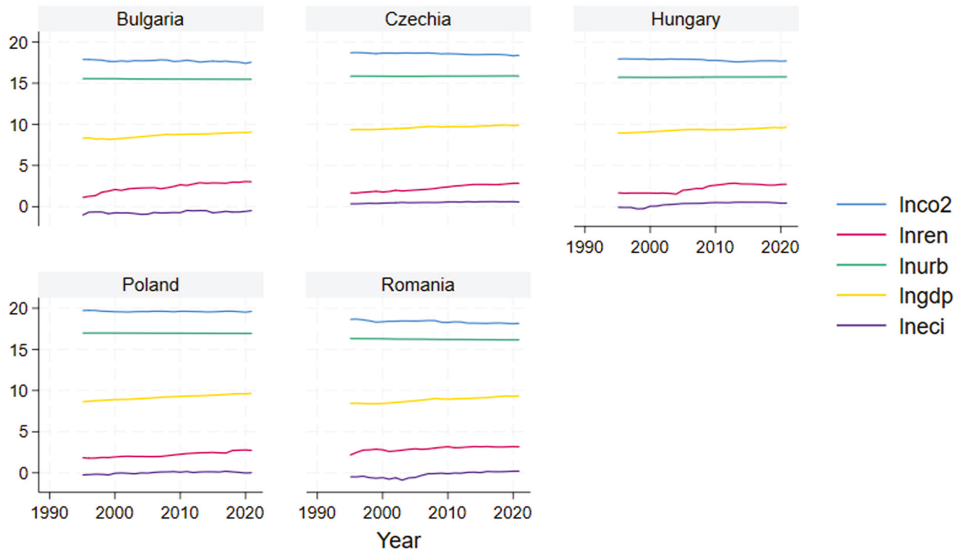

Figure 4. Variables presentation.

2.2. Methodological Approach

The general model is given by the equation below:

$$CO2_{it} = \beta_0 + \beta_1 REN_{it} + \beta_2 URB_{it} + \beta_3 GDP_{it} + \beta_4 ECI_{it} + \varepsilon_{it} \quad (1)$$

We use the cointegration regression (CCR), fully modified OLS, and dynamic OLS (FMOLS–DOLS) approach as the primary models. Moreover, we used Driscoll–Kraay estimation regression to test the robustness of the results. While FMOLS transforms the regressand [61], CCR estimation [62] is based on transforming the regressand and the regressors.

First, we tested the stationarity of the variables included in the model using the Levin–Lin–Chu [63], confirming a cointegration I(1) for all our variables. This test is better for our model specificity, where the panel number and time ratio tend to zero (N < T) by fitting an augmented Dickey–Fuller regression for each panel. The next step was to apply a cointegration test to check for a long-run equilibrium relationship between series.

FM-OLS regression, originally created by [61] and further developed by [64,65], can be presented as follows:

$$Y_{i,t} = \alpha_i + \beta_i X_{i,t} + \varepsilon_{i,t} \qquad \forall_t = 1, \ldots, T, \qquad i = 1, \ldots, N \quad (2)$$

$Y_{i,t}$ and $X_{i,t}$ are cointegrated with slopes β_i [66].

DOLS introduced by [67,68] was recognized in the literature [69] as being a superior technique in a small sample and can be presented as follows:

$$Y_t = \alpha_i + \beta X'_t + D'_{1t} D' \gamma_1 \sum_{j=-q}^{r} \Delta X'_{t+j} \rho + v_{1,t} \quad (3)$$

Finally, to check the robustness of the model, we applied a nonparametric covariance matrix estimator that produces heteroskedasticity- and autocorrelation-consistent standard errors, named the Driscoll and Kraay estimator [70,71]. Driscoll and Kraay's standard errors of the coefficient estimates represent the square roots of the diagonal elements of the asymptotic (robust) covariance matrix [71].

3. Results and Discussion

3.1. Descriptive Statistics

In Table 3, we present descriptive statistics for all the variables analyzed. Figures 5–8 provide hexagon plots for variable interaction. We can easily observe that carbon emissions have evolved from 36 million to 377 million. Additionally, renewable energy consumption has increased over the years, and countries have grown from 3% to 24.40%. Moreover, the urban population increased over time by almost five times, while the economic complexity index ranges from 0.35 to 1.84, with a mean of 1.08 over the panel.

Table 3. Descriptive statistics.

Variable	Obs.	Mean	Std Dev	Minimum	Maximum
CO_2	135	128,720,131.00	104,375,068.00	36,533,612.00	377,285,400.00
REN	135	12.31	5.72	3.00	24.40
URB	135	10,871,046.00	6,522,611.00	5,228,804.00	23,842,562.00
GDP	135	10,063.67	418.37	3540.56	20,206.43
ECI	135	1.08	0.46	0.35	1.84

Note: CO_2 = Carbon emissions; REN = Renewable energy consumption; URB = Urbanization; GDP = Economic growth; ECI = Economic complexity index.

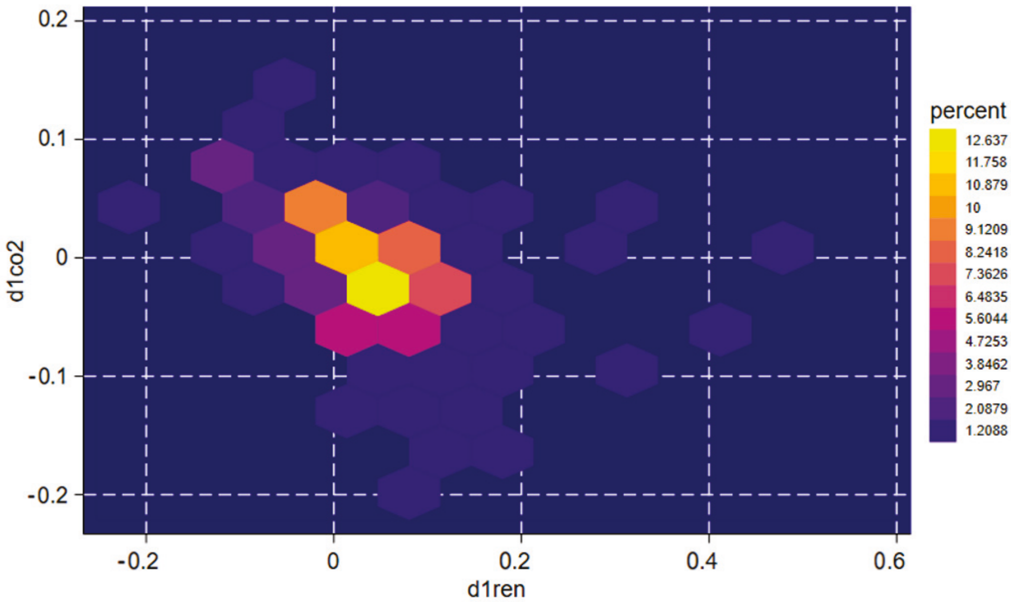

Figure 5. Hexagon plot of REN and CO_2.

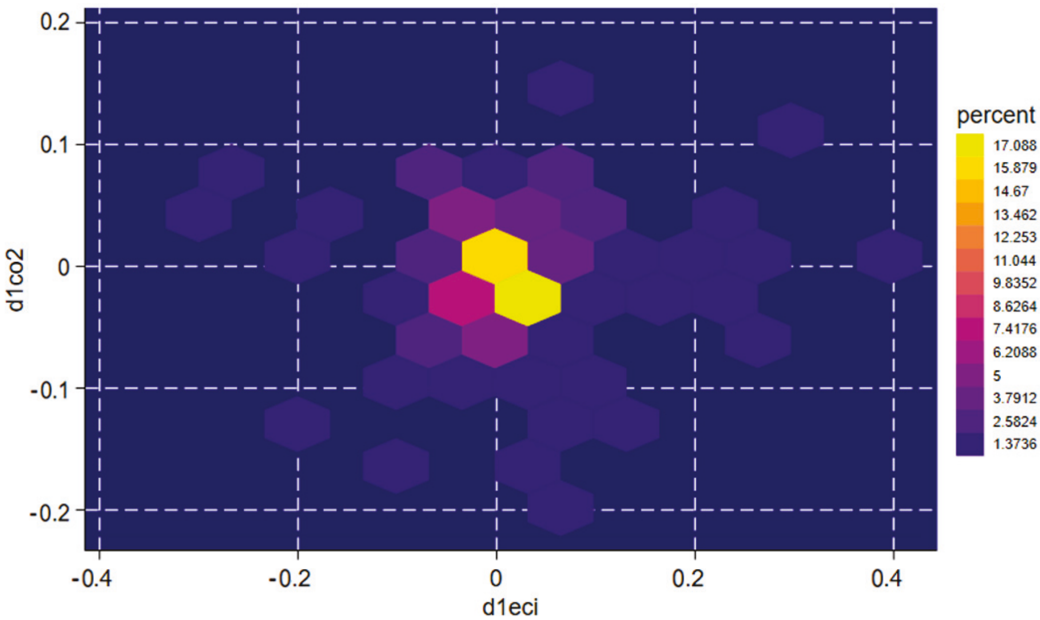

Figure 6. Hexagon plot of REN and ECI.

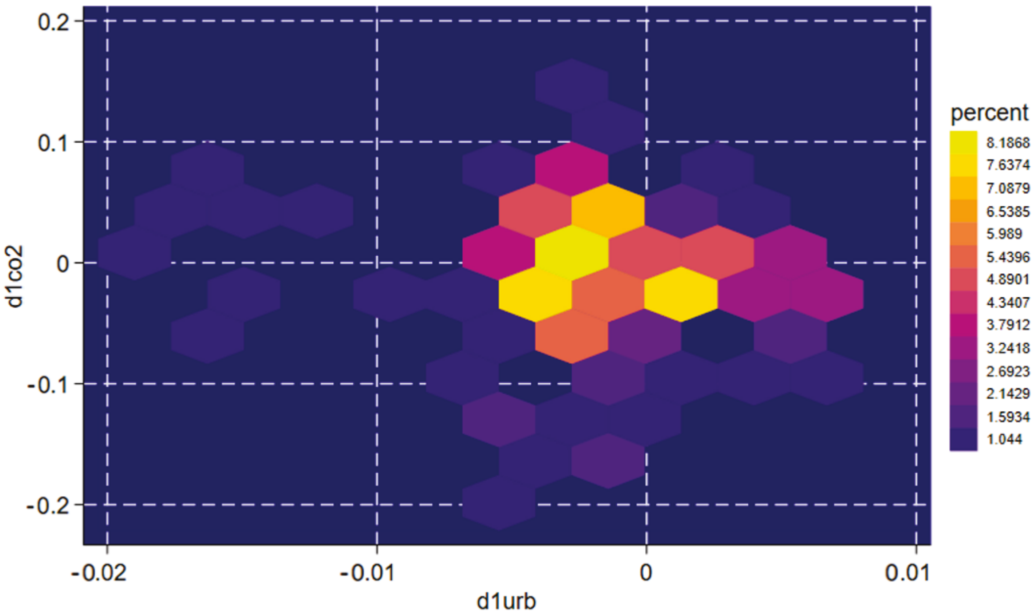

Figure 7. Hexagon plot of REN and URB.

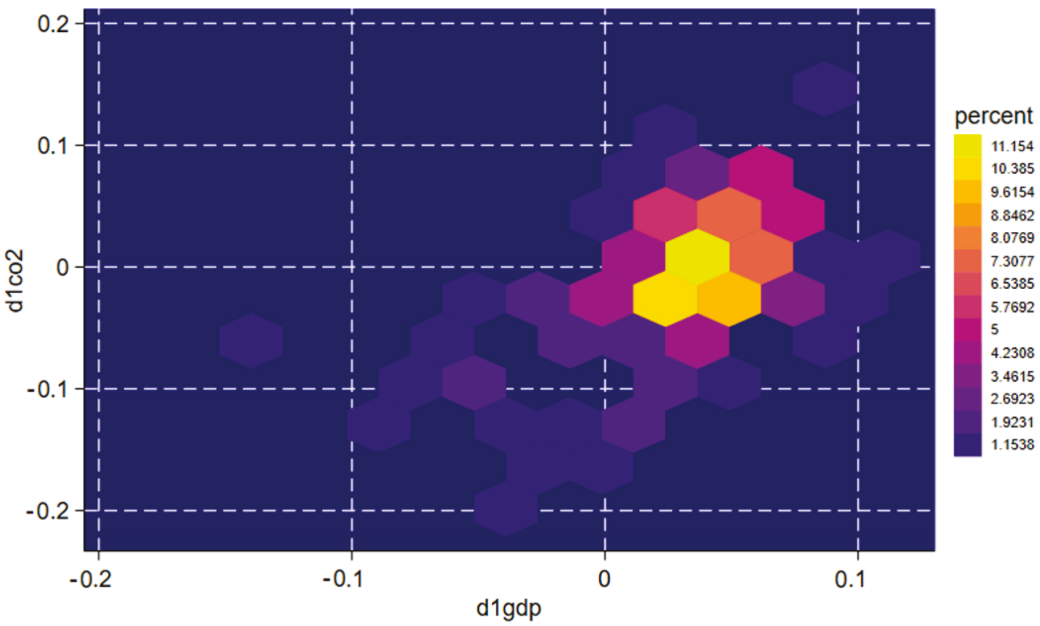

Figure 8. Hexagon plot of REN and GDP.

3.2. Estimations and Discussion

Table 4 presents the evaluation of the stationarity of the variable. It can be observed that, at the level, the variables analyzed were not stationary, but they became stationary after calculating the first difference. Kao test results for cointegration, showing the long-run equilibrium relationship between series, are given in Table 5.

The estimation results presented in Table 6 are obtained by applying three methodologies (CCR, FMOLS, DOLS) to test the impact of renewable energy consumption, urbanization, economic growth, and economic complexity index on carbon emissions.

Table 4. Panel unit root using Levin, Lin and Chu test.

	At Level		At First-Difference	
	Statistic	**Prob.**	**Statistic**	**Prob.**
CO_2	−2.3621	0.0091	−5.4301	0.0000
REN	−1.4938	0.0676	−5.0162	0.0000
URB	−2.0126	0.0221	−2.6920	0.0036
GDP	−0.6961	0.2432	−3.2296	0.0006
ECI	−1.8530	0.0319	−4.0191	0.0000

Note: CO_2 = Carbon emissions; REN = Renewable energy consumption; URB = Urbanization; GDP = Economic growth; ECI = Economic complexity index.

Table 5. Kao test for cointegration.

	Statistic	**Prob.**
Modified Dickey–Fuller t	−3.7190	0.0001
Dickey–Fuller t	−2.6932	0.0035
Augmented Dickey–Fuller t	−3.2065	0.0007
Unadjusted modified Dickey–Fuller t	−3.6983	0.0001
Unadjusted Dickey–Fuller t	−2.6880	0.0036

Table 6. Estimation results.

Variable	**CCR**	**FMOLS**	**DOLS**
REN	−0.4223719 *** (0.0906546)	−0.4269709 *** (3.2980)	−0.3411899 *** (0.107547)
URB	1.225076 *** (0.0833503)	1.224115 *** (0.0836648)	1.235086 *** (0.0792092)
GDP	0.8452406 *** (0.2488771)	0.8392762 *** (0.2403853)	1.183213 *** (0.3340071)
ECI	−0.5634005 *** (0.2234512)	−0.5657797 *** (0.2224739)	−0.832764 *** (0.2873171)
Constant	−7.973767 *** (2.656103)	−7.89175 *** (2.58248)	−11.42552 *** (3.520044)
R^2	0.821	0.818	0.960

Note: REN = Renewable energy consumption; URB = Urbanization; GDP = Economic growth; ECI = Economic complexity index. Standard errors in parentheses; *** $p < 0.01$.

It can be observed that all estimation methods generated statistically significant results with the same impact direction. Another element to note is that the estimations using the DOLS approach were higher than those obtained using the other methodologies, except for renewable energy consumption. From Table 6, several important facts emerge. First, the negative sign of economic complexity in relation to carbon emissions was statistically significant in all approaches, in line with [24,39], but different from [66] findings, which could be explained by the inclusion of additional countries in the panel with lower levels of economic complexity, such as Russia or Turkey. This result underlines the important impact of complex, innovation-driven products developed and commercialized by a country on its sustainable development. High and greener technologies are needed to produce these kinds of products, which positively influence environmental quality.

Further, these results can be linked with the direction of the impact of economic growth (measured by GDP per capita) on carbon emissions, which differs from the ECI sign. This can be explained by the fact that overall economic activity increases CO_2 emissions, and being based on different kinds of technologies, it is not entirely cleaner. Also, economic growth is driven by all sources of economic activities, including industrial and agricultural ones, known as pollution sources, which is in line with [48] results.

Stakeholders should consider these results, as new policies need to be set for development, and structural economic changes should be determined to fit the development path with a more sustainable perspective.

The effect of renewable energy consumption was found to be negative, in line with [30] for Australia and with [40] for emerging countries in Europe and Asia. In this sense, a unit increase in renewable energy reduces carbon emissions by 0.422% (CCR), 0.426% (FMOLS), and 0.341% (DOLS). This can be explained by minimizing pollution levels of energy from solar, wind, water, or other renewable sources. Enlarging the share of renewables in the energy mix will result in lower levels of carbon emissions and an improvement in environmental quality. The alignment of our results with other studies proves that the central point of decarbonization is strongly connected to the intensity of using renewable energy at industrial, firm, and household levels.

Additionally, the urbanization process required by the specific countries analyzed in the panel on their path to development has a positive effect on carbon emissions. Thus, considering our methodologies, a unit increase in URB will lead to an increase of 1.225%, 1.224%, and 1.235% in carbon emissions. According to these three different approaches, these findings are in line with [1,72–74] and can be explained by the process specificity per se. In this sense, a larger number of people will increase the demand for transportation services and employment in different energy-intensive sectors, such as construction, waste generation, and water availability, besides its positive impact (economic growth and development, increased educational opportunities, health services, and other welfare-related features).

The results have significant reverberations from an economic point of view. In this sense, emerging states must adopt a development model based on environmentally friendly technologies while improving the potential of meeting the fundamental needs of their citizens in a "no one being left behind" philosophy. Evolving strongly connected to the energy transition path and net-zero targets, and being aware of the harmful potential of climate change, will increase their resilience and improve their competitive capacity and ability to adapt to future challenges rapidly. Further development and urbanization should be built on greener and smarter strategies; therefore, public transportation optimization, improvements in waste management processes, and reducing fossil fuel-based activities must be considered. As [53] recently highlighted, innovative waste management could diminish environmental damage by using municipal solid waste as a renewable energy source, for example.

The homogeneity of the analyzed countries, all ex-communist states with similar backgrounds and perspectives, enhanced the potential of our study results. Furthermore, their status as European Union countries will properly guide Bulgaria, the Czech Republic, Hungary, Poland, and Romania's path to decarbonization. Specific but commune policies will govern the sustainable development of these countries.

3.3. Robustness Tests

To test the robustness of our analysis, we employed the Driscoll–Kraay estimator, addressing problems related to cross-sectional dependency or heteroscedasticity.

The results shown in Table 7 are in line with the main estimation methods utilized above. Thus, the negative sign of renewable energy consumption and economic complexity was confirmed, as well as the positive signs for urbanization and economic growth. All estimators are statistically significant, with lower levels for estimates in Driscoll–Kraay estimation.

Table 7. Robustness check.

Variable	Driscoll–Kraay
REN	−0.3636167 *** (0.0327409)
URB	1.252701 *** (0.0205278)
GDP	0.6379311 *** (0.1437608)
ECI	−0.3646452 *** (0.0804456)
Constant	−6.666599 *** (1.051817)
R^2	0.932

Note: REN = Renewable energy consumption; URB = Urbanization; GDP = Economic growth; ECI = Economic complexity index. Standard errors in parentheses; *** $p < 0.01$.

4. Conclusions

This study investigated the impact of the economic complexity index on environmental degradation in several emerging European countries during 1995–2021. Additionally, factors such as renewable energy consumption, urbanization, and economic growth have been evaluated as control variables in our models. The study used a triple primary investigation methodology (CCR, FMOLS, DOLS) and a superior results robustness check (Driscoll–Kraay estimator).

The most relevant results of this research highlight the negative sign of ECI and REN in connection with carbon emissions in selected European countries. As such, a higher economic complexity index in these countries has beneficial effects on sustainable development. More innovative, complex, and technology-based products create the context for cleaner development, with less pressure on the environment. This is also correlated with another result related to the estimated sign of renewable energy consumption, which is also found to be negative in relation to environmental degradation. Thus, the ambitious European Commission plans for energy transition are a good tool to increase the usage of renewable energy and limit the pollution generated by producing and using dirty energy. Additionally, energy efficiency increases and interconnected energy systems will become increasingly important for a proper energy transition.

Moreover, the impact of economic growth and urbanization on carbon emissions was found to be harmful. An increase in urbanization is responsible for environmental degradation in selected countries, which is explained by the rapid consumption of resources, the increase in transportation needs, and waste generation. In this sense, local stakeholders must identify methods for diminishing the impact by implementing smart mechanisms for urban transportation, policies and technologies for waste management, and rational strategies for resource usage. Economic growth, the main objective of emerging economies, must be warranted by clean technologies, proper environmental norms, and a more intense understanding among citizens about the importance of their environmental impact.

The conclusions of this study highlight the importance of decoupling nations' growth from fossil fuels and environmentally damaging behaviors. Adopting technology for innovative products with a small ecological footprint and enhancing the usage of renewable energy sources should become the normal for all stakeholders.

This study's limitations and further directions could be considered as follows: while considering CO_2 emissions to capture environmental degradation, a broader variable to be used in future studies could be the ecological footprint, considering various aspects besides carbon emissions. Furthermore, considering a longer period or enlarging the cross-sections could be additionally explored to enhance knowledge in this matter. Also, exploring the impact of different kinds of renewable energy sources could be analyzed in future studies.

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Do Structural Transformations in the Energy Sector Help to Achieve Decarbonization? Evidence from the World's Top Five Green Leaders

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Abstract: The purpose of this study is to examine the role of structural transformation in the energy sector to accelerate the decarbonization process in the world's top five green leaders, Germany, Canada, Sweden, Denmark, and Poland. To test this empirically, we collected annual data from a panel of the top five green leaders from 2000–2023. A key contribution of our study lies in assessing multiple critical metrics, including CO_2 emissions, carbon intensity, carbon intensity of electricity, production-based carbon emissions, and consumption-based carbon emissions, to capture holistic progress towards carbon neutrality. We applied the augmented mean group (AMG) model to estimate the long-term results. The Dumitrescu–Hurlin test is used to test the causal relationship among the modeled variables. The findings of the AMG model reveal that renewable energy production and consumption significantly reduce CO_2 emissions, production-based CO_2 emissions, consumption-based CO_2 emissions, carbon intensity, and the carbon intensity of electricity. Conversely, fossil-fuel-derived energy exacerbates these metrics. However, the impact of these energy sources varies by country in terms of their magnitude. The outcomes of the Dumitrescu–Hurlin test indicate that a bidirectional causality exists between renewable energy production and CO_2 emissions and between renewable energy consumption and carbon intensity. However, a unidirectional causality exists between fossil fuel consumption and CO_2 emissions and between renewable energy consumption and the carbon intensity of electricity. Our results indicate the detrimental impacts of continued fossil fuel use and conclude that a structural transformation in the energy sector is critical to decarbonization. Based on our results, we suggest that policy efforts should prioritize structural reforms in the energy sector by emphasizing a shift towards renewable energy sources. Such reforms are essential for achieving net-zero carbon emissions and mitigating broader environmental degradation.

Keywords: renewable energy; fossil-fuel-derived energy; COP-28; decarbonization; green leaders

1. Introduction

In the contemporary era, the drive for rapid industrialization has led to a rise in significant environmental challenges. The expansion of economic and industrial activities necessitates an increased demand for energy that is predominantly met through the combustion of fossil fuels [1]. The excessive reliance on fossil fuels has resulted in unprecedented levels of greenhouse gases (GHGs) in the atmosphere. Evidence shows that nearly 78% of the total increase in GHGs is due to burning fossil fuels during industrial activities [2]. Moreover, global CO_2 emissions have risen by approximately 1.5% per year as a result of fossil fuel combustion [3]. This dramatic increase in global CO_2 poses severe threats to the global ecosystem, and its consequences are starkly dire, manifesting in the form of climate change and global warming. The Intergovernmental Panel on Climate Change (IPCC) has warned that without significant reductions in greenhouse gas emissions, the world is on track to surpass 1.5 °C of global warming by as early as 2030 [4]. This would hinder economic stability and growth, increase socio-economic disruptions, intensify extreme weather events, and threaten the survival of future generations.

Recognizing the severe impact of these environmental problems, governments around the globe have decided to address these issues through collaborative efforts. A notable example of such collaborative efforts is the Paris Agreement (COP-21), which brought environmental concerns to the forefront of global policy discussions. In this agreement, the importance of achieving decarbonization was first recognized as a crucial step in addressing ongoing environmental challenges. The signatory states of COP-21 set ambitious targets aimed at achieving decarbonization. They pledged to limit the global temperature rise to well below 2 °C. However, despite this, countries have failed to meet these decarbonization targets. The primary reason for this failure has been the inability to significantly reduce dependency on fossil fuels [5]. In response to the shortcomings of the Paris Agreement, new agendas and targets have been set in subsequent international conferences. The latest of these conferences is COP-28, which was held under the United Nations climate conference on 30 November 2023, in the UAE. Importantly, COP-28 marked a pivotal moment in the global climate effort by setting a new agenda to achieve decarbonization. This conference concluded with a decisive call for a "Transition away from Fossil Fuels" to achieve decarbonization by the end of 2050. In light of this call, the signatory states of COP-28 pledged to make a structural transformation in the production and consumption of energy. The signatories committed to reducing dependency on fossil fuels and increasing renewable energy production to at least 11,000 GW by 2030 [6].

It is worth mentioning that the success of the COP-28 largely depends on structural transformation in the energy sector. In light of commitments made at COP-28, transitioning away from fossil fuels to renewable energy sources is not merely optional but essential for achieving decarbonization. Academic practitioners have concluded that without a structural shift in the production of energy, the ambitious targets of achieving net-zero carbon emissions set by COP-28 will remain out of reach [7]. Undoubtedly, fossil fuels have long been recognized as a critical engine for promoting economic growth. However, they are now recognized as the biggest contributor, resulting in devastating effects on the environment. The continuous use of fossil fuels generates significant negative externalities, hinders sustainable economic progress, and exacerbates environmental challenges [8]. In contrast, the transition from fossil-fuel-based to renewable energy offers numerous benefits that drive economic growth and provide viable solutions to combat climate change. Renewable energy sources are far less carbon-intensive and produce significantly fewer greenhouse gases [9]. They also decouple the negative externalities from the production process and accelerate the transition towards a carbon-free economy. Hence, it becomes increasingly urgent to transit from fossil-fuel-based energy to renewable energy to achieve the carbon neutrality target.

1.1. Research Gap

Undoubtedly, the literature is enriched with several studies that have examined the impact of renewable and non-renewable energy on CO_2 under various contexts. Earlier studies documented that a reduction in CO_2 emission is a road map to accelerating the decarbonization process. However, whilst reducing CO_2 emissions is a necessary condition, it is not sufficient to meet the targets of carbon neutrality or decarbonization. CO_2 serves merely as an indicator of environmental pollution [10]. The mere reduction in CO_2 does not guarantee progress towards a carbon-free economy. Achieving carbon neutrality requires a comprehensive approach, encompassing not only a reduction in overall carbon emissions but also a decrease in carbon intensity [11]. The existing literature frequently neglects this dual focus, which is essential for a more accurate and holistic understanding of the effectiveness of renewable energy in achieving carbon neutrality.

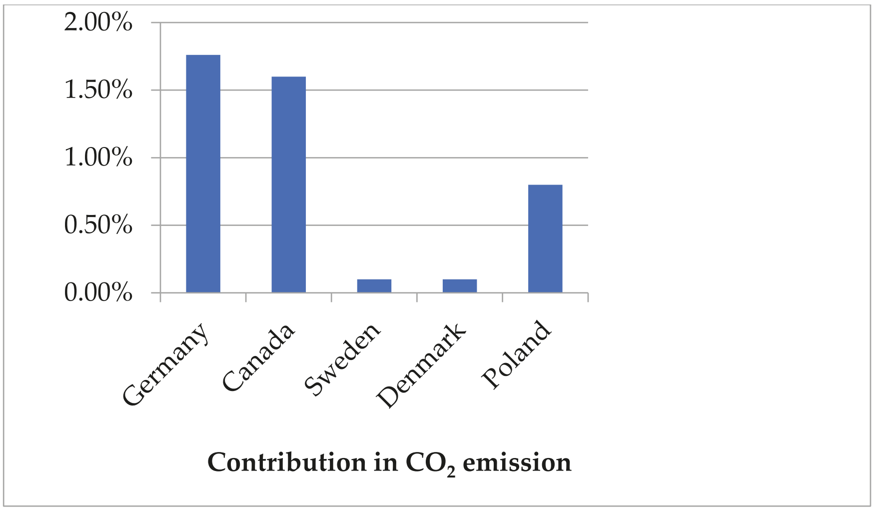
Another limitation in the existing literature is that most researchers have focused on renewable energy consumption when investigating its impact, with only a few considering renewable energy production. It is important to acknowledge that overall carbon emissions encompass both consumption-based and production-based CO_2 emissions. In this context, discussions centered on production attribute emissions to production-based categories, while discussions centered on consumption attribute emissions to consumption-based categories. Although the impact of renewable energy on overall carbon emissions has been thoroughly explored, there is a substantial void in studies specifically examining its effects on production-based and consumption-based CO_2 emissions. Additionally, while many studies have extensively analyzed the influence of renewable and non-renewable energy consumption on carbon emissions, a significant gap remains in the literature regarding the simultaneous evaluation of their effects on various metrics, including total CO_2 emissions, consumption-based CO_2 emissions, production-based CO_2 emissions, carbon intensity, and the carbon intensity of electricity. Therefore, to truly assess whether the transition towards renewable energy genuinely contributes to achieving decarbonization, it is imperative to analyze the impact of renewable energy on the environment from multiple perspectives.

1.2. Contributions and Significance

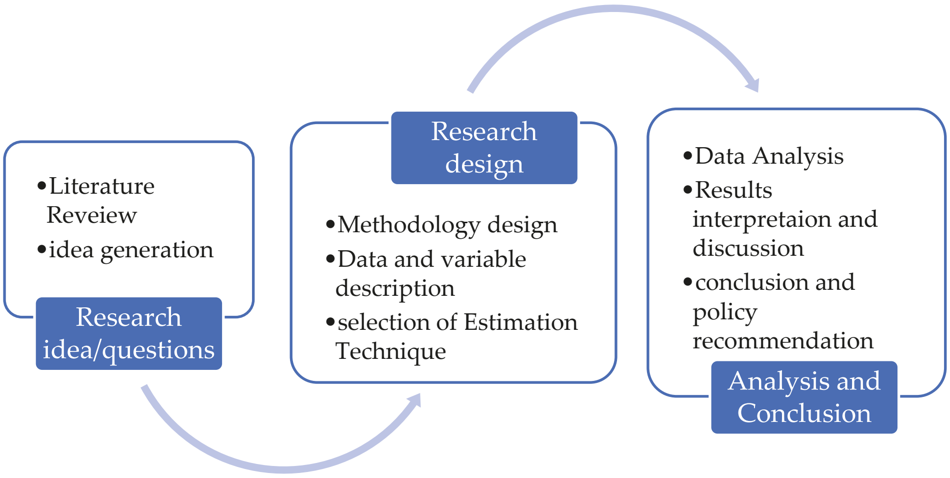
Against this backdrop, our study makes a momentous contribution to the existing body of knowledge. Unlike previous studies, which have primarily focused on carbon emissions, our study adopts a holistic approach by considering various critical metrics, including CO_2 emissions, carbon intensity, carbon intensity of electricity, production-based carbon emissions, and consumption-based carbon emissions. Moreover, our study goes beyond the common focus on renewable energy consumption and also incorporates renewable energy production into our analysis. This dual focus offers a more complete picture of the renewable energy sector's impact on the achievement of decarbonization targets. A distinctive aspect of our study is its focus on the world's top five green leaders. Our study also conducts a detailed cross-country comparison of these top five green leaders. By achieving this, our study evaluates whether the structural transformations in energy policy proposed at COP-28 are effective in achieving decarbonization. The outcomes of our study are particularly relevant to the targets set at COP-28. By evaluating the policies and structural changes implemented by leading green nations, our study assesses the true efficacy of these measures in achieving decarbonization. The findings of our study set a new standard by demonstrating that achieving decarbonization requires not only reducing carbon emissions but also addressing carbon intensity. The insights from our study are expected to be instrumental in assisting policymakers and targeted policy decisions for achieving decarbonization.

1.3. Rationale of the Study

Notably, examining the top five green leaders is crucial for several reasons. Firstly, these countries or regions are often at the forefront of implementing innovative policies and technologies aimed at reducing carbon emissions and enhancing sustainability [12]. The contributions of top five green leaders in terms of global CO_2 emissions is presented in the follow bar graph, which indicates that in 2023, the contributions of Germany, Canada, Sweden, Denmark, and Poland to global CO_2 emissions were 1.7%, 1.6%, 0.1%, 0.1%, and 0.8%, respectively.



Their pioneering efforts serve as models for other nations. Secondly, these leaders are prominent signatories of the COP conferences and are heavily invested in efforts to achieve decarbonization, often setting ambitious targets and spearheading international climate initiatives [13]. Their commitments and actions are instrumental in driving global progress toward climate goals. Thirdly, by studying these leaders, we can identify best practices and benchmark strategies that have proven effective in achieving significant reductions in carbon emissions and improvements in carbon intensity. This knowledge can be disseminated globally to assist other nations in adopting similar successful practices. Fourthly, green leaders often have more comprehensive and reliable data on their environmental policies and outcomes, making them ideal subjects for in-depth analysis. By analyzing the top green leaders, we can understand the challenges and successes they have encountered, providing valuable lessons that can be applied to other countries striving to meet their decarbonization goals. The flowchart of this study's steps and structure is described in figure below.



Steps and Structure of the Study

The steps and structure of the study indicate that in Section 2, this study reviewed the existing literature to develop idea and research question. In Section 3, this study described the methodology design, variable description and data sources, and discussed the criteria to select estimation technique. Furthermore, in the last section analysis and conclusion, this study provided results, their interpretation, and discussion. Study also provided conclusion based on discussion and policy suggestion based on conclusions.

2. Literature Review

2.1. Fossil-Fuel-Based Energy and Decarbonization

The literature is populated with several studies that have documented that the consumption and production of fossil-fuel-derived energy is a detriment to environmental quality (EQ) and hinders efforts to achieve carbon neutrality targets. For instance, Zeng and Stringer [14] conducted their research on 98 countries to examine the impact of fossil-fuel-derived energy on CO_2. Their research revealed that the combustion of fossil fuels during the energy production process significantly raises CO_2 levels. Li and Haneklaus [15] worked on similar lines in the context of China and revealed similar findings. Their research showed that a 1% increase in fossil fuel use per capita results in a 0.352% rise in CO_2 emissions per capita in the long term. Abbasi and Shahbaz [16] showed that a dependency on coal, oil, and natural gas hinders efforts to mitigate climate change by increasing levels of CO_2.

Yi and Abbasi [17] tested the impact of renewable and non-renewable energy on the EQ of the U.S. Their research showed a positive impact of renewable energy and a negative impact of non-renewable energy on EQ. The authors concluded that the continued use of fossil fuels is a significant obstacle to achieving carbon neutrality goals. However, a reliance on renewable energy sources helps to achieve decarbonization. Zimon and Pattak [18] documented the same. Their research showed that a reliance on fossil fuels in the industrial sector significantly contributes to CO_2 emissions and makes decarbonization targets harder to achieve. Bukhari and Pervaiz [19] also concluded the same. The authors showed that a dependency on non-renewable energy sources, i.e., oil, gas, and coal, is a detriment to environmental quality. The authors found that the continued use of fossil fuels significantly contributes to increased CO_2 emissions and other pollutants, which further exacerbate environmental challenges. Hou and Lu [20] investigated the environmental impacts of fossil fuel use in the context of OECD economies. Their research showed a strong positive correlation between fossil fuel consumption and CO_2 emissions. Their study concluded that a persistent reliance on oil, coal, and natural gas for energy production continues to elevate GHG emissions, which will hinder global efforts to achieve carbon neutrality targets.

Madaleno and Nogueira [21] investigated the impact of energy consumption patterns on 56 developed and developing economies. The findings of their study showed that countries with a higher reliance on fossil fuels experience greater environmental degradation and higher CO_2 emissions. Their study concluded that fossil fuel dependency poses significant challenges to environmental sustainability. Ahmed and Kousar [22] conducted their research in the context of South Asia and revealed similar findings. Their study showed that a dependency on non-renewable energy is significantly associated with elevated levels of CO_2. However, a reliance on renewable energy sources reduces the level of CO_2 emissions, promotes green economic growth, and helps to achieve decarbonization. Omri and Saadaoui [23] carried out similar research in the context of France and showed that an increase in fossil fuel consumption directly correlates with a rise in CO_2 emissions. Their study highlighted that fossil fuel reliance hampers efforts to achieve decarbonization. Dar and Asif [24] also showed that a dependency on fossil-fuel-derived energy hinders efforts to achieve carbon neutrality targets.

Summing up, a synthesis of the reviewed literature indicates that using fossil-fuel-derived energy is counterproductive to achieving carbon neutrality targets. The existing studies collectively call for a transition from fossil-fuel-derived energy to renewable energy sources.

2.2. Renewable Energy and Decarbonization

The literature contains several studies that have demonstrated that the consumption and production of renewable energy is propitious for EQ and helps to accelerate efforts to achieve decarbonization and carbon neutrality targets. For instance, Zhao and Wang [25] conducted their research across 78 global economies to examine the impact of renewable energy on CO_2 emissions. Their findings revealed that increasing the share of renewable energy in the energy mix leads to a significant reduction in CO_2 emissions. Ref. [26] performed a similar analysis in the context of Australia and documented the favorable role of renewable energy consumption in reducing CO_2. The authors concluded that a transition towards renewable energy sources is crucial for achieving decarbonization targets. Usman [27] investigated the role of renewable energy in achieving carbon neutrality in G7 economies. Their study utilized panel data from 1995 to 2020 and found significant contributions of renewable energies towards reducing CO_2.

Madaleno and Nogueira [21] also documented the favorable impact of renewable energy on the reduction in carbon emissions and the achievement of carbon neutrality targets. Madaleno and Nogueira performed their research in the context of OECD economies. The findings of their study unveiled that the production of energy through renewable sources, supported by energy innovation [28], i.e., solar, wind, and hydro, helps in the abatement of CO_2 and promotes sustainability. Mirziyoyeva and Salahodjaev [29] conducted their research on highly globalized economies and showed that the production of electricity through renewable energy sources is vital to achieving carbon neutrality targets. Apergis and Kuziboev [30] investigated the impact of renewable and non-renewable energy consumption on the carbon emissions of Uzbekistan. The outcomes of their study unveiled that renewable energy consumption tends to reduce carbon emissions beyond a certain threshold and helps to achieve decarbonization targets. Kuldasheva and Salahodjaev [31] also provided empirical evidence that renewable energy is favorable for the EQ of rapidly urbanizing countries. Their study concluded that a dependency on renewable energy not only reduces CO_2 emissions but also decouples negative externalities from the production process and promotes sustainable growth.

Wang, Wen [32] stated that a dependency on renewable energy sources is an effective policy choice to lessen environmental problems and to promote sustainability in urban areas. Yi and Abbasi [17] showed that countries with a higher investment in renewable energy projects excel in terms of EQ. Awosusi and Ozdeser [33] performed their research on the top energy transition countries and showed that a transition from fossil fuels towards renewable energy sources is vital to limiting global environmental concerns. Zaho, Wang [34] showed that a transition towards cleaner energy sources is significantly associated with climate risk mitigation. Malcher and Gonzalez-Salazar [35] also showed that a transition towards renewable energy sources helps to curb CO_2 emissions and helps to achieve decarbonization. Kirikkaleli and Awosusi [36] further showed the favorable impact of renewable energy consumption on the reduction in carbon emissions. Raihan and Bari [37] conducted their research in the context of China and investigated the long-term and short-term impacts of renewable energy adoption on EQ. Their study unveiled that the adaptation of renewable energy could reduce CO_2 emissions by 1.39% in the long term and by 0.50% in the short term. Their study concluded that a transition towards renewable energy is a promising strategy to achieve carbon neutrality targets. Ding and Khattak [38] concluded the same. The authors stated that a transition towards renewable energy unlocks the potential to achieve decarbonization. Hence, in light of the existing literature, we postulate that the following:

H_1: *Reliance on renewable energy helps to achieve decarbonization and carbon neutrality targets, while reliance on fossil-fuel-derived energy hinders the process of decarbonization.*

Conclusively, this study found that the existing literature has mostly used CO_2 emissions to measure the concept of decarbonization. However, decarbonization is a complex and multidimensional phenomenon that requires a range of strategies aiming at reducing overall carbon footprints rather than just reducing CO_2 emissions. So, this study contributes to the existing literature by utilizing various critical metrics, including CO_2 emissions, carbon intensity, carbon intensity of electricity, production-based carbon emissions, and consumption-based carbon emissions to measure the concept of decarbonization. Moreover, the existing literature has examined the role of renewable energy consumption in terms of CO_2 emissions, while our study examined the role of renewable energy production along with renewable energy consumption to achieve the target of decarbonization.

2.3. Theoretical Foundations of the Study

The present study draws on the energy transition theory to examine the hypothesized relationships among the modeled variables relating to energy consumption and CO_2 emissions. This theory offers a crucial framework for understanding the necessary shifts in global energy sources. The theory posits that significant shifts in the energy structure are of utmost importance to meet rising energy demands and to reduce environmental impacts [39]. Evidence shows that the Industrial Revolution brought a transition from a biomass-based energy structure to a reliance on coal. This was subsequently followed by a gradual transformation from the use of coal to the use of oil and natural gas. However, each of these shifts introduced new environmental challenges, particularly related to increased carbon emissions [40]. The energy transition theory states that modern transitions need to focus on moving from using coal, oil, and natural gas to less carbon-intensive energy sources, such as wind, solar, and hydroelectric power, which are far less carbon-intensive [41]. Hence, the theory advocates for a systematic shift in energy sources to address the growing environmental challenges. It helps us to understand the potential environmental benefits of structural transformations in the energy sector. Therefore, building upon the premises of the energy transition theory, our study aims to examine the impact of both fossil fuels and renewable energy on environmental sustainability by employing various proxies. By achieving this, we aim to empirically test the theory's propositions. This investigation seeks to determine whether a shift from fossil fuels to renewable energy sources would mitigate environmental challenges and aid in achieving carbon neutrality targets. Accordingly, the conceptual framework of our study is presented in Figure 1.

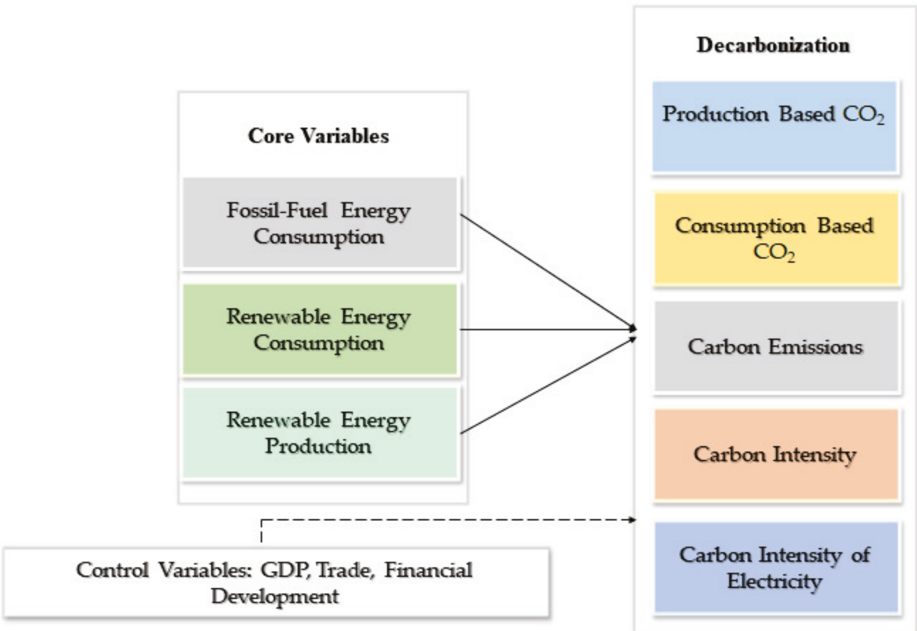


Figure 1. Conceptual framework of the study.

3. Methods and Data

The IPAT and STIRPAT Models

Ehrlich and Holdren introduced the IPAT approach in 1971 and highlighted the main determinants that affect the natural environment [42]. The IPAT equation is written as follows:

$$I = P \times A \times T \tag{1}$$

I represents the environmental growth rate, P represents the urban population growth rate, A represents prosperity, measured in GDP per capita, and T indicates technology. Based on the IPAT model, York and Rosa [43] developed the STIRPAT model with the same variables but introduced randomness to overcome the unit elastic assumption and introduced a modified equation as follows:

$$\mathrm{I} = \mathrm{a}\ P_i^b A_i^c T_i^d e_i \tag{2}$$

After taking the log, the equation will be transformed as follows:

$$\mathrm{LnI} = \mathrm{a} + \mathrm{b}\ (\mathrm{Ln}\ P_{it}) + \mathrm{c}\ (\mathrm{Ln}\ A_{it}) + \mathrm{d}\ (\mathrm{Ln}\ T_{it}) + e_i \tag{3}$$

In the above equation, i indicates the cross section (country), and t indicates a period varying between 2000 to 2023. Similarly, "a" represents a constant, e_i is the error term, and b, c, and d are estimated coefficients that indicate the size of the impact of P, A, and T on the natural environment. Moreover, based on the STIRPAT model, this study developed 5 models to determine the key impact factors of decarbonization as follows:

$$\mathrm{LnCBCO2} = \mathrm{a} + \mathrm{b}\ (\mathrm{Ln}\ P_{it}) + \mathrm{c}\ (\mathrm{Ln}\ A_{it}) + \mathrm{d}\ (\mathrm{Ln}\ REC_{it}) + \mathrm{e}\ (\mathrm{Ln}\ FFEC_{it}) + e_i \tag{4}$$

$$\mathrm{LnPBCO2} = \mathrm{a} + \mathrm{b}\ (\mathrm{Ln}\ P_{\mathrm{it}}) + \mathrm{c}\ (\mathrm{Ln}\ A_{\mathrm{it}}) + \mathrm{d}\ (\mathrm{Ln}\ REP_{it}) + \mathrm{e}\ (\mathrm{Ln}\ FFC_{it}) + e_i \tag{5}$$

$$\mathrm{LnCO2} = \mathrm{a} + \mathrm{b}\ (\mathrm{Ln}\ P_{\mathrm{it}}) + \mathrm{c}\ (\mathrm{Ln}\ A_{\mathrm{it}}) + \mathrm{d}\ (\mathrm{Ln}\ REC_{it}) + \mathrm{e}\ (\mathrm{Ln}\ REP_{it}) + \mathrm{f}(\mathrm{Ln}\ FFEC_{it}) + e_i \tag{6}$$

$$\mathrm{LnCI} = \mathrm{a} + \mathrm{b}\ (\mathrm{Ln}\ P_{\mathrm{it}}) + \mathrm{c}\ (\mathrm{Ln}\ A_{\mathrm{it}}) + \mathrm{d}\ (\mathrm{Ln}\ REC_{it}) + \mathrm{e}\ (\mathrm{Ln}\ REP_{it}) + \mathrm{f}(\mathrm{Ln}\ FFEC_{it}) + e_i \tag{7}$$

$$\mathrm{LnCIOE} = \mathrm{a} + \mathrm{b}\ (\mathrm{Ln}\ P_{\mathrm{it}}) + \mathrm{c}\ (\mathrm{Ln}\ A_{\mathrm{it}}) + \mathrm{d}\ (\mathrm{Ln}\ REC_{it}) + \mathrm{e}\ (\mathrm{Ln}\ REP_{it}) + \mathrm{f}(\mathrm{Ln}\ FFEC_{it}) + e_i \tag{8}$$

This study measured EI by utilizing 5 indicators of decarbonization, namely, CO_2 emissions, consumption-based CO_2 emissions, production-based CO_2 emissions, carbon intensity, and carbon intensity of electricity, while technology (T) represents the structural transformation in the energy sector, as measured by three main energy variables, namely, fossil fuel energy consumption, renewable energy consumption, and renewable energy production [44–46]. Moreover, urban population and economic growth are used as control variables.

The measurements of the variables and data sources are provided in Table 1.

Table 1. Measurements of variables.

Variable	Measurement	Notation	Data Source
Carbon Emissions	CO_2 emissions (kt)	CO_2	WDI
Consumption-Based Carbon Emissions	Metric tons of CO_2 emission	$CBCO_2$	Our World in Data
Production-Based Carbon Emissions	Metric tons of CO_2 emission	$PBCO_2$	Our World in Data
Carbon Intensity	Energy intensity or energy consumption per unit of GDP—kilowatt-hours per international unit	CI	Our World in Data
Carbon Intensity of Electricity	Carbon intensity of electricity production—grams of carbon emitted per kilowatt-hour	CIOE	Our World in Data
Fossil Fuel Energy Consumption	Fossil fuel energy consumption (% of total)	FFEC	WDI

Table 1. *Cont.*

Variable	Measurement	Notation	Data Source
Renewable Energy Consumption	Renewable energy consumption (% of total final energy consumption)	REC	WDI
Renewable Energy Production	Share of electricity generated by renewable power plants in total electricity generated by all types of plants	REP	WDI
Population	Urban population (% of total population)	URB	WDI
Gross Domestic Product	Constant, in 2015 USD	GDP	WDI

The value of the Jarque–Bera test in the descriptive statistics shown in Table 2 indicates that all series are normally distributed at less than a 5% level of significance. The correlation analysis indicates that PBCO2, CBCO2, CO_2, CI, and CIOE are strongly correlated because their correlation values are greater than 0.7, so five models were developed to examine the impact of the key factors on decarbonization. A heatmap of the correlation matrix is presented in Figure 2.

Table 2. Descriptive statistics and correlation analysis.

	PBCO2	**CBCO2**	**CO_2**	**CI**	**CIOE**	**FFEC**	**REC**	**REP**	**GDP**	**URB**
Mean	19.10	19.28	12.10	−1.27	5.63	4.20	2.89	3.31	27.34	78.17
Maximum	20.63	20.80	13.65	−0.03	6.86	4.57	4.07	4.41	28.91	88.49
Minimum	17.16	17.57	7.62	−2.40	3.66	3.22	1.18	0.41	26.26	60.04
Std. Dev.	1.25	1.11	1.31	0.52	1.04	0.40	0.67	1.01	0.91	9.50
Jarque–Bera	1.99	2.22	5.45	1.97	2.96	3.42	2.73	2.42	3.03	1.77
Correlation Analysis										
PBCO2	1									
CBCO2	0.99	1								
CO_2	0.93	0.929	1							
CI	0.66	0.584	0.62	1						
CIOE	0.48	0.409	0.43	0.67	1					
FFEC	0.71	0.535	0.57	0.77	0.94	1				
REC	−0.64	−0.600	−0.60	−0.53	−0.45	−0.51	1			
REP	−0.34	−0.292	−0.30	−0.62	−0.20	−0.55	0.44	1		
GDP	0.80	0.851	0.76	0.12	0.08	0.21	−0.27	0.12	1	
URB	0.59	0.540	0.53	0.55	0.94	0.13	−0.37	−0.52	0.31	1

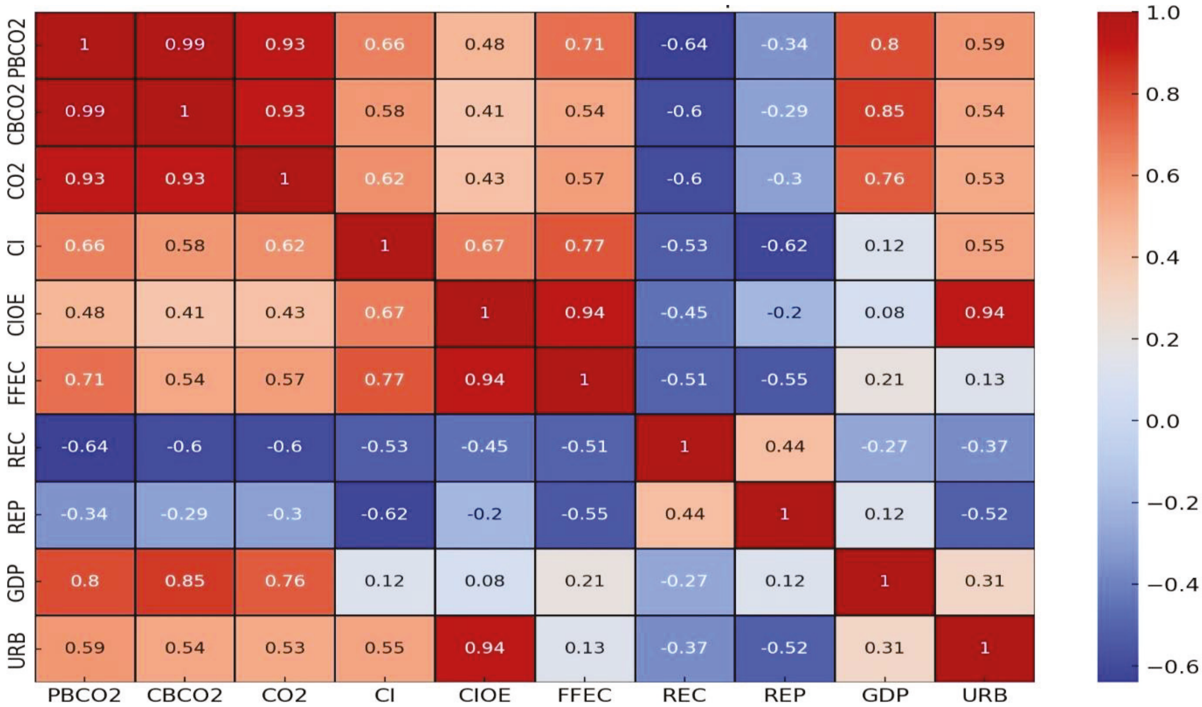


Figure 2. Correlation heat map.

4. Steps Involved in Empirical Estimation of the STIRPAT Model

This study estimates the STIRPAT model by following four steps, namely, the cross-section dependence test, unit root test, co-integration test, and cross-sectional autoregressive distributive lag model. The cross-section dependence test is used to check whether any shock in one country will have an impact on other cross-sections or not. If cross-section dependence exists, the second-generation unit root test is used to test the stationarity of the series. Moreover, if the variables are stationary in a mixed order, a co-integration test is used to find the long-term co-integration among the modeled series. In addition, the augmented mean group (AMG) estimator is used to produce the long-term estimates. A methodological flowchart of this study is presented in Figure 3. It is worth mentioning that we transformed all the variables into their natural logarithmic forms to obtain more accurate results.

4.1. Cross-Sectional Dependence

Checking for cross-sectional dependence is necessary to obtain reliable results in panel data analysis [47]. Cross-sectional dependence might be caused by geographic location and interactions of socioeconomic networks within the cross-section [48]. Cross-sectional dependency refers to a situation where one unit within the panel experiences a shock or change; it can affect the other units as well. This study utilized the Pesaran CD test to check for the existence of cross-sectional dependence in the panel series based on following Pesaran CD equation.

$$\mathrm{CD} = \sqrt{2T/N(N-1)} \quad \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij}\right) \tag{9}$$

The Pesaran CD test assumes the null hypothesis that no cross-sectional dependence exists. Moreover, for fixed values of N (cross-sections) and T (time), the CD statistics have a mean of exactly zero for homogeneous/heterogeneous dynamic models and even for non-stationary models.

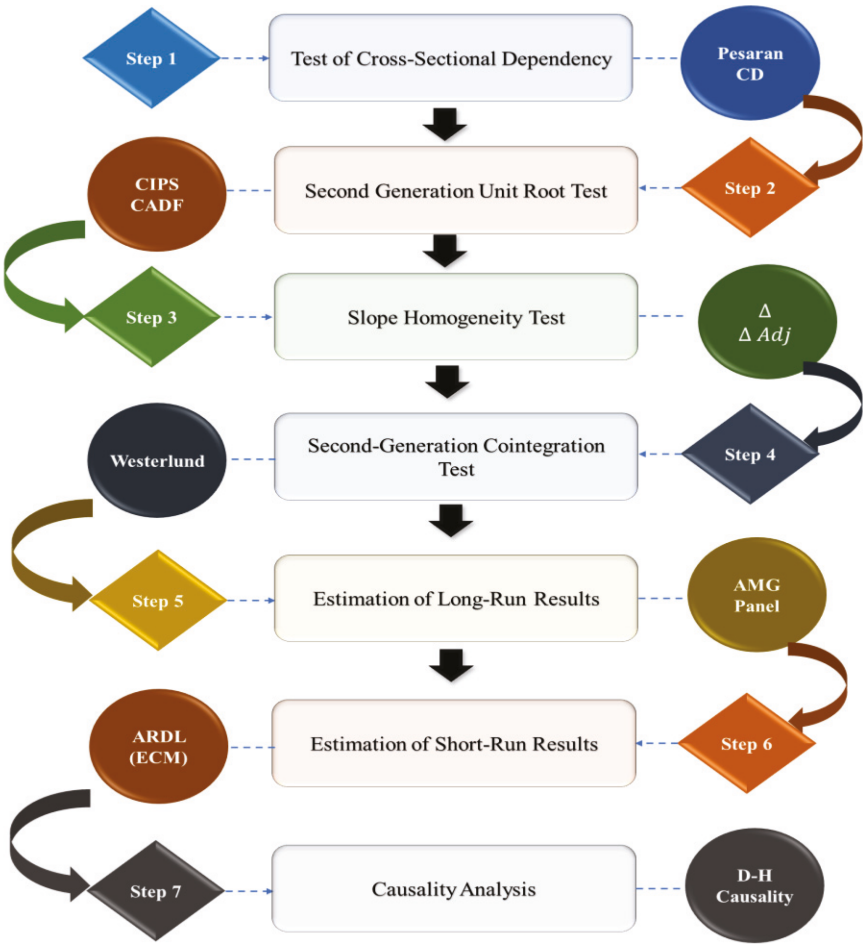


Figure 3. Methodological flowchart.

4.2. Second-Generation Unit Root Test

First-generation unit root tests such as those by Levin and Lin [49]; Hadri [50]; and Maddala and Wu [51] become inefficient when cross-sectional dependence exists in panel data. So, in the presence of cross-sectional dependence, second-generation unit root tests such as CADF and CIPS become necessary. These second-generation tests are designed to control cross-sectional dependency and produce more accurate results in the presence of correlated errors across panel units. Thus, the choice between first- and second-generation unit root tests depends crucially on whether cross-sectional dependency is present in the panel data being analyzed or not. The CADF test is a second-generation unit root test; it produces strong results when the period is greater than the cross-section. It was developed by Pesaran [52] and uses the Monte Carlo simulation method to calculate the critical values. Moreover, the CADF test is used to test unit roots for every unit-forming panel and for the panel itself. The CADF statistics are based on the following equation:

$$\Delta Y_{it} = \propto_i + b_i\, Y_{i,t-1} + \sum\nolimits_{j=1}^{pi} c_{ij}\, Y_{i,t-1} + d_i \mathrm{t} + h_i\, Y_{t-1} + \sum\nolimits_{j=0}^{pi} \sigma_{ij}\, \Delta Y_{t-1} + \in_{i,t} \tag{10}$$

This equation assumes the null hypothesis that the series has a unit root. $\propto_i$ indicates a constant, $\in_{i,t}$ is an error term, t is a trend, Y_{t-1} is the lag of the difference, and ΔY_{it} is the one-term lag of Y_t.

Similarly, the CIPS unit root test is an augmented form of the IPS unit root test. It includes cross-sectional averages of the series under consideration and helps to account for potential cross-sectional dependence among the units in the panel. The statistics of the CIPS test are based on the following equation,

$$\text{CIPS} = \sum_{i-1}^{N} \sum_{t=1}^{T} p_{it} / \sqrt{T} / \sqrt{N} \tag{11}$$

where T is time and N is the cross-section, while p_{it} indicates the estimated autocorrelation of Y_{it} .

4.3. Panel Co-Integration Tests

Due to cross-sectional dependence, traditional co-integration tests like those by Kao [53] and Pedroni [54] may produce biased results. So, to obtain unbiased and robust estimates, this study adopted the Westerlund [55] panel error correction cointegration test to find the long-term relationships among the modeled variables

Westerlund Co-Integration Test

The Westerlund error-correction-based co-integration test was developed by Westerlund [55]; the test is good and efficient in cases of the existence and non-existence of cross-sectional dependence. Moreover, this test produces reliable results even in small samples. The Westerlund panel produces model statistics based on panel-specific AR and the same AR based on the following equations.

$$\text{VR} = \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{E_{it}^{2}} \hat{R_{i}}^{-1} \tag{12}$$

$$\text{VR} = \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{E_{it}^{2}} \left(\sum_{i=1}^{N} \hat{R_{i}} \right)^{-1} \tag{13}$$

4.4. Panel Long-Term Parameter Estimates

After the confirmation of long-term co-integration, this study employed a dynamic common correlated model to estimate the long-term estimates.

4.4.1. Augmented Mean Group (AMG) Estimator

Traditional panel data techniques are unable to produce reliable long-term estimates in the presence of cross-sectional dependence and slope heterogeneity, as shown by Wang and Dong [56]. However, second-generation panel data methodologies like the augmented mean group (AMG) estimation technique developed by Eberhardt and Bond [57] and Eberhardt and Teal [58] are appropriate for producing reliable and robust estimators in the presence of cross-sectional dependence and slope heterogeneity. The AMG technique utilizes a common dynamic effect coefficient to address CSD. The AMG technique is performed by following two steps; in the first step, estimators are obtained based on the following equation:

$$\Delta Y_{it} = \alpha_i + \beta_i \Delta X_{it} + \delta_i f_i + \sum_{t-2}^{T} \pi_i \, \Delta D_i \, + \in_i \tag{14}$$

In the second stage, the AMG estimators are based on the following equation:

$$\hat{\beta}_{AMG} - \text{N} \sum_{i-1}^{N} \hat{\beta_i} \tag{15}$$

α_i is a constant term, $\in_i$ is an error term, Y_{it} and X_{it} are the dependent and independent variables, Δ is the initial difference operator, f_i is a common latent component with a heterogeneous slope factor, π_i represent time dummy coefficients, and $\hat{\beta}_{AMG}$ is the group mean estimator.

4.4.2. Error Correction Model for Short-Term Estimates

This study also estimated the short-term coefficients/elasticity of the decarbonization variable concerning changes in P, A, REC, REP, and FD. This study utilized the ECM to calculate the short-term estimates of these short-term impacts, as earlier utilized by

Mimi [59]. This study estimated the short-term estimates by using the following ECM equation.

$$\text{Ln}\Delta\text{CBCO}_2 = \text{a} + \gamma_1\Delta(\text{Ln } P_{it}) + \gamma_2\Delta((\text{Ln } A_{it}) + \gamma_3\Delta((\text{Ln } REC_{it}) + \gamma_4\Delta((\text{Ln } FFEC_{it}) + \gamma_5\text{ECM} + e_i \quad (16)$$

$$\text{Ln}\Delta\text{PBCO}_2 = \text{a} + \sigma_1\Delta\ ((\text{Ln } P_{it}) + \sigma_2\Delta\ (\text{Ln } A_{it}) + \sigma_3\Delta\ (\text{Ln } REP_{it}) + \sigma_4\Delta\ (\text{Ln } FFEC_{it}) + \ \sigma_5\ \text{ECM} + e_i \quad (17)$$

$$\text{Ln}\Delta\text{CO}_2 = \text{a} + \varphi_1\Delta\ (\text{Ln } P_{it}) + \varphi_2\Delta\ (\text{Ln } A_{it}) + \varphi_3\Delta\ (\text{Ln } REC_{it}) + \varphi_4\Delta\ (\text{Ln } REP_{it}) + \varphi_5\Delta\ (\text{Ln } FFEC_{it}) + \ \varphi_6\ \text{ECM} + \ e_i \quad (18)$$

$$\text{Ln}\Delta\text{CI} = \text{a} + \psi_1\Delta\ (\text{Ln } P_{it}) + \psi_2\Delta\ (\text{Ln } A_{it}) + \psi_3\Delta\ (\text{Ln } REC_{it}) + \psi_4\Delta(\text{Ln } REP_{it}) + \psi_5\Delta(\text{Ln } FFEC_{it}) + \ \psi_6 ECM + e_i \quad (19)$$

$$\text{Ln}\Delta\text{CIOE} = \text{a} + \pi_1\Delta\ (\text{Ln } P_{it}) + \pi_2\Delta\ (\text{Ln } A_{it}) + \pi_3\Delta\ (\text{Ln } REC_{it}) + \pi_4\Delta\ (\text{Ln } FFC_{it}) + \pi_5\Delta\ (\text{Ln } FFEC_{it}) + \pi_6\ \text{ECM} + e_i \quad (20)$$

$\gamma_{1,\ldots4}$, $\sigma_{1,\ldots4}$, $\varphi_{1,\ldots5}$, $\psi_1, \ldots \psi_5$, and $\pi_{1,\ldots5}$, while the e_i terms are error terms. Similarly, γ_5, σ_5, φ_6, ψ_6, and π_6 are error correction terms.

4.5. Dumitrescu–Hurlin (D-H) Panel Non-Causality Test

After investigating the long-term estimates, this study utilized the D-H panel non-causality test developed by Dumitrescu and Hurlin [60] because the traditional causality test, the Engle–Granger causality, is unable to account for slope heterogeneity. The D-H panel non-causality test accounts for slope heterogeneity and CSD and produces reliable and efficient results. The D-H test is a robust causality test based on the individual non-causality Granger [61] and Wald test statistics estimated through averaging across individual cross-sections. The D-H test estimates panel non-causality against the null hypothesis, i.e., there is no causality among the modeled variables, by using the following equation:

$$Y_{it} {=} \propto_i {+} \sum\nolimits_{j=1}^{j} \delta\ Y_{i,*t-j)} {+} \sum\nolimits_{j=0}^{j} \eta\ \ Xi\big(_{t-1}\big) + \in_{i,t} \quad (21)$$

X and Y are observable variables, while δ and η are autoregressive coefficients that are subject to fluctuation across each cross-section. Moreover, this study estimated the Wald statistics based on the following equation:

$$\hat{W_{N,T}} {-} \text{N}^{-1} \sum\nolimits_{i-1}^{N} \hat{W_{i,t}}$$

$\hat{W_{N,T}}$ is used to represent the individual Wald test statistics for all individual cross-sections. A list of abbreviations is also provided in Appendix A (see Table A6).

5. Empirical Analysis for Panel Data

In the first step, this study checked for CSD through the Pesaran CD test, and the results of the Pesaran cross-sectional dependence are reported in Table 3, which shows that for all series, the p-value of the CD test was less than the 0.05% level of significance, so the null hypothesis, i.e., there is cross-sectional independence, is rejected. Thus, the CD statistics ensure that cross-sectional dependence exists in all series across the cross-sections. Therefore, in the second step, this study employed the second-generation unit root test, the cross-sectionally augmented Im–Pesaran–Shin (CIPS) test, and the cross-sectional augmented Dickey–Fuller (CADF) unit root test, which produce reliable results in the presence of CSD. The results of the CIPS and CADAF tests are reported in Table 3.

The results indicate that carbon intensity and FD were stationary at a level, while all the other variables, i.e., production-based carbon emissions, consumption-based carbon emissions, carbon dioxide emissions, carbon intensity of electricity, renewable energy consumption, renewable energy production, fossil fuel consumption, GDP, and URB, were stationary at the first difference.

In the third step, this study employed the slope homogeneity test and the Westerlund co-integration, and the results are reported in Table 4. The results of the slope homogeneity test state that slopes were heterogeneous across the cross-sections and the results of the Westerlund co-integration revealed that long-term co-integration existed in all five models at the 10% level of significance.

Table 3. Cross-sectional dependence and unit root test.

Pesaran (2004) Cross-Sectional Dependence Test			CIPS Unit Root Test		CADF Unit Root Test	
H_o: Cross-Sectional Independence			H_0: Homogeneous Non-Stationary			
			With constant		With constant and trend	
Variable	CD-test	*p*-value	Level	Difference	Level	Difference
PBCO2	7.48	0.000	−1.404	−4.898 ***	−1.655	−4.034 ***
CBCO2	7.30	0.000	−1.680	−5.735 ***	−1.470	−3.476 ***
CO_2	3.21	0.001	−0.032	−3.646 ***	0.231	−2.768 ***
CI	14.88	0.000	−2.765 ***		−2.360	−4.022 ***
CIOE	12.00	0.000	−2.378	−4.952 ***	−2.176	−3.434 ***
FFEC	7.44	0.000	−0.045	−3.952 ***	−1.146	−5.312 ***
REC	12.00	0.000	−1.862	−4.763 ***	−2.192	−3.109 ***
REP	13.88	0.000	−2.534	−4.662 ***	−2.306	−2.549 ***
GDP	14.78	0.000	−1.308	−3.163 ***	−2.142	−2.320 ***
URB	2.75	0.06	0.881	−4.106 *	0.346	4.529 *

Note: *** indicate the significance level at less than 1% while * indicate the significance at less than 5%.

Table 4. Slope homogeneity test and Westerlund co-integration.

Models	Slope Homogeneity Test		Westerlund Co-Integration	
			Variance Ratio	
	Δ	$\Delta Adj.$	Statistics	*p* Value
Model 1	6.04 *	7.02 *	−1.5263 **	0.0635
Model 2	7.069 *	8.223 *	−1.3110 **	0.0949
Model 3	7.405 *	8.613 *	−1.4921 **	0.0678
Model 4	4.533 *	5.272 *	1.3514 **	0.0883
Model 5	10.119 *	11.770 *	−1.5254	0.0636

Note: ** and * indicate significance level at less than 5% and 10% respectively.

After the confirmation of long-term co-integration in the five models, in the fourth step, this study employed the augmented mean group technique to estimate long-term estimators for the five models, while the ARDL error correction model was used to produce the error correction term and short-term estimates. The results of the AMG- and ARDL-based error correction models are reported in Tables 5–9. In the following section, this study aims to present and interpret the results model-wise.

Leading green economies are greatly committed to international agreements like the Paris Agreement, which sets targets for reducing greenhouse gas emissions. Leading green economies exert significant influence in global politics through the successful demonstration of decarbonization strategies, which can encourage other nations to follow suit and collaborate on global environmental goals. Thus, to check to what extent leading green economies are successful in their aim, this study investigated the key determinant of decarbonization in leading green economies. The results of the AMG test (long-term estimates) for the panel and individual cross-sections are reported in Table 5.

In model 1, the results indicated that fossil fuel energy consumption had a positive and significant impact on production-based CO_2 emissions in Canada (β = 1.65 *). Our results were consistent with Erdoğan et al., [62] who reported that although Canada is trying to transform its energy production process, it still heavily relies on fossil fuels for electricity generation, heating, transportation, and industrial processes [63]. Moreover, despite having substantial hydroelectric power, fossil fuels still play a key role in electricity generation, especially in provinces in Canada without abundant hydro resources.

Table 5. Augmented mean group (AMG) panel and full sample results; model 1.

IV	DV = $PBCO_2$					
	Panel	**Germany**	**Canada**	**Denmark**	**Poland**	**Sweden**
LOGFFEC	0.37 (0.50)	0.1 (0.22)	1.65 * (0.58)	0.03 (0.60)	−0.03 (0.09)	1.17 (−0.86)
LOGREP	−0.15 * (0.06)	−0.29 * (0.05)	−0.15 * (0.08)	0.18 (0.29)	−0.13 ** (0.06)	−0.07 * (0.03)
LOGGDP	0.74 * (0.17)	1.09 * (0.25)	0.89 * (0.24)	0.66 * (0.18)	0.2 (0.15)	0.73 * (0.13)
URB	0.07 * (0.03)	0.11 * (0.04)	0.12 * (0.05)	−0.04 * (0.02)	0.08 * (0.03)	0.05 * (0.02)
C	−6.88 (7.27)	−19.4 * (6.53)	−22.12 * (9.53)	8.54 (5.91)	8.1 (5.16)	−9.14 (5.29)
ARDL-based Error Correction Model (short-term estimates)						
ECM	−0.28 * (0.14)	−0.33 * (0.10)	−0.21 * (0.07)	−0.66 * (0.19)	−0.54 * (0.24)	−0.18 * (0.05)
ΔLOGFFEC	0.42 (0.26)	0.66 * (0.24)	−0.23 * (0.11)	−0.79 (0.55)	−0.07 (0.13)	1.28 (1.56)
ΔLOGREP	−0.36 * (0.10)	−0.37 * (0.06)	−0.21 (0.31)	−0.12 (0.27)	−0.13 (0.11)	−0.10 ** (0.05)
ΔLOGGDP	−0.45 * (0.10)	−0.32 (0.23)	0.03 (0.12)	0.27 (0.26)	−0.37 (0.32)	−0.68 ** (0.34)
ΔURB	−0.06 (0.06)	−0.15 (0.08)	1.72 (0.92)	−0.07 (0.09)	0.02 (0.12)	−0.22 (0.20)
C	−0.63 (0.61)	1.08 (2.21)	−0.21 (1.07)	16.53 (4.66)	2.46 (5.36)	−0.98 (1.11)

Note: standard errors are in (), while * and ** represent significance levels of less than 5% and 10%, respectively.

Table 6. Augmented mean group (AMG) full sample; model 2.

IV	DV = CBCO2					
	Panel	**Germany**	**Canada**	**Denmark**	**Poland**	**Sweden**
LOGFFEC	−0.49 (0.59	0.46 ** (0.24)	0.06 (0.54)	1.34 ** (0.69)	−0.07 (0.08)	1.80 ** (0.98)
LOGREC	−0.32 * (0.14)	0.13 (0.10)	−0.06 (0.05)	−0.64 * (0.21)	−0.24 * (0.09)	−0.24 * (0.08)
LOGGDP	0.36 (0.28)	0.82 * (0.16)	0.16 (0.19)	−0.64 * (0.19)	0.63 * (0.10)	0.46 * (0.07)
URB	0.02 (0.03)	−0.09 ** (0.05)	0.03 (0.04)	0.08 * (0.02)	0.01 (0.03)	0.01 (0.02)
C	3.55 (7.28)	1.34 (5.59)	13.67 (7.78)	39.48 * (6.72)	3.04 (4.04)	15.13 * (6.28)
ARDL-based Error Correction Model (short-term estimates)						
ECM	−0.24 * (0.13)	−0.27 * (0.11)	−0.25 * (0.06)	−0.33 * (0.10)	−0.26 * (0.11)	−0.69 * (0.37)
ΔLOGFFEC	0.01 (0.86)	1.46 * (0.71)	−1.43 (0.98)	−2.3 * (0.69)	0.02 (0.23)	2.29 (2.07)
ΔLOGREC	−0.04 (0.26)	0.62 ** (0.33)	0.31 * (0.12)	−0.92 * (0.33)	−0.1 (0.27)	−0.1 (0.14)
ΔLOGGDP	−0.93 (0.13)	−0.76 * (0.13)	−0.92 * (0.24)	−1.40 * (0.38)	−0.86 (0.53)	−0.68 (0.48)
ΔURB	−0.07 (0.06)	−0.15 (0.16)	−0.23 (0.14)	0.12 (0.11)	0.05 (0.21)	−0.12 (0.17)
C	−0.06 (0.09)	−0.4 (2.06)	0.04 (0.42)	0.01 (0.28)	0.09 (0.49)	−0.05 (4.55)

Note: standard errors are in (), while * and ** represent significance levels of less than 5% and 10%, respectively.

Table 7. Augmented mean group (AMG) full sample; model 3.

IV	DV = CO_2					
	Panel	**Germany**	**Canada**	**Denmark**	**Poland**	**Sweden**
LOGFFEC	−1.21 (0.69)	2.43 * (0.17)	2.2 (1.39)	−0.04 (0.58)	0.245 ** (0.13)	−19.69 (15.59)
LOGREC	−0.33 * (−0.04)	0.07 (0.05)	0.2 (0.22)	−0.39 * (0.19)	−0.06 (0.10)	−1.47 * (0.43)
LOGREP	−0.23 * (−0.11)	0.03 (0.11)	0.13 (0.09)	−0.81 * (0.17)	−0.458 * (0.17)	0.97 (0.91)
LOGGDP	0.06 (−0.44)	0.64 * (0.16)	0.19 (0.50)	0.75 * (0.13)	−0.291 (0.20)	−1.32 (1.61)
URB	−0.04 (−0.08)	0.04 (0.04)	−0.22 (0.12)	−0.04 * (0.01)	0.06 (0.07)	−0.72 * (0.28)
C	3.32 (−9.79)	−0.69 (5.29)	16.53 (20.09)	−0.04 (4.95)	15.979 (8.73)	19.93 (81.11)
ARDL-based Error Correction Model (short-term estimates)						
ECM	0.16 * (0.07)	−0.15 * (0.05)	−0.34 * (0.13)	−0.32 * (0.02)	0.451 * (0.015)	−0.13 * (0.022)
ΔLOGFFEC	−0.19 (0.76)	2.32 * (0.52)	−0.88 (0.70)	−2.39 * (0.67)	0.046 (0.205)	−0.055 (1.946)
ΔLOGREC	−0.17 * (0.06)	−0.31 * (0.06)	−0.14 (0.11)	−0.07 (0.29)	−0.301 (0.169)	−0.014 (0.074)
ΔLOGREP	−0.06 (0.29)	0.67 * (0.22)	0.42 * (0.09)	−1.00 * (0.31)	−0.158 (0.252)	−0.266 * (0.114)
ΔLOGGDP	−0.81 * (0.20)	−0.85 * (0.34)	−0.54 * (0.25)	−1.53 * (0.36)	−0.721 (0.492)	−0.396 (0.458)
ΔURB	−0.05 (0.04)	−0.07 (0.12)	−0.18 ** (0.10)	0.07 (0.10)	−0.026 (0.193)	−0.027 (0.088)
C	−2.69 (3.47)	2.31 (2.08)	−16.44 (14.50)	0.70 (0.80)	−0.115 (0.379)	0.122 (1.102)

Note: standard errors are in (), while * and ** represent significance levels of less than 5% and 10%, respectively.

Similarly, renewable energy production significantly and negatively affected PBCO2 in Germany (β = −0.29 *), Canada (β = −0.15)*, Poland (β = −0.13 **), and Sweden (β = −0.07 *) in the long-term results. In addition, economic prosperity (GDP) significantly and positively affected PBCO2 emissions in all countries (β = 0.74 *; β = 1.09 *; β = 0.66 *; β = 0.73 *), except for Poland. Moreover, population positively and significantly affected PBCO2 in a panel of the green leaders group and in all individual cross-sections (β = 0.07 *; β = 0.11 *; β = 0.12 *; β = 0.08 *; β = 0.05 *), except for Denmark, where population and PBCO2 had a negative and significant association in the long-term period (β = −0.04 *).

Furthermore, the ARDL-based ECM estimates indicated that the model was stable; however, the speed of convergence varied across all cross-sections. The results indicated that in Denmark, the speed of convergence resulting from any shock was higher compared to the others; an almost 66% convergence took place in one year. Moreover, the results indicated that REP had a significant and negative impact on PBCO2 in the panel (β = −0.36 *), Germany (β = −0.37 *), and Sweden (β = −0.10 **) in the short-term period.

Moreover, the results of the full panel in model 1 indicated that REP negatively and significantly affected PBCO2 in the long-term (β = −0.15 *) as well as in the short-term period (β = −0.36 *), while GDP and urban population had a significant and positive impact on PBCO2 emissions in the long-term period (β = 0.74 *; β = 0.07 *) as well as in the short-term period. Our results implying that REP significantly increases decarbonization by lowering PBCO2 emissions is consistent with [62,63]. According to Zhang and Li [8], as the production of energy from renewable sources like wind, solar, and hydro increases, it will directly replace traditional energy sources and fossil fuel power plants in industries. So, this transition from coal, oil, and gas heating to electric heating will cause a significant reduction in CO_2 emissions from production processes. Furthermore, a higher share of renewable energy in the electricity network means that all electricity-consuming production activities become greener as renewable energy diminishes carbon emissions [64].

Table 8. Augmented mean group (AMG) full sample; model 4.

IV	DV = CI					
	Panel	Germany	Canada	Denmark	Poland	Sweden
LOGFFEC	−0.13 (0.26)	0.17 (0.20)	−0.73 (0.64)	0.23 (0.55)	0.21 * (0.08)	3.09 * (1.54)
LOGREC	−0.1 (0.08)	0.05 (0.06)	−0.02 (0.09)	−0.37 * (0.16)	−0.11 ** (0.06)	−0.12 * (0.04)
LOGREP	−0.03 (0.12)	0.06 (0.15)	0.04 (0.04)	−0.53 * (0.17)	−0.29 * (0.09)	−0.02 (0.10)
LOGGDP	0.07 (0.14)	−0.24 (0.24)	0.40 ** (0.23)	−0.17 (0.18)	0.1 (0.16)	0.29 (0.24)
URB	−0.05 ** (0.02)	0.19 * (0.06)	−0.11 * (0.05)	−0.05 * (0.01)	−0.02 (0.03)	−0.01 (0.03)
C	1.57 (3.83)	−10.23 (8.13)	−0.06 (8.91)	10.22 (7.22)	−0.43 (4.77)	7.86 (9.42)
ARDL-based Error Correction Model (short-term estimates)						
ECM	−0.25 * (0.10)	−0.62 * (0.16)	−0.27 * (0.07)	−0.28 * (0.11)	−0.19 * (0.08)	−0.30 * (0.07)
ΔLOGFFEC	0.34 (0.35)	0.14 (0.79)	1.24 (0.86)	−0.51 (0.32)	−0.26 * (0.11)	1.10 (1.33)
ΔLOGREC	−0.04 (0.06)	−0.13 (0.11)	0.05 (0.09)	−0.25 (0.14)	0.08 (0.09)	0.04 (0.05)
ΔLOGREP	−0.16 * (0.08)	−0.24 (0.36)	−0.07 (0.10)	−0.39 (0.17)	−0.15 (0.13)	0.07 (0.07)
ΔLOGGDP	−0.10 * (0.05)	−0.05 (0.48)	−0.15 (0.25)	−0.02 (0.20)	0.02 (0.25)	−0.28 (0.26)
ΔURB	0.03 (0.09)	0.21 (0.18)	0.18 (0.11)	0.05 (0.05)	−0.02 (0.10)	−0.28 (0.17)
C	1.24 (0.83)	5.18 (4.01)	0.68 (0.86)	1.72 (1.73)	0.76 (0.99)	2.83 (2.08)

Note: standard errors are in (), while * and ** represent significance levels of less than 5% and 10%, respectively.

In model 2, this study estimated the long-term estimates of key impact factors on consumption-based CO_2 emissions. The results are reported in Table 6. The results indicated that FFEC had a positive and significant long-term association with CBCO2 emissions in Germany (β = 0.46 *), Denmark (β = 1.34 *), and Sweden (β = 1.80 *).

In addition, the results indicated that REC had a negative and significant long-term association with CBCO2 emissions in Denmark (β = −0.64 *), Poland (β = −0.24 *), and Sweden (β = −0.24 *). Furthermore, the results indicated that GDP had a positive and significant long-term association with $CBCO_2$ emissions in Germany (β = 0.82 *), Poland (β = 0.63 *), and Sweden (β = 0.46 *), while it had a negative and significant long-term association with $CBCO_2$ emissions in Denmark (β = −0.64 *). Similarly, population growth had a positive and significant impact on $CBCO_2$ emissions in Denmark (β = 0.08 *) and a positive and significant impact on $CBCO_2$ emissions in Germany (β = −0.09 **). In terms of the ARDL-based ECM (short-term estimates), the results shown in the lower part of Table 7 indicate that model 2 was stable and converged to the equilibrium growth path in the panel as well as in all cross-sections. The speed of the convergence was 24%, 27%, 25%, 33%, 26%, and 69%, respectively.

The result of the full panel in model 2 indicated that REC significantly lowered $CBCO_2$ emissions and enhanced the decarbonization process in the leading green economies (β = −0.32 *). Our findings coincide with the existing literature [63,65] that has documented that renewable energy consumption helps to achieve carbon neutrality. The consumption of renewable energy from sources such as wind, solar, and hydro instead of fossil fuels will tend to reduce CO_2 emissions from energy use [66]. Similarly, the utilization of electric vehicles and heating and cooling systems powered by renewable energy will further boost the process of decarbonization by lowering CO_2 emissions from the consumption of goods and services.

In model 3, this study estimated the long-term estimates of the key impact factors on CO_2 emissions, and the results are reported in Table 7. The results indicated that FFEC had a positive and significant long-term association with CO_2 emissions in Germany (β = 2.43 *) and Poland (β = 0.245 *).

Table 9. Augmented mean group (AMG) full sample; model 5.

	Dep. Var. = CIOE					
	Panel	**Germany**	**Canada**	**Denmark**	**Poland**	**Sweden**
LOGFFEC	0.12 (0.18)	1.75 * (0.46)	4.05 * (1.28)	−0.6 (0.85)	0.43 (0.50)	0.82 (0.68)
LOGREC	−0.41 ** (0.22)	−0.47 * (0.14)	0.03 (0.19)	−1.10 * (0.30)	−0.53 * (0.13)	0.01 (0.01)
LOGREP	−0.04 ** (0.02)	−1.13 * (0.24)	−0.07 (0.10)	−0.01 (0.29)	−1.13 * (0.54)	−0.04 (0.04)
LOGGDP	0.07 (0.15)	0.02 (0.59)	0.19 (0.49)	−0.3 (0.33)	0.52 (0.73)	−0.02 (0.07)
URB	0.04 (0.07)	−0.11 (0.11)	0.17 (0.11)	−0.04 (0.03)	0.2 (0.15)	−0.01 (0.02)
C	−4.51 (11.70)	6.16 (13.88)	−31.57 (19.04)	3.73 (10.85)	−25.92 (25.43)	4.49 (4.49)
	ARDL-based Error Correction Model (short-term estimates)					
ECM	−0.32 * (0.12)	−0.13 * (0.06)	−0.47 * (0.11)	−0.48 * (0.14)	−0.57 * (0.16)	−0.22 * (0.02)
ΔLOGFFEC	0.63 (0.71)	2.91 * (1.18)	1.24 (1.32)	−1.05 ** (0.55)	0.66 * (0.34)	−0.63 (0.57)
ΔLOGREC	−0.44 * (0.16)	−0.79 * (0.16)	−0.13 (0.14)	−0.82 * (0.29)	−0.43 (0.25)	−0.03 (0.02)
ΔLOGREP	0.12 (0.27)	1.19 * (0.51)	−0.24 (0.17)	−0.21 (0.22)	−0.08 (0.39)	−0.07 * (0.03)
ΔLOGGDP	−0.44 (0.43)	−1.15 (0.73)	0.82 * (0.41)	0.03 (0.30)	−1.63 * (0.69)	−0.28 * (0.12)
ΔURB	−0.02 (0.05)	−0.01 (0.26)	−0.05 (0.21)	0.13 ** (0.07)	−0.19 (0.33)	0.01 (0.07)
C	3.47 (5.07)	1.42 (2.49)	1.35 (5.83)	2.93 (7.75)	2.94 (6.04)	0.74 (0.66)

Note: standard errors are in (), while * and ** represent significance levels of less than 5% and 10%, respectively.

In addition, the results indicated that REP had a negative and significant long-term association with CO_2 emissions in Denmark (β = −0.81 *) and Poland (β = −0.458 *). The results also indicated that REC had a negative and significant long-term association with CO_2 emissions in Denmark (β = −0.39 *) and Sweden (β = −1.47 *).

Furthermore, the results indicated that GDP had a positive and significant long-term association with CO_2 emissions in Germany (β = 0.64 *) and Denmark (β = 0.75 *). Similarly, population growth had a negative and significant impact on CO_2 emissions in Denmark (β = −0.04 *) and Sweden (β = −0.72 *). In terms of the ARDL-based ECM (short-term estimates), the results in the lower part of Table 8 indicate that model 3 was stable and converged to the equilibrium growth path in the panel as well as in all cross-sections. The speed of the convergence was 16%, 15%, 34%, 32%, 45%, and 13%, respectively.

The results of the impact of FFEC, REP, REC, GDP, and urban POP on CO_2 emissions in the full panel of the leading green economies are reported in Table 7 for model 3. The results are very interesting and reinforce our previous results of model 1 and model 2. The results showed that fossil fuel use had an insignificant relationship with CO_2 emissions (β = −1.21). Our results indicated that the leading green economies have significantly lowered their reliance on fossil fuel for energy production, so the contribution of fossil fuels to CO_2 emissions was minor and insignificant [67]. In the leading green economies, a greater proportion of the energy mix comes from solar, wind, and hydro power, which produces little or no CO_2 emissions. Moreover, it has been examined that in leading green economies, policies and strict regulations ensure keeping CO_2 emissions at a minimum level, and they also use carbon capture and storage (CCS) technologies to capture CO_2 emissions from fossil fuel power plants [68]. The results of the full panel in model 3 also indicated that renewable energy production and consumption significantly lowered CO_2 emission and enhanced the decarbonization process in the leading green economies. The results of model 3 were similar to those of model 1 and model 2, as [34] showed that the transition towards cleaner energy sources is significantly associated with reductions in CO_2 emissions, and [35] stated that the transition towards renewable energy consumption and production helps to curb CO_2 emissions and to achieve decarbonization targets.

In model 4, this study estimated the long-term estimates of key impact factors on CI, and the results are reported in Table 8. The results indicated that FFEC had a positive and significant long-term association with CI in Poland (β = 0.21 *) and Sweden (β = 3.09 *). In addition, the results indicated that REP and REC had a negative and significant long-term association with CI in Denmark (β = −0.53 *; β = −0.37 *), Poland (β = −0.29 *; β = −0.11 *), and Sweden (β = −0.22 *; β = −0.12 *). Furthermore, the results indicated that GDP had a positive and significant long-term association with CI in Canada (β = 0.40 *), while population growth had a negative and significant impact on CI in Germany (β = −0.19 *), Canada (β = 0.11 *), and Denmark (β = −0.05 *). In terms of the ARDL-based ECM (short-term estimates), the results in the lower part of Table 9 indicate that model 3 was stable and converged to the equilibrium growth path in the panel as well as in all cross-sections. The speed of the convergence was 25%, 62%, 27%, 28%, 19%, and 30%, respectively.

The overall results for the full panel in model 4 state that FFEC, REP, and REC had insignificant associations with carbon intensity (CI), the amount of carbon dioxide (CO_2) emissions produced per unit of a specific activity. The reason behind this relationship is the high utilization of renewable energy sources in these countries. This means that even if some fossil fuels are used in specific instances (e.g., backup power or in sectors hard to electrify), their overall contribution to carbon intensity remains minimal due to the predominance of low-carbon or carbon-neutral energy sources. Similarly, the leading green economies have already achieved a high penetration of renewable energy in their energy mix, which has significantly reduced the carbon intensity to a minimum level. Thus, further increases in renewable energy consumption may have a minimal impact on reducing overall carbon intensity. The initial shift to renewables has already significantly lowered their carbon intensity, making additional reductions more challenging and less impactful relative to economies with higher fossil fuel dependence.

In model 5, this study estimated the long-term estimates of the key impact factors of CIOE, and the results are reported in Table 9. The results indicated that FFEC had a positive and significant long-term association with CIOE in Germany (β = 1.75 *) and Canada (β = 4.05 *).

In addition, the results indicated that REP and REC had a negative and significant long-term association with CIOE in Germany (β = −1.13 *; β = −0.47 *) and Poland (β = −1.13 *; β = −0.53 *), and REC also had a significant and negative impact on CIOE in Denmark (β = −1.10 *).

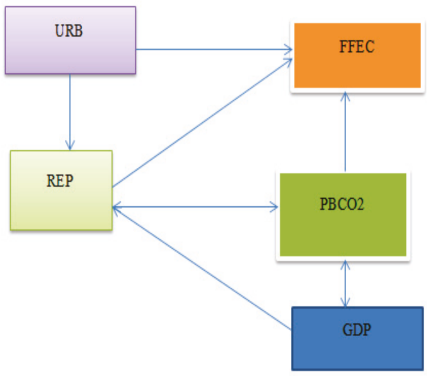
Furthermore, the results indicated that GDP and population had insignificant impacts on CIOE in all cross-sections. In terms of the ARDL-based ECM (short-term estimates), the results in the lower part of Table 9 indicate that model 3 was stable and converged to the equilibrium growth path in the panel as well as in all cross-sections. The speed of the convergence was 32%, 13%, 47%, 48%, 57%, and 22%, respectively.

The results indicated that REP and REC had a negative and significant long-term association with CIOE in the full panel of the leading green economies (β = −0.04 *;

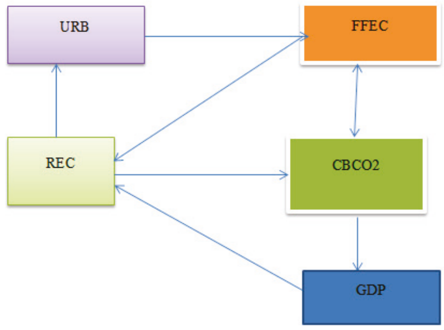
β = −0.41 *). In other words, increased REC and REP values promote decarbonization by lowering CIOE, in line with [69,70]. Similarly, hydro and geothermal power also lower CIOE because they produce electricity with minimal or zero direct emissions.

Dumitrescu–Hurlin (D-H) Panel Causality

After investigating the long-term estimates of the five developed models, it was imperative to determine the direction of the causality relationship among the variables [71,72]. For this purpose, this study utilized the Dumitrescu and Hurlin [60] non-causality tests and obtained evidence of bidirectional, unidirectional, and neutral relationships among the defined variables. The detailed results are reported in Appendix A (see Tables A1–A5). However, a graphical representation of the five models based on Tables A1–A5 are presented in following figure with the names model 1, 2, 3, 4, and 5.

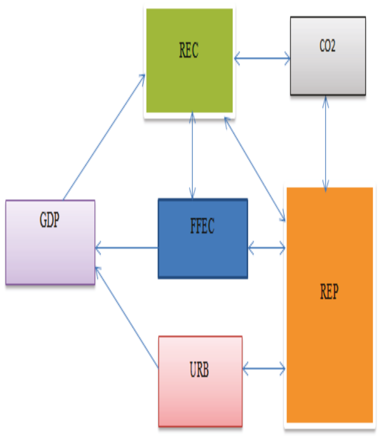


Model 1. D-H causality flowchart

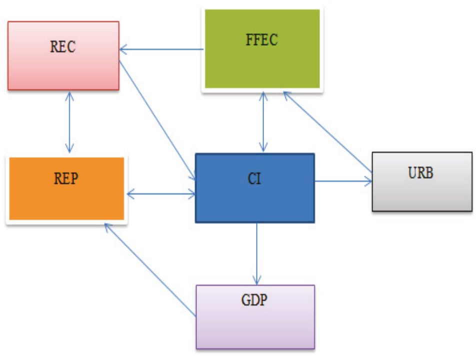


Model 2. D-H causality flowchart

The results of model 1 indicate that there was a bidirectional causality between production-base CO_2 emissions and GDP, while there was a unidirectional causality between production-based CO_2 emissions and FFEC; GDP and renewable energy production; urban population and renewable energy production; urban population and FFEC; and GDP and REP. Similarly, model 2 indicated that there was a bidirectional causality between CBCO2 and FFEC, while there was a unidirectional causality between consumption-based CO_2 emissions and GDP; GDP and renewable energy consumption; REC and CBCO2; REC and urban population; and REC and FFEC.



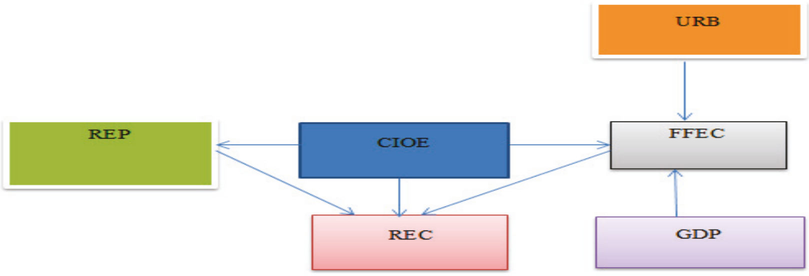
Model 3. D-H causality flowchart



Model 4. D-H causality flowchart

The causality relationship flowchart of model 3 is reported, and the results indicated that there was a bidirectional causality between REC and FFEC; REP and FFEC; REC and CO_2; REP and CO_2; REC and REP; and REP and urban population. Moreover, there was a unidirectional causality between urban population and GDP; GDP and REC; and FFEC and

GDP. Similarly, model 4 indicated that there was a bidirectional causality between REP and REC; REP and CI; and FFEC and CI, while there was a unidirectional causality between GDP and REP; FFEC and REC; urban population and FFEC; REC and CI; and CI and GDP. Similarly, model 5 indicated that there was no bidirectional causality in the model. However, there was a unidirectional causality between REP and REC; CIOE and REP; CIOE and REC; CIOE and FFEC; GDP and FFEC; FFEC and REC; and urban population and FFEC.



Model 5. D-H causality flowchart

6. Conclusions

This study investigated the impact of fossil fuel energy consumption (FFEC), renewable energy production (REP) and renewable energy consumption (REC), urban population, and economic affluence on decarbonization in the context of leading green economies from 2000 to 2023. This study utilized five measurements to measure decarbonization, including production-based CO_2 emissions (PBCO2), consumption-based CO_2 emissions (CBCO2), CO_2 emissions, carbon intensity (CI), and carbon intensity of electricity (CIOE). Thus, this study developed five models to assess the impact of key impact factors, namely, fossil fuel energy consumption, renewable energy production and renewable energy consumption, urban population, and economic affluence on decarbonization. This study utilized the augmented mean group (AMG) technique to assess the long-term estimates among the modeled variables. The findings are described model-wise as follows.

The findings of model 1 indicate, in the full panel, that REP significantly lowered PBCO2 and enhanced the decarbonization process in the leading green economies, while economic affluence and urban population significantly increased PBCO2 and hindered the process of decarbonization in the leading green economies. Similar results were obtained in Germany, Canada, Poland, and Sweden. However, in Denmark, REP increased PBCO2 emissions and hindered the decarbonization process, while urban population significantly lowered PBCO2 emissions and facilitated the process of decarbonization.

The findings of model 2 indicate that, in the full panel, REC significantly lowered CBCO2 emissions and enhanced the decarbonization process, while economic affluence significantly lowered decarbonization by increasing CBCO2 emissions. Similarly, the findings of model 2 indicate that in Germany, FFEC decreased decarbonization by increasing CBCO2 emissions, while urban population enhanced decarbonization by reducing CBCO2 emissions. In Denmark. FFEC and urban population significantly lowered decarbonization by increasing CBCO2 emissions, while REC and economic affluence significantly enhanced the decarbonization process by decreasing CBCO2 emissions. Furthermore, in Poland, REC significantly improved decarbonization, and economic affluence decreased the decarbonization process. Similar results were found in Sweden.

The findings of model 3 indicate that, in the full panel, REP and REC significantly lowered CO_2 emissions and increased the decarbonization process. In Germany, FFEC and economic prosperity significantly increased CO_2 emissions and lowered decarbonization. In Denmark, REP, REC, and urban population significantly increased the decarbonization process by lowering CO_2 emissions, while economic prosperity increased CO_2 emissions and lowered decarbonization. Furthermore, the results indicate that in Poland, FFEC lowered decarbonization, and REP enhanced the decarbonization process, while in Sweden, REC and urban population significantly enhanced decarbonization by lowering CO_2 emissions.

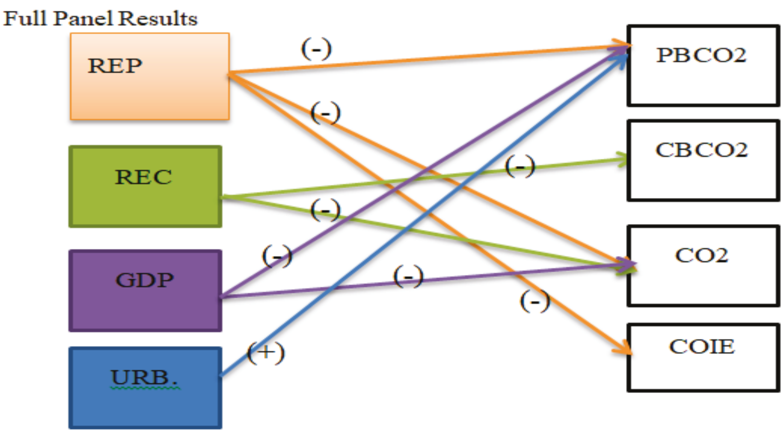
The findings of model 4 indicate that, in the full panel, only urban population significantly enhanced decarbonization by lowering carbon intensity, while in Germany, urban population increased carbon intensity and lowered decarbonization. In Canada, economic affluence increased CI and lowered decarbonization, while urban population decreased CI and enhanced the decarbonization process. The results also indicate that in Denmark, REC, REP, and urban population significantly lowered CI and enhanced decarbonization. Similarly, in Poland, FFEC decreased decarbonization, and REP and REC significantly lowered CI and enhanced decarbonization. In Sweden, FFEC significantly lowered decarbonization by increasing CI, and REC enhanced decarbonization in Sweden by decreasing CI.

The findings of model 5 indicate that, in the full panel, REP and REC significantly lowered CIOE and enhanced decarbonization, while in Germany, FFEC significantly lowered decarbonization. Similarly, REP and REC significantly enhanced decarbonization by decreasing CIOE. in Canada, FFEC significantly lowered the decarbonization process, while in Denmark, REC significantly improved the decarbonization process. In Poland, REP and REC significantly enhanced the decarbonization process.

6.1. Graphical Presentation of Results and Policy Suggestions

Results for Full Panel

The flow diagram of the full-panel results indicates that REP significantly and negatively affected PBCO2, CO_2, and COIE. Similarly, REC negatively affected CBCO2 and CO_2 emissions in the leading green economies. GDP negatively and significantly affected PBCO2 emissions and CO_2 emissions, while urban population affected PBCO2 emissions positively and significantly in the leading green economies. The findings suggest that renewable energy consumption and renewable energy production should be promoted to achieve a zero-carbon economy. Moreover, this study suggests that planned urbanization is required to lower PBCO2 emissions and to increase the process of decarbonization.



Based on the findings of this study, policymakers in leading green economies should focus on comprehensive strategies to reduce fossil fuel energy consumption (FFEC) and promote renewable energy production (REP) and consumption (REC) to enhance decarbonization efforts. To reduce FFEC, policymakers should implement regulations such as carbon taxes to make fossil fuel use more expensive and less attractive, thereby incentivizing businesses and consumers to shift towards cleaner energy sources. They should also phase out subsidies for fossil fuel industries and redirect those funds to support renewable energy projects, ensuring a financial shift towards greener energy. Setting stringent emissions reduction targets and implementing cap-and-trade systems to limit the total amount of CO_2 emissions are crucial steps in this transition. Promoting REP and REC requires providing financial incentives like grants, tax credits, and low-interest loans for the development and installation of renewable energy infrastructure, including solar farms and wind turbines. Investing in renewable energy infrastructure, such as smart grids and energy storage systems, will ensure a stable and efficient energy supply, making renewable energy more viable. Additionally, implementing feed-in tariffs to guarantee that renewable energy producers receive a fixed price for the energy they generate can encourage more investment in this sector.

In country-specific contexts, we suggest that Germany should prioritize environmentally friendly development projects, including promoting green urban policies like green urban planning, sustainable transportation solutions, and energy-efficient building codes. Public awareness campaigns to encourage pro-environmental behaviors among the urban population are also essential. In Denmark, policymakers should continue supporting renewable energy initiatives and consider policies that reduce urban CO_2 emissions further, such as expanding public transportation options and promoting bicycle use through improved infrastructure. Poland and Sweden should focus on increasing the share of renewable energy in their energy mix and improving urban planning to integrate more green spaces and energy-efficient public infrastructure.

Limitations and Future Research Direction:

This study included only five countries, namely, Germany, Canada, Sweden, Denmark, and Poland due to data availability. Moreover, this study did not analyze the impact of global events like COVID-19 on decarbonization. Future studies can incorporate global events into their empirical models. Furthermore, varying levels of technology adoption and innovation can affect the decarbonization process, so future studies can investigate that how different levels of technology adoption can affect the decarbonization process.

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Appendix A

Table A1. Pairwise Dumitrescu–Hurlin panel causality tests; model 1.

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.	Decision
LOGFFEC $\nrightarrow$ LOGPBCO2	3.61	1.13	0.26	No causality
LOGPBCO2 $\nrightarrow$ LOGFFEC	16.54	12.08	0.00	PBCO2 causes FFEC
LOGREP $\nrightarrow$ LOGPBCO2	2.71	0.36	0.72	No causality
LOGPBCO2 $\nrightarrow$ LOGREP	4.27	1.68	0.09	Bidirectional causality
LOGGDP $\nrightarrow$ LOGPBCO2	5.60	2.81	0.01	
LOGPBCO2 $\nrightarrow$ LOGGDP	16.93	12.40	0.00	Bidirectional causality
URB $\nrightarrow$ LOGPBCO2	5.39	2.63	0.01	
LOGPBCO2 $\nrightarrow$ URB	1.64	−0.55	0.58	No causality
LOGREP $\nrightarrow$ LOGFFEC	20.79	15.67	0.00	REP causes FFEC
LOGFFEC $\nrightarrow$ LOGREP	3.27	0.83	0.41	No causality
LOGGDP $\nrightarrow$ LOGFFEC	7.96	4.80	0.00	No causality
LOGFFEC $\nrightarrow$ LOGGDP	2.96	0.58	0.57	No causality
URB $\nrightarrow$ LOGFFEC	6.40	3.48	0.00	URB causes FFEC
LOGFFEC $\nrightarrow$ URB	2.05	−0.20	0.84	No causality
LOGGDP $\nrightarrow$ LOGREP	5.03	2.32	0.02	GDP causes REP
LOGREP $\nrightarrow$ LOGGDP	2.53	0.21	0.83	No causality
URB $\nrightarrow$ LOGREP	4.97	2.27	0.02	URB causes REP

Table A2. Pairwise Dumitrescu–Hurlin panel causality tests; model 2.

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.	Decision
LOGFFEC $\nrightarrow$ LOGCBCO2	4.89	2.21	0.03	Bidirectional causality
LOGCBCO2 $\nrightarrow$ LOGFFEC	4.99	2.29	0.02	
LOGREC $\nrightarrow$ LOGCBCO2	4.97	2.28	0.02	REC $\rightarrow$ CBCO2
LOGCBCO2 $\nrightarrow$ LOGREC	10.48	6.94	0.00	No causality
LOGGDP $\nrightarrow$ LOGCBCO2	8.55	5.31	0.00	No causality
LOGCBCO2 $\nrightarrow$ LOGGDP	17.97	13.29	0.00	CBCO2 $\rightarrow$ GDP
URB $\nrightarrow$ LOGCBCO2	8.41	5.19	0.00	No causality
LOGCBCO2 $\nrightarrow$ URB	3.41	0.95	0.34	No causality
LOGREC $\nrightarrow$ LOGFFEC	2.88	0.51	0.61	No causality
LOGFFEC $\nrightarrow$ LOGREC	6.44	3.52	0.00	FFEC $\rightarrow$ REC
URB $\nrightarrow$ LOGFFEC	6.40	3.48	0.00	URB $\rightarrow$ FFEC
LOGFFEC $\nrightarrow$ URB	2.05	−0.20	0.84	No causality
LOGGDP $\nrightarrow$ LOGREC	8.86	5.57	0.00	No causality
LOGREC $\nrightarrow$ LOGGDP	2.04	−0.20	0.84	No causality
URB $\nrightarrow$ LOGREC	8.66	5.40	0.00	No causality
LOGREC $\nrightarrow$ URB	5.40	2.64	0.01	REC $\rightarrow$ URB

Table A3. Pairwise Dumitrescu–Hurlin panel causality tests; model 3.

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.	Decision
LOGFFEC $\nrightarrow$ LOGCO2	4.37	4.20	0.00	No causality
LOGCO2 $\nrightarrow$ LOGFFEC	4.57	4.46	0.00	No causality
LOGREC $\nrightarrow$ LOGCO2	2.22	1.43	0.15	No causality
LOGCO2 $\nrightarrow$ LOGREC	4.48	4.34	0.00	No causality
LOGREP $\nrightarrow$ LOGCO2	7.86	8.70	0.00	Bidirectional causality
LOGCO2 $\nrightarrow$ LOGREP	3.22	2.71	0.01	
LOGGDP $\nrightarrow$ LOGCO2	7.16	7.81	0.00	No causality
LOGCO2 $\nrightarrow$ LOGGDP	2.37	1.62	0.11	No causality
URB $\nrightarrow$ LOGCO2	5.33	5.44	0.00	No causality
LOGCO2 $\nrightarrow$ URB	1.21	0.11	0.91	No causality
LOGREC $\nrightarrow$ LOGFFEC	1.71	0.77	0.44	No causality
LOGFFEC $\nrightarrow$ LOGREC	3.95	3.66	0.00	Bidirectional causality
LOGREP $\nrightarrow$ LOGFFEC	10.47	12.08	0.00	
LOGFFEC $\nrightarrow$ LOGREP	2.43	1.69	0.09	Bidirectional causality
LOGGDP $\nrightarrow$ LOGFFEC	8.27	9.24	0.00	
LOGFFEC $\nrightarrow$ LOGGDP	2.73	2.08	0.04	FFEC $\rightarrow$ GDP
URB $\nrightarrow$ LOGFFEC	5.60	5.79	0.00	No causality
LOGFFEC $\nrightarrow$ URB	4.77	4.71	0.00	No causality
LOGREP $\nrightarrow$ LOGREC	18.83	22.87	0.00	Bidirectional causality
LOGREC $\nrightarrow$ LOGREP	3.89	3.58	0.00	
LOGGDP $\nrightarrow$ LOGREC	4.12	3.87	0.00	GDP $\rightarrow$ REC
URB $\nrightarrow$ LOGREP	8.08	9.00	0.00	Bidirectional causality
LOGREP $\nrightarrow$ URB	19.55	23.81	0.00	
URB $\nrightarrow$ LOGGDP	2.47	1.75	0.08	URB $\rightarrow$ GDP
LOGGDP $\nrightarrow$ URB	6.29	6.68	0.00	No causality

Table A4. Pairwise Dumitrescu–Hurlin panel causality tests; model 4.

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.	Decision
LOGFFEC ↛ LOGCI	6.64	3.69	0.00	Bidirectional causality
LOGCI ↛ LOGFFEC	5.22	2.48	0.01	
LOGREC ↛ LOGCI	5.40	2.64	0.01	REC → CI
LOGCI ↛ LOGREC	7.36	4.30	0.00	No causality
LOGREP ↛ LOGCI	6.86	3.88	0.00	Bidirectional causality
LOGCI ↛ LOGREP	5.70	2.89	0.00	
LOGGDP ↛ LOGCI	4.18	1.61	0.11	No causality
LOGCI ↛ LOGGDP	5.75	2.93	0.00	CI → GDP
URB ↛ LOGCI	4.11	1.55	0.12	No causality
LOGCI ↛ URB	6.78	3.81	0.00	CI →URB
LOGFFEC ↛ LOGREC	6.44	3.52	0.00	FFEC → REC
LOGREP ↛ LOGFFEC	20.79	15.67	0.00	
LOGFFEC ↛ LOGREP	3.27	0.83	0.41	No causality
LOGGDP ↛ LOGFFEC	7.96	4.80	0.00	No causality
LOGFFEC ↛ LOGGDP	2.96	0.58	0.57	No causality
URB ↛ LOGFFEC	6.40	3.48	0.00	URB → FFEC
LOGFFEC ↛ URB	2.05	−0.20	0.84	No causality
LOGREP ↛ LOGREC	56.13	45.62	0.00	Bidirectional causality
LOGREC ↛ LOGREP	5.91	3.07	0.00	
LOGGDP ↛ LOGREC	8.86	5.57	0.00	No causality
LOGREC ↛ LOGGDP	2.04	−0.20	0.84	No causality
LOGREC ↛ URB	5.40	2.64	0.01	REC → URB
LOGGDP ↛ LOGREP	5.03	2.32	0.02	GDP → REP

Table A5. Pairwise Dumitrescu–Hurlin panel causality tests; model 5.

DV = CIOE				
Null Hypothesis	**W-Stat.**	**Zbar-Stat.**	**Prob.**	**Decision**
LOGFFEC ↛ LOGCIOE	5.64	1.30	0.19	No causality
LOGCIOE ↛ LOGFFEC	9.17	3.48	0.00	CIOE → FFEC
LOGREC ↛ LOGCIOE	5.94	1.48	0.14	No causality
LOGCIOE ↛ LOGREC	8.15	2.85	0.00	CIOE → REC
LOGREP ↛ LOGCIOE	2.65	−0.55	0.58	No causality
LOGCIOE ↛ LOGREP	6.74	1.98	0.05	CIOE → REP
LOGGDP ↛ LOGCIOE	3.89	0.21	0.83	No causality
LOGCIOE ↛ LOGGDP	10.46	4.28	0.00	No causality
URB ↛ LOGCIOE	4.24	0.43	0.67	No causality
LOGCIOE ↛ URB	2.73	−0.51	0.61	No causality
LOGFFEC ↛ LOGREC	7.02	2.15	0.03	FFEC → REC
LOGREP ↛ LOGFFEC	17.00	8.34	0.00	REP → FFEC
LOGFFEC ↛ LOGREP	2.71	−0.52	0.60	No causality
LOGGDP ↛ LOGFFEC	8.47	3.05	0.00	GDP → FFEC
LOGFFEC ↛ LOGGDP	4.06	0.32	0.75	No causality
URB ↛ LOGFFEC	7.37	2.37	0.02	URB → FFEC
LOGFFEC ↛ URB	4.88	0.83	0.41	No causality
LOGREP ↛ LOGREC	46.78	26.78	0.00	REP → REC
LOGREC ↛ LOGREP	4.95	0.87	0.38	No causality
LOGGDP ↛ LOGREC	8.95	3.35	0.00	GDP → REC
LOGREC ↛ URB	9.03	3.40	0.00	REC → URB
URB ↛ LOGREP	6.70	1.95	0.05	URB → REP

Table A6. List of abbreviations.

Variable	Notation	Tests	Notation
Carbon Emissions	CO_2	Augmented mean group	AMG
Consumption-Based Carbon Emissions	$CBCO_2$	Greenhouse gases	GHGs
Production Based Carbon Emissions	$PBCO_2$	Conference of the Parties	COP
Carbon Intensity	CI	The Organization for Economic Cooperation and Development	OECD
Carbon Intensity of Electricity	CIOE	Dumitrescu–Hurlin	D-H
Fossil Fuel Energy Consumption	FFEC	Cross-sectional dependance	CSD
Renewable Energy Consumption	REC	Cross-sectional augmented Dickey–Fuller	CADF
Renewable Energy Production	REP	Cross-sectionally augmented Im–Pesaran–Shin	CIPS
Population	URB	Pesaran cross-sectional dependance	Pesaran CD
Gross Domestic Product	GDP	Stochastic Regression on Population, Affluence, and Technology	STIRPAT

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Do the Energy-Related Uncertainties Stimulate Renewable Energy Demand in Developed Economies? Fresh Evidence from the Role of Environmental Policy Stringency and Global Economic Policy Uncertainty

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Abstract: Despite earlier research on green energy, there is still a significant gap in understanding how energy-related uncertainties affect renewable energy consumption (REN), especially in developed nations. Thus, this study explicitly looks into how the energy-related uncertainty index (EUI) can promote (or diminish) REN in sixteen wealthy nations between 2000 and 2020. Furthermore, we attempt to specify the factors of REN and explore whether environmental policy stringency (EPS) and global economic policy uncertainty (GEPU) could help moderate (or intensify) the EUI-REN nexus. To achieve this, we employ different panel data methods. The results underscore that the EUI significantly impacts REN, denoting that higher uncertainties related to energy markets lead to promoting REN. Additionally, the (EUI × EPS) underlines that EPS has a favorable role in increasing the positive effect of the EUI on REN in sample developed countries while (EUI × GEPU) has a detrimental effect. Remarkably, the findings underline that the effect of the EUI on REN is more positive in high EPS countries and that the positive effect of the EUI is more moderate when GEPU is high. The findings also underscore that the development of the financial market, FDI, personal remittances, and EPS positively stimulate REN whereas CO_2, total natural resources rents, economic activity, and GEPU have a detrimental impact. The results are robust, and authorities and policymakers are advised to implement a wide range of policy proposals to accomplish sustainable development goals (SDGs) 7 and 13.

Keywords: renewable energy demand; energy-related uncertainty; ecological policy; economic policy uncertainty; developed countries; SDGs; panel quantile regression

1. Introduction

The issue of renewable energy (RENE) has garnered substantial interest from scholars and decision-makers across the globe as a result of the deteriorating state of the air and the expanding consequences of climate change. Ref. [1] found that ecological pollution negatively impacts human health; as a result, declining air quality was associated with 5.5 million early deaths. According to [2], the use of RENE caused carbon emissions to drop from 2.1% in 2018 to 0.5% in 2019. Furthermore, RENE issues have gained more importance due to fluctuating fossil fuel prices and increasing global warming. Remarkably, about 80% of the world's primary energy consumption is derived from fossil fuels, which contributes to an increase in greenhouse gas emissions, climate change, and global warming. Transitioning nations from conventional fossil fuels to RENE sources contributes to mitigating climate change and expediting the achievement of the SDGs. When opposed to traditional energy, RENE offers advantages that are both ecologically friendly and replenishable. According to [3], promoting RENE is a better way to accomplish the goal of the Paris Climate Conference (COP-21) and is more appropriate for economic development.

In the last two decades, authorities and policymakers have implemented several laws and initiatives to expedite the transition from conventional to green energy. These initiatives include standardization, tax breaks, incentive programs, and less expensive credits, among many others. To lower greenhouse gas emissions, slow down climate change, and achieve ecological sustainability, these initiatives seek to increase household REN, boost R&D in the green energy sector, and invest in RENE [4,5]. Ref. [6] reported that these actions contributed to a 3% global increase in REN in 2020 and investments in RENE increased from less than $50 billion in 2004 to over $300 billion in 2015. Ref. [7] emphasized that green funding for RENE projects needs to rise to $1.1 trillion between 2021 and 2030 to meet the SDGs and reduce greenhouse gas emissions.

The increased debate regarding global warming and the role of clean energy has led to research examining the major factors influencing the decline or increase of REN in various nations employing the demand modeling method. Studies suggest, for instance, that the development of the financial markets promotes REN [8,9] and that investors can access external funds at lower costs more easily when the capital market is more developed. In addition, the development of a financial market might promote more R&D efforts in clean energy, improve ecological knowledge, and raise the level of RENE planning due to the easier accessibility of various financial facilities. Furthermore, research has demonstrated (e.g., [9,10]) that economic openness is one of the major factors that stimulate REN and an increased inflow of FDI increases access to external funds and enables firms and investors to borrow at lower costs to invest in RENE plans. In previous studies (e.g., [11]), it has also been found that increasing economic openness enables improved managerial expertise and cleaner technologies to be transmitted, which ultimately contributes to the growth of renewable energy. Furthermore, prior studies have demonstrated that economic activity either positively (e.g., [12]) or negatively impacts REN (e.g., [8]).

In the same vein, several studies (e.g., [8,13]) have revealed that technological innovations promote REN and that a higher level of ecological technology could improve energy productivity and hasten a nation's transition to green economies. Furthermore, technological improvements allow for significant reductions in the investment costs of new RENE installations [14]. Additionally, some research has shown that the influx of international remittances encourages the development of REN [15]. A greater inflow of remittances encourages households to finance RENE programs and makes it easier for them to adopt homes with green systems. Nevertheless, several studies have shown that GEPU reduces REN (e.g., [9,16]). As EPU increases worldwide, consumers (demand side) are less encouraged to switch to RENE sources because of the reduction in their income [17]. Ref. [9] revealed that a 1% increase in GEPU declines REN by 0.16% in OECD nations. As a consequence, it also has a negative effect on the supply side by increasing the price of private-sector investment [18].

Likewise, several studies have shown that CO_2 ([12]) and natural resources rents [9] diminish REN. In particular, Ref. [12] demonstrated that in OECD countries, a 1% increase in natural resources rents and CO_2 results in a decrease in REN of 0.03% and 0.35%, respectively. Previous research has demonstrated that in contexts with higher rents for natural resources, the switch from conventional energy to RENE occurs more slowly [19]. Previous studies [9,20] have also emphasized the importance of green ecological strategies in contributing to the rise in REN. The authors contended that the adoption of ecologically friendly strategies contributes to the expansion of RENE capacity. In general, previous research indicates that authorities and policymakers should develop a range of approaches to persuade householders and investors to switch from fossil fuels to RENE to achieve the SDGs and ecological quality.

What about the elements of REN in the setting of developed countries? Although some works have studied REN in different blocks like BRICS (e.g., [8]), limited studies have uncovered the elements of REN in general and developed countries specifically. As shown in Figure 1, fossil fuels will remain the leading energy source in the world whereas RENEs have a small supply share of 5%. Since countries attempt to achieve carbon neutrality, environmental quality, and also attain SDGs, identifying the elements of REN could be an effective approach to promoting RENEs globally.

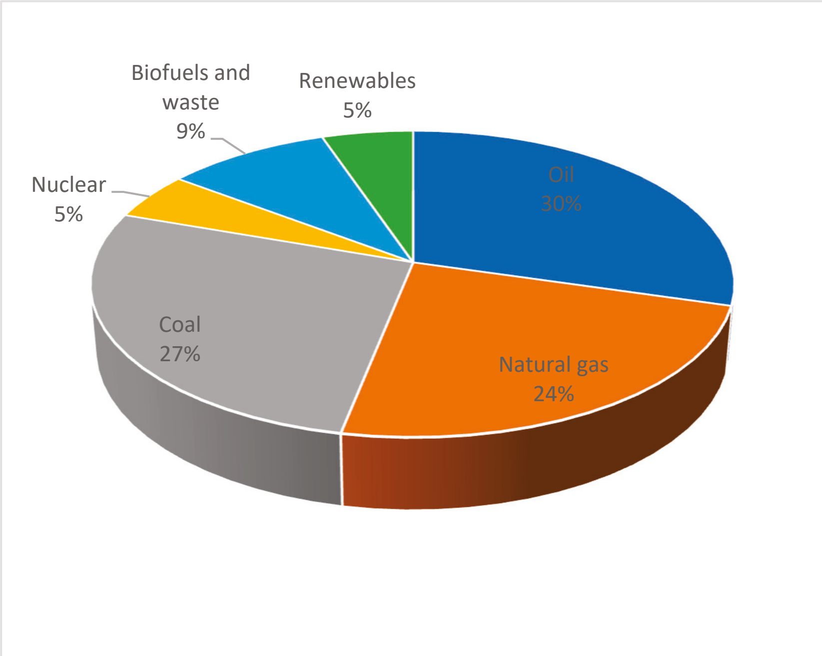


Figure 1. Global total energy supply by source (2021). Authors' calculations (Source: https://www.iea.org/data-and-statistics/, accessed on 1 June 2024).

By classifying countries, Figure 2 shows that the developed countries accounted for 66% of the world's total supply of RENE in 2021, a substantial percentage higher than that of developing countries (34%). The higher share of RENE supply by the developed countries emphasizes the significance of this work. Since clean energy could be used as a substitute for conventional energy sources, it is essential to identify the important elements of REN mostly in the developed countries, which have the higher share of RENE supply, directing to plan climate change policies, achieve ecological quality, and eventually attain the SDGs. In light of the aforementioned arguments, the developed economies are an important case for scrutinizing.

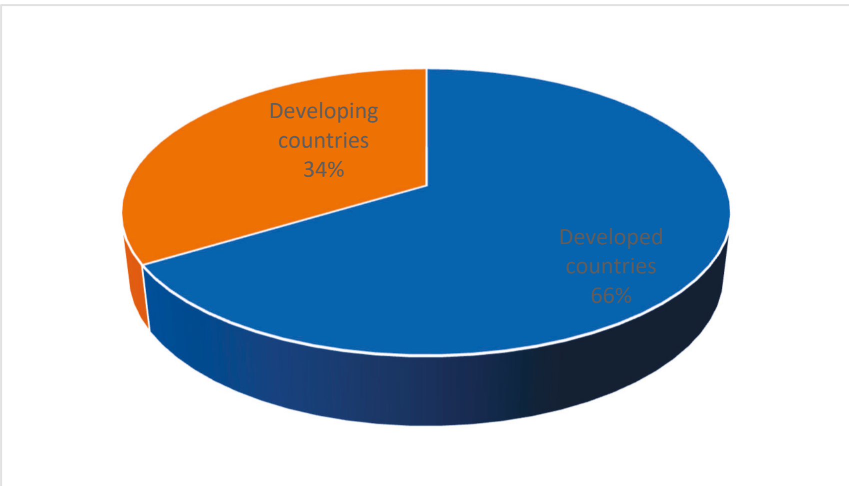


Figure 2. Total RENE supply by developing and developed countries (2021); Authors' calculations (Source: https://www.iea.org/data-and-statistics/, accessed on 1 June 2024).

It is important to conduct this study for several reasons. First, policymakers and governments can increase the supply and demand of RENE by identifying REN factors in developed countries, thus reducing fossil fuel usage and achieving SDG 7 and SDG 13. Second, by highlighting the role of EUI, EPS, and GEPU policymakers could plan and improve more efficient plans in developed economies for encouraging REN, reducing the adverse effect of GEPU, adopting stricter ecological policies, and eventually attaining SDGs in the future.

Several contributions are made by the present study. First, in contrast to previous recent studies (e.g., [8,9,12]), which examined REN in OECD and BRICS countries, this study probed the factors contributing to REN in developed countries comprising more control factors. This study is particularly noteworthy for its consideration of EUI effects on REN. Despite the majority of recent studies investigating the EUI's impact on oil volatility forecasting [21] and stock market returns [22], no study has examined the EUI's impact on REN. The current research will contribute to the literature by using a novel country-based EUI, as suggested by [23]. The index may aid policymakers in comprehending the intricate and interconnected relationships between different elements in energy markets, as it aggregates energy-related and economic uncertainty across a wide range of words. Unlike uncertainty indicators, the EUI is particularly built to capture information on uncertainties linked with energy markets like energy price shocks and war risk. Furthermore, we employ a novel country-based EPS index, which is widely used for policy evaluation focusing on climate change and air pollution lessening plans. Second, despite prior works (e.g., [9,24]) that tested the effects of EPS and GEPU on REN in high- and middle-income and OECD economies, this work contributes by probing the moderator or catalyst role of EPS and GEPU on the EUI–REN association in 16 developed nations. Third, this study estimates models and finds robust results by using advanced panel data estimation techniques based on fixed effects and quantiles. Notably, the quantile panel data technique offers a more comprehensive explanation of the data since it allows us to examine a covariate's impact on y's entire distribution as opposed to simply its conditional mean.

Overall, the purpose of this research is to identify factors contributing to REN in developed countries. Particularly, the current study aims to analyze the role of the EUI in promoting REN (or diminishing it). In addition, we seek to discover whether either EPS or GEPU attenuates or exacerbates the impact of the EUI on REN. The current research can be reviewed as follows: (i) What are the significant factors of REN, and which factors have a positive or negative impact on REN? (ii) How does the EUI influence REN? (iii) Is the EUI–REN nexus moderated or exacerbated by EPS and GEPU?

This research yields some noteworthy highlights. First, the results uncover that the EUI positively affects REN, denoting that rising uncertainties related to the energy market stimulate developed countries to increase their REN. Second, the results unearth that EPS positively affects REN, implying that stricter ecological strategies encourage developed countries to increase REN. This is while GEPU has a detrimental effect and leads to diminishing REN. Third, the interaction results underscore that EPS has a catalyst role in triggering REN by increasing the EUI ($EUI \times EPS > 0$), although GEPU has a moderator role ($EUI \times GEPU < 0$). This implies that stricter ecological plans could be an important channel to upsurge REN when the EUI is high. In contrast, GEPU moderates the increase in REN while the EUI is high. More specifically, the findings underscore that the effect of the EUI on REN is more positive in high EPS countries and that the positive effect of the EUI is more moderate when GEPU is high. Our results recommend that policymakers should focus on scheming effective clean ecological policy instruments and reducing uncertainties related to economic policy to help trigger the REN by increasing EUI and eventually help achieve SDGs in the future. Fourth, the positive and negative determinants of REN provide insight for policymakers to enhance REN, which ultimately helps decrease the potential negative consequences of climate change and attain a clean environment.

The study's remaining is organized as follows. In Section 2, the literature review is explained. The data and technique are explained in Section 3. The results are discussed and the robustness check is shown in Sections 4 and 5. Section 6 is the summary.

2. Uncertainties and Renewable Energy: A Literature Review

Numerous studies explored the effects of uncertainties on RENE. In the literature, prior works used various measurements for measuring uncertainties like GEPU, geopolitical risk (GPR), and climate policy uncertainty (CPU). For example, Refs. [12,20,25] found that GEPU decreases RENE. From the demand side, GEPU increases adversely affect the income levels of consumers, thereby delaying the transition to a clean economy in the long run [17]. From the supply side, the GEPU reduces RENE supply by increasing private investment costs [18]. Ref. [26] revealed a negative long-run nexus between EPU and REN, indicating that higher levels of the country's vulnerability reduce its REN. Ref. [27] showed a negative effect of EPU on REN in G7 countries. Ref. [28] also showed that EPU has a significant negative impact on REN in most subperiods.

Furthermore, Ref. [29] documented that GPR is a significant positive driver in developing RENE in the U.S. and GPR encourages economies to rely on RENE sources to decrease fossil fuel inflows' risk. Ref. [17] underscored that GPR positively impacted REN in developing countries between 1996 and 2015 and that its effect is more prominent in the long run. Ref. [30] underscored that GPR shocks positively affect the growth of REN over time. Ref. [31] in a global study uncovered that GPR has a significantly considerable impact on green investments both in the short and in the long run. Ref. [12] discovered that increased GPR diminishes REN and undermines climate change mitigation efforts.

Moreover, some works indicated that the global CPU plays an important role in encouraging both the demand and the supply of RENE. According to works by Refs. [32,33], when CPUs rise, firms invest more in clean energy schemes (supply side) and promote the clean energy sector as a consequence of climate change. Furthermore, Ref. [34] demonstrated that the CPU promotes RENs (demand side) for a long time. Ref. [35] revealed that the CPU has a greater ability to forecast RENE volatility than other uncertainty indices, including the EPU and GPR variables. In a study by Ref. [28], the causal relationship between REN and CPU is both positive and negative. When the Administration is supportive of climate change alleviation, the correlation between REN and CPU is positive, but when it is not, the correlation is negative. Ref. [36] also showed that when extreme climate events or major climate policy changes are faced, the causal nexus between CPU and RENE will increase significantly. Ref. [37], using the novel Fourier augmented autoregressive distributed lag model, found that CPU diminishes REN across the long and short run. Ref. [38] highlighted that CPU has a significant negative effect on the long-term clean energy market's volatility. Ref. [39] found that CPU favorably affects REN in the U.S. in the short and long term between 2005–2021.

In contrast to conventional uncertainty indicators, Ref. [23] recently created the energy-related uncertainty index (EUI), which is based on energy and economic uncertainty components specifically designed to capture information on uncertainties related to energy markets (e.g., war risk, energy price shocks). Ref. [23] created EUIs for 28 advanced and developing nations by examining words associated with energy and uncertainty in The Economist Intelligence Unit's (EIU) monthly national reports. When it comes to the other uncertainty indicators, the EUI is unique and has specific benefits. First, the EUI is built by looking for the relevant terms using the text search method. Second, the EUI's construction is predicated on the EIU's monthly nation reports, which aid in distinguishing the EUI's regional variations. Third, compared to when it comprised information on a single nation or category, the EUI can more accurately reflect significant information like oil crises, military crises, etc.

Given the specific advantages, some studies using the EUI attempted to delve into forecasting oil price volatility and stock market return. For example, Ref. [21] discovered evidence of information spillovers from the EUI to the oil market in a recent study. According to their findings, the EUI can foresee oil price volatility, and figuring out this connection enables response to international political and economic issues as well as the promotion of ecological protection and sustainable growth (e.g., [40–42]). Moreover, Ref. [22] uncovered that the EUI has a significant role in predicting stock market returns in China and that the EUI outperforms economic factors. Using the ARCH model, Ref. [43] concluded that the global EUI is highly volatile, so a shift from fossil fuels to RENE and a clean economy is essential for achieving SDGs. As RENE is less susceptible to exogenous shocks and price fluctuations, it can reduce energy dependency and uncertainty in energy markets.

It has been evident from several studies that the EUI is a better uncertainty indicator to use and has relatively greater advantages than other uncertainty indicators. Nevertheless, there has not been sufficient literature to use the EUI and examine the EUI–REN nexus. Moreover, no prior research has examined the EUI–REN nexus in light of EPS and GEPU's role. Therefore, the current research efforts are designed to illuminate these research gaps in the framework of developed economies between 2000 and 2020.

3. Data and Methodology

3.1. Data

The following research initially focuses on developed economies between 2000 and 2022 to examine the factors of REN. However, 16 developed countries between 2000 and 2020 make up the final sample because of data shortages and mismatches across different data sources. The sample economies are shown in Table A1 in Appendix A.

Based on the results of earlier studies (e.g., [9,34]), the traditional factors were selected. Data for the control variables were gathered from the World Bank for the current study. Furthermore, data were obtained from the websites of the OECD and policy uncertainty, respectively, for the GEPU and the EPS. Thirteen policy tools targeted at mitigating air pollution and climate change make up the EPS index. In particular, this work collects data from the policy uncertainty website, which was built by Ref. [38] for the EUI. Table 1 provides clarifications on the factor descriptions.

Table 1. Variables explanations.

Variables	Codes	Measurements	Links
Renewable energy consumption	REN	Renewable energy consumption (% of total final energy consumption)	World Bank
Financial market development	STV	Stocks traded, total value (% of GDP)	World Bank
Economic openness	FDI	Foreign direct investment, net inflows (% of GDP)	World Bank
Remittances	REMIT	Personal remittances received (% of GDP)	World Bank
Carbon dioxide emissions	CO_2	CO_2 emissions (kt)	World Bank
Natural resources rents	TNRR	Total natural resources rents (% of GDP)	World Bank
Economic activity	GDPC	GDP per capita (current US$)	World Bank
Energy-related uncertainty	EUI	Energy-related uncertainty index	www.policyuncertainty.com, 20 May 2024
Global economic policy uncertainty	GEPU	Global economic policy uncertainty index	www.policyuncertainty.com, 20 May 2024
Environmental policy stringency	EPS	Environmental policy stringency index	https://stats.oecd.org/, 20 May 2024

Note: Table 1 presents the codes, measurements, and links of variables.

Figure 3 illustrates the expected signs for each determinant. Based on the findings of prior works, we expect that STV, FDI, REMIT, EPS, and the EUI positively impact REN whereas TNRR has a negative effect. Furthermore, Figure 3 shows that GDPC, CO_2, and GEPU impact REN either negatively or positively.

Furthermore, the Scatterplot Matrix was plotted in Figure 4 to show the distribution of data between the examined variables. Meanwhile, Figure 5 plots REN, EUI, EPS, and

GEPU for the entire economies during 2000 and 2020. As illustrated in Panel A, there is a positive movement between REN and the EUI, denoting that a rise in the EUI leads to an increase in REN. In addition, it shows that EPS and GEPU positively move together and that developed countries improve their environmental policies by increasing GEUP, particularly after 2004.

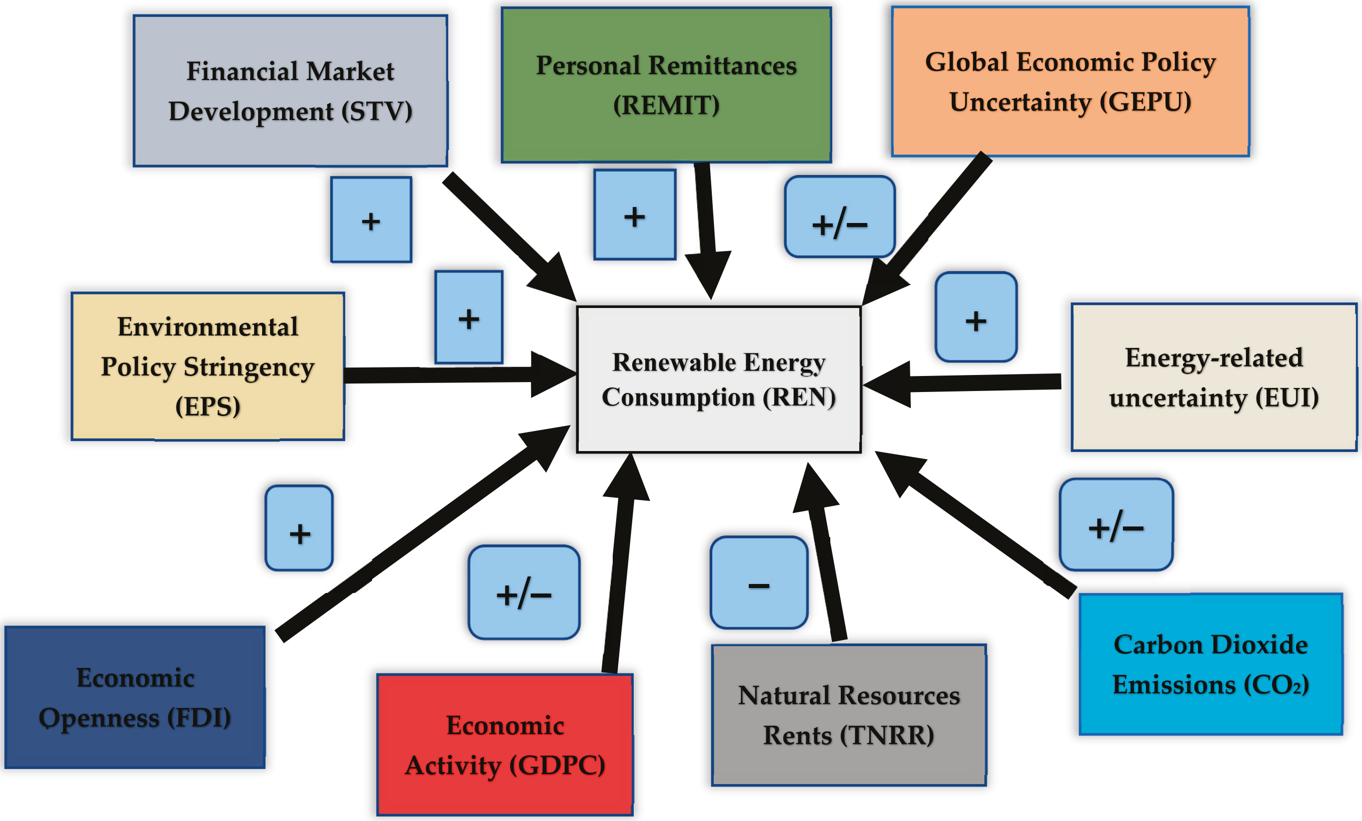


Figure 3. Variables' Expected signs.

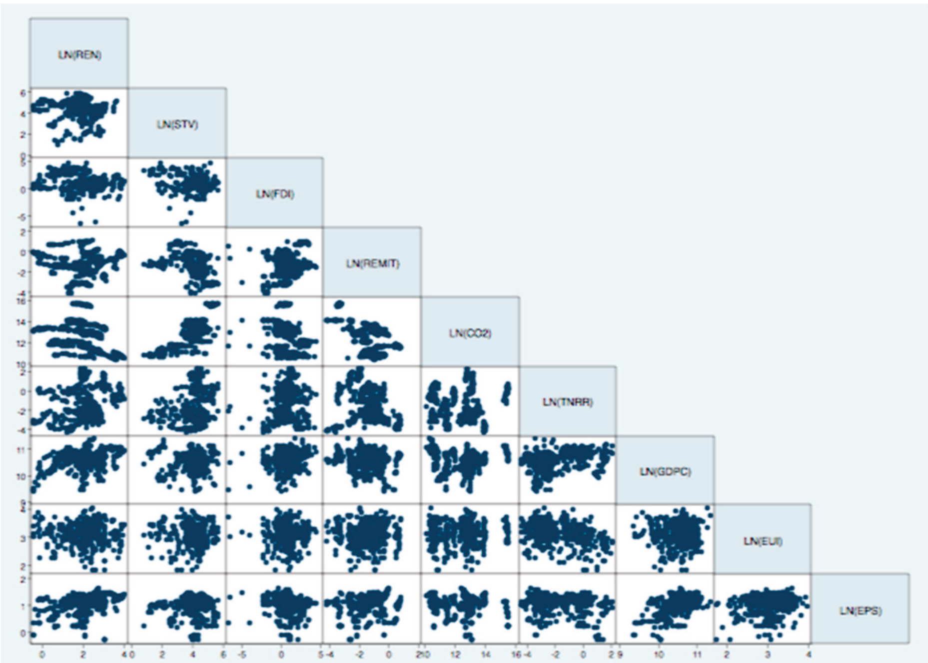
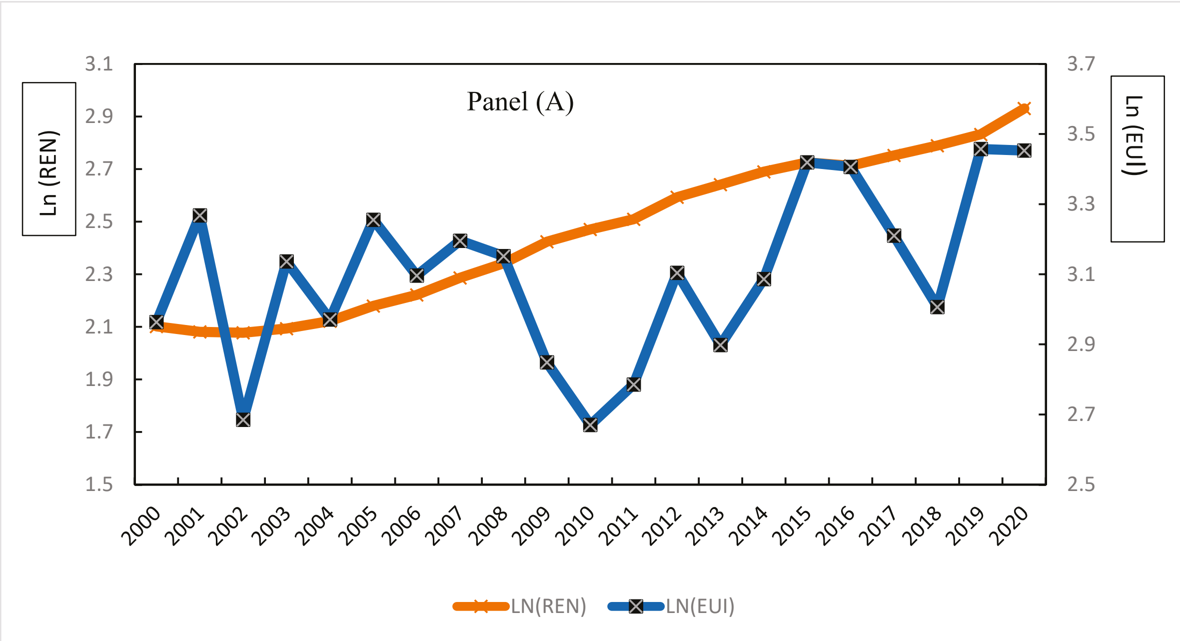


Figure 4. Scatterplot matrix.



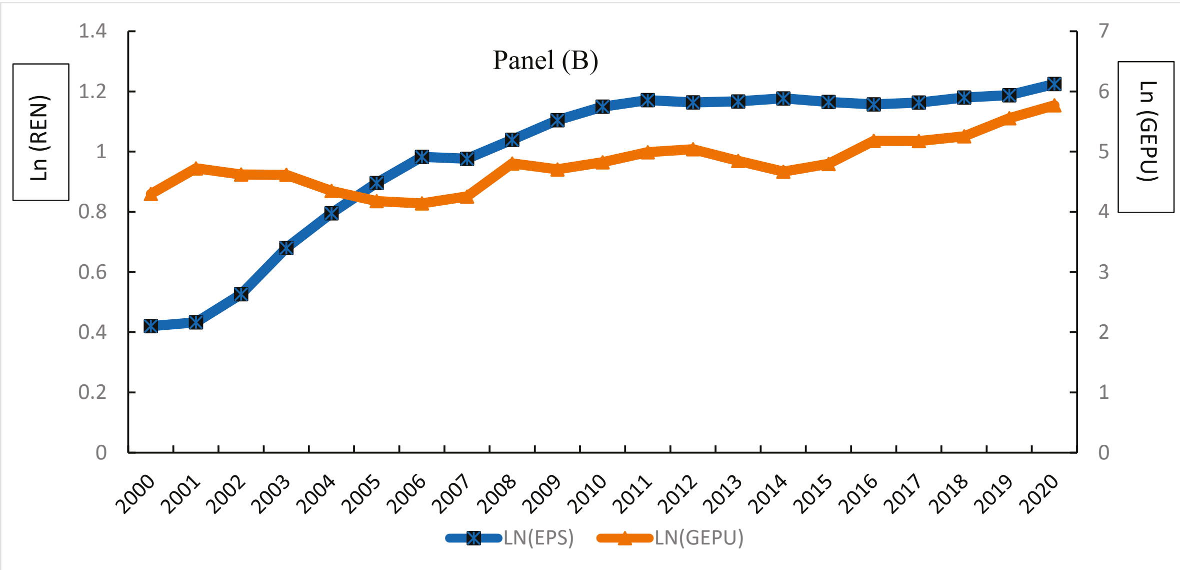


Figure 5. Panel (**A**,**B**) Time series plot of Ln(REN), Ln(EUI), Ln(EPS), and Ln(GEPU) for the years 2000–2020.

Multicollinearity is not present among the factors, as Table 2 illustrates, and the equation can be estimated by integrating all feasible determinants.

Table 2. Pearson correlation matrix.

	STV	FDI	REMIT	CO_2	TNRR	GDPC	EUI	EPS	GEPU	VIF
STV	1.000									1.04
FDI	0.066	1.000								1.01
REMIT	−0.248 *	0.051	1.000							1.08
CO_2	−0.041	−0.135 *	−0.273 *	1.000						1.09
TNRR	0.229 *	−0.038	−0.248 *	0.022	1.000					1.14
GDPC	−0.192 *	0.134 *	−0.078	0.137 *	0.234 *	1.000				1.03
EUI	−0.113 *	0.002	0.013	0.048	−0.317 *	0.036	1.000			1.11
EPS	−0.294 *	−0.133 *	0.081	−0.212 *	−0.136 *	0.245 *	0.14 6*	1.000		1.05
GEPU	−0.188 *	−0.162 *	0.052	−0.121 *	−0.057	0.264 *	0.292 *	0.261 *	1.000	1.12

Note: Table 2 presents the Pearson correlation matrix and Variance Inflation Factor (VIF). * is statistically significant at 1%.

3.2. Model and Methodology

In examining the research questions and identifying the elements of REN, this work follows the prior works (e.g., [9,12]) and applies the linear model. Thus, we use the baseline Equation (1) to scrutinize the effect of the EUI for each investigated country (i) on REN during the period of the work (t) by including the controlling factors. In estimating Equation (1), we use the time and country dummies, but, for parsimony, the coefficients do not present it.

$$\mathbf{REN_{it}} = \alpha_0 + \alpha_1\mathbf{STV_{it}} + \alpha_2\mathbf{FDI_{it}} + \alpha_3\mathbf{REMIT_{it}} + \alpha_4\mathbf{CO_{2it}} + \alpha_5\mathbf{TNRR_{it}} + \alpha_6\mathbf{GDPC_{it}} + \alpha_7\mathbf{EUI_{it}} + \alpha_8\mathbf{GEPU_t} + \alpha_9\mathbf{EPS_{it}} + \varepsilon_{it} \quad (1)$$

A winsorization of all variables at the top and bottom 1% was carried out before estimating Equation (1). Additionally, the natural logarithm was used to normalize each factor. Next, by clustering standard errors at the national level, this work assessed the reliability of findings using the fixed effects (FE) panel data approach. In the FE, all time-invariant disparities between individuals are controlled so that omitted time-invariant characteristics cannot bias the estimate of coefficients. Furthermore, in addition to improving estimation efficiency [44], using the panel data method helps manage multicollinearity and heterogeneity issues. As part of the present study, a Hausman test result was used to choose between fixed and random effects, and a cross-sectional dependence (CD) post-estimation test was also applied to test robustness [45] to ensure that findings are robust.

Aside from the FE method, the study follows prior research (e.g., [9]) by estimating Equation (1) using quantile regression at multiple points in the distribution of the LnREN. This approach allows for estimating the model by describing the relationship at distinct points in the conditional distribution of the LnREN. A quantile is the intersection of a continuous, smaller interval with equal probabilities in a probability distribution. Using quantile regression, we can understand the associations between factors at different quantile levels rather than the mean. This method is useful for investigating outcomes that do not follow a normal distribution and are not linear.

Quantile regression estimator for quantile q, therefore, minimizes the objective function for a linear function ($y = \beta X' + \varepsilon$) by;

$$\mathbf{Q}\left(\beta_q\right) = \sum_{i:y_i \geq X_i'\beta}^{N} \mathbf{q}|\mathbf{y_i} - \mathbf{X_i'}\beta_q| + \sum_{i:y_i < X_i'\beta}^{N} (\mathbf{1} - \mathbf{q})|\mathbf{y_i} - \mathbf{X_i'}\beta_q| \quad (2)$$

4. Results

4.1. Univariate Results

A descriptive summary of the 16 developed countries is presented in Table 3. It shows that $LnCO_2$ has the highest mean (12.515), ranging from 10.217 to 15.569. The second highest mean (10.536) is for LnGDPC, which ranges from 9.355 to 11.362. Meanwhile, LnREMIT (−1.408) and LnTNRR (−1.566) have the lowest means. Additionally, the descriptive statistics reveal that LnFDI, with a standard deviation of 1.474, and LnTNRR, with a standard deviation of 1.659, have the highest variation of all other variables but that LnEPS and LnGDPC, with their respective standard deviations of 0.350 and 0.368, exhibit the lowest variation.

Table A1 displays descriptive statistics for the variables of the sample of developed countries. Korea has the lowest mean LnREN (0.379), whereas Sweden has the highest mean (3.796). Furthermore, with a mean of 5.366 for LnSTV and a mean of 15.479 for $LnCO_2$, the United States leads the other sample countries in both of these categories. Likewise, Australia has the lowest LnEUI on average at 2.682, and France has its highest LnEUI on average at 3.329. Moreover, the United States has the lowest LnEPS on average at 0.671, and Japan has the highest on average at 1.196.

LnREN and LnEUI are specifically compared in Figure 6 for developed economies between 2000 and 2020. According to Figure 6 panel A and Figure 6 panel B, Sweden has the highest LnREN and Korea has the lowest LnREN. Australia and France also have the lowest and highest LnEUI, respectively, as shown in Figure 6B.

Table 3. Descriptive summary (2000–2020).

Variables	No. of Obs.	Mean	Median	St.dev	Minimum	Maximum
Ln(REN)	336	2.114	2.182	0.931	−0.371	4.067
Ln(STV)	336	4.010	4.203	0.980	0.893	5.768
Ln(FDI)	336	0.839	0.837	1.474	−6.524	4.460
Ln(REMIT)	336	−1.408	−1.425	1.083	−4.163	0.900
Ln(CO_2)	336	12.515	12.758	1.296	10.217	15.569
Ln(TNRR)	336	−1.566	−1.976	1.659	−4.343	2.166
Ln(GDPC)	336	10.536	10.612	0.368	9.355	11.362
Ln(EUI)	336	3.050	3.072	0.400	1.782	3.997
Ln(EPS)	336	0.965	1.051	0.350	−0.325	1.587
Ln(GEPU)	336	4.799	4.797	0.425	4.140	5.771

Note: Table 3 presents the descriptive statistics of variables.

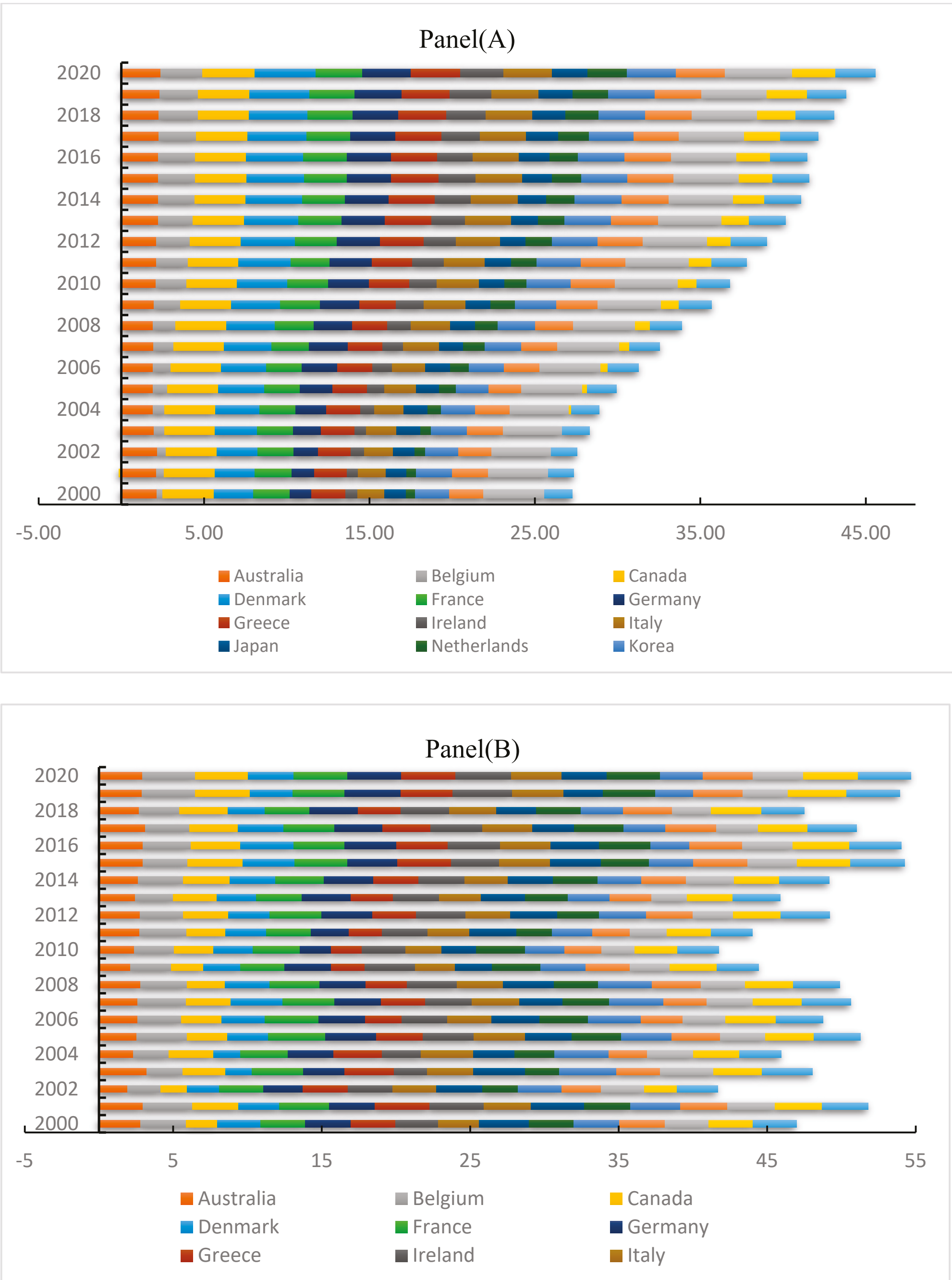


Figure 6. Panel (**A**): Average of Ln(REN) among the selected developed countries. Panel (**B**): Average of Ln(EUI) among the selected developed countries.

4.2. Empirical Results

A CD test, a unit root test, and a direction of relations test were performed before estimating models in this research. The CD test was conducted according to Ref. [45] to accomplish this. The CD-tests indicate that any variation in one country will undoubtedly impact the other countries in the sample, as shown in Table 4.

Table 4. Cross-sectional dependence.

	REN	STV	FDI	REMIT	CO_2	TNRR	GDPC	EUI	EPS
Pesaran's test	11.588 **	20.537 *	34.216 **	22.447 *	18.634 *	22.548 *	14.822 **	25.413 **	18.488 *

Note: * and ** denote statistical significance at the 1% and 5% levels, respectively.

Furthermore, as shown in Table 5, all factors are stationary, and the panels do not contain unit roots using the Ref. [46] (Panel A) and Ref. [47] (Panel B) panel unit root tests.

Table 5. Panel unit root test.

Variables	Panel (A): LLC (2002)		Panel (B): IPS (2003)	
	With Trend	With Cross-Sectional Dependence	With Trend	With Cross-Sectional Dependence
LnREN	−5.436 *	−4.354 *	−4.314 *	−4.283 *
LnSTV	−3.551 *	−5.285 *	−5.621 *	−5.556 *
LnFDI	−6.546 *	−3.669 *	−4.232 *	−4.332 *
LnREMIT	−4.258 *	−5.261 *	−3.182 *	−3.106 *
$LnCO_2$	−2.218 **	−2.115 **	−2.926 *	−4.258 *
LnTNRR	−3.689 *	−2.226 **	−2.218 **	−3.324 *
LnGDPG	−2.026 **	−6.753 *	−4.565 *	−2.214 **
LnEUI	−3.448 *	−2.288 **	−6.637 *	−5.652 *
LnEPS	−5.386 *	−3.395 *	−5.765 *	−6.448 *
LnGEPU	−2.135 **	−4.522 *	−4.391 *	−4.523 *

Note: * and ** denote statistical significance at the 1% and 5% levels, respectively.

Moreover, the Granger causality test is used to examine how the relationship between the variables is directed. Based on the results of Table 6, it can be concluded that the model does not suffer from endogeneity problems and that there is no reverse causality between the independent and dependent factors. For developed economies, this means historical information about explanatory variables can be used to predict future changes to REN.

Table 6. Granger causality test.

	H_0		F-Statistics	[Probability]	Decision
LnSTV	→	LnREN	6.363 *	[0.000]	✓
LnFDI	→	LnREN	4.425 *	[0.000]	✓
LnREMIT	→	LnREN	2.224 **	[0.023]	✓
$LnCO_2$	→	LnREN	5.348 *	[0.000]	✓
LnTNRR	→	LnREN	4.856 *	[0.001]	✓
LnGDPG	→	LnREN	2.151 **	[0.019]	✓
LnEUI	→	LnREN	6.653 *	[0.000]	✓
LnEPS	→	LnREN	5.846 *	[0.000]	✓
LnGEPU	→	LnREN	2.252 **	[0.026]	✓

Note: * and ** imply 1% and 5% statistical significance levels, correspondingly.

4.2.1. Multivariate Results

The estimation results of Equation (1) are presented in Table 7. The findings highlight that LnSTV positively affects LnREN, with significant coefficient in Q.25 (α = 0.381), Q.75 (α = 0.205), and Q.95 (α = 0.264) at a 1% and 10% significance level. Likewise, Table 7 reveals that LnFDI, LnREMIT, and LnEPS positively affect LnREN at the various quantiles in the sample developed economies. Nevertheless, the results indicate that $LnCO_2$, LnTNRR, and LnGDPC negatively impact LnREN at the various quantiles. Furthermore, as expected, LnEUI positively impacts LnREN with significant coefficient at the quantiles Q.25 (α = 0.042), Q.50 (α = 0.378), Q.75 (α = 0.237), and Q.95 (α = 0.108) in the sample developed nations. According to the FE method, the results reveal that a 1% rise in EUI upsurges REN by 0.03%. Moreover, the results underscore that LnGEPU negatively impacts LnREN with significant coefficient at the quantiles Q.25 (α = −0.515), Q.50 (α = −0.419), Q.75 (α = −0.486), and Q.95 (α = −0.506) in the sample developed nations. The results show that REN is lowered by 0.27% for every 1% rise in GEPU based on the FE method.

Table 7. The impact of the EUI on REN (2000–2020).

Independent Variables	Quantile Estimated Coefficients				FE
	Q.25	Q.50	Q.75	Q.95	Coefficients
LnSTV	0.381 *	0.064	0.205 ***	0.264 *	0.087 **
	(4.70)	(0.41)	(1.67)	(3.35)	(2.03)
LnFDI	0.052	0.037 **	0.007	0.018 *	0.036 **
	(0.80)	(2.06)	(0.16)	(4.39)	(2.15)
LnREMIT	0.164	0.045	0.019 **	0.077 *	0.009 ***
	(1.41)	(0.43)	(2.13)	(4.18)	(1.73)
$LnCO_2$	−0.171 **	−0.061	−0.213 **	−0.317 *	−1.049 *
	(−2.07)	(−0.41)	(−2.18)	(−4.22)	(−5.56)
LnTNRR	−0.163 *	−0.216 *	−0.212 *	−0.237	−0.074
	(−3.36)	(−3.74)	(−5.91)	(−1.22)	(−1.07)
LnGDPC	−0.124	−0.393 **	−0.533 *	−0.176	−0.941 *
	(−0.774)	(−2.04)	(−3.09)	(−0.62)	(−4.78)
LnEUI	0.042 *	0.378 **	0.237 **	0.108 *	0.035 **
	(4.24)	(2.05)	(2.12)	(3.04)	(2.14)
LnGEPU	−0.515 *	−0.419 *	−0.486 *	−0.506 **	−0.271 **
	(−2.65)	(−3.01)	(−3.79)	(−2.02)	(−2.14)
LnEPS	0.441 **	0.657 **	0.827 *	0.251 *	0.109 ***
	(2.03)	(2.40)	(3.73)	(5.63)	(1.73)
CD-test (*p*-value)	---	---	---	---	(0.339)
Time dummy	✓	✓	✓	✓	✓
Country dummy	✓	✓	✓	✓	✓

Note: Table 7 specifically presents the impact of the EUI on REN by considering the control variables. Table 1 reveals the variables' explanations. The 25th, 50th, 75th, and 95th percentiles of the LnREN are reported. *, **, and *** denote the significance level at 1%, 5%, and 10%, respectively.

The positive and significant effect of LnSTV, LnFDI, and LnREMIT underscore the important role of internal and external financing in promoting REN in developed countries. Following prior research (e.g., [8,48]), investors and companies developing the financial market are more able to borrow loans at lower funding costs. This encourages them to shift from using conventional energies to green energies and to stimulate them to invest in RENE projects which ultimately results in increasing REN and helping achieve ecological quality [49]. In addition, the development of the capital market could ease the accessibility of various financial facilities, leading to motivating firms to upsurge R&D activities in renewable energy, advancing ecological technologies, and developing RENE plans.

Furthermore, following prior works (e.g., [8,9,50]), the positive and significant effect of LnFDI uncovered that increasing economic openness leads to inflowing massive amounts of capital, which helps to facilitate the accessibility of external finances for investors for RENE plans, to transmit better cleaner know-how, and eventually to increase the share of RENE in providing worldwide energy. Similarly, consistent with the findings of prior studies (e.g., [15]), rising personal remittances (LnREMIT) are a significant positive driver in financing RENE schemes, providing knowledge and skills related to renewable energy, and promoting REN.

Furthermore, the study by Ref. [12], which found that a 1% increase in CO_2 produced a fall in REN by 0.35% in OECD nations, is corroborated by the negative and substantial effect of $LnCO_2$, in contrast to Ref. [16]. Moreover, following past research (e.g., [19,51]), the negative and significant effects of LnTNRR suggest that REN is lower in countries with higher TNRR, and in such environments, the transition of conventional energy to RENE has a low speed. In this line, Ref. [12] unearthed that a 1% rise in TNRR causes a decrease in REN by 0.03% in OECD economies.

Likewise, the adverse and significant impact of LnGDPC confirms some research (e.g., [8,10]) which found that economic development adversely impacts REN. However, the finding is in contradiction with prior studies (e.g., [12,52]). Additionally, the negative and significant effect of LnGEPU is consistent with prior research (e.g., [16,25]), indicating that an increasing economic policy uncertainty results in decreasing investors' and households' income levels causing less motivation to replace traditional fuels with RENEs and diminish REN.

In addition, the results reveal that LnEUI has a positive statistically significant effect on REN. This implies that rising uncertainties related to the energy market are an important driver to stimulate the consumption of RENE and vice versa. Consistently, Ref. [43] stressed that due to the high volatility of the global EUI, using RENEs could be vital for economies to attain ecological sustainability and diminish climate change threats. As RENE is less susceptible to exogenous shocks and price fluctuations, a higher supply and consumption of RENE could help decrease energy dependency and uncertainty in energy markets.

Moreover, the favorable and significant effect of LnEPS supports earlier studies (e.g., [9,20]) that uncovered that the adoption of clean ecological techniques led to an increase in REN. The primary objective of EPS is to achieve a clean environment without compromising the goal of economic expansion. Strict ecological policies are essential to promoting ecological sustainability [53,54]. Some works indicated that EPS is effective in developing RENE capacity development and that the productivity of ecological plans is associated with the type of RENE sources (e.g., [55,56]). Nevertheless, Ref. [57] indicated a mixed effect of EPS on REN in different quantiles.

4.2.2. Further Analysis: Do the GEPU and EPS Play a Moderator or Catalyst Role?

Specifically, Table 8 scrutinizes the interaction effects of (EUI $\times$ EPS) and (EUI $\times$ GEPU) on REN in developed economies by including the control factors and classifying economies based on the level of EPS and GEPU. As presented in Table 8, (LnEUI $\times$ LnGEPU) is negative and statistically significant in developed economies. This implies that the positive effect of the EUI on REN is moderated by an increase in GEPU. Additionally, the findings indicate that the EUI has relatively less positive effects on REN when GEPU is high and vice versa.

Table 8. The role of GEPU and EPS between EUI and REN (2000–2020).

Independent Variables	Global Economic Policy Uncertainty (GEPU)			Environmental Policy Stringency (EPS)			Sample Countries
	Low GEPU	High GEPU	Sample Countries	Low EPS	High EPS	Sample Countries	
LnEUI	0.455 *	0.638 **	0.951	0.254 **	0.286 *	0.342	0.126 **
	(3.64)	(2.02)	(1.17)	(2.11)	(4.66)	(1.24)	(2.07)
LnGEPU	−0.143	−0.165	−0.175 **	−0.086	−0.194 **	−0.515 *	−0.316
	(−1.16)	(−1.44)	(−2.08)	(−0.64)	(−2.05)	(−5.56)	(−0.58)
LnEPS	0.363	0.462 **	0.628 *	0.197	0.213	0.441 **	0.144
	(1.12)	(2.18)	(4.49)	(1.44)	(0.69)	(2.03)	(1.22)
LnEUI × LnGEPU	−0.093 **	−0.126 *	−0.213 ***	---	---	---	−0.088 ***
	(−2.22)	(−5.17)	(−1.89)	---	---	---	(−1.71)
LnEUI × LnEPS	---	---	---	0.014 **	0.032 *	0.009 ***	0.023 **
	---	---	---	(2.01)	(3.18)	(1.73)	(2.16)
Control variables	✓	✓	✓	✓	✓	✓	✓
Time dummy	✓	✓	✓	✓	✓	✓	✓
Country dummy	✓	✓	✓	✓	✓	✓	✓
Adj R^2	0.26	0.32	0.41	0.23	0.29	0.36	0.43

Note: Table 8 reveals the interaction effects of GEPU and EUI and also EPS and EUI on REN using the fixed effects method. *, **, and *** present the significance level at 1%, 5%, and 10%, respectively.

The findings of the study also confirm that (LnEUI × LnEPS) is positive and statistically significant in developed economies, suggesting that the positive impact of the EUI on REN is intensified by stricter environmental policies. Further, the findings reveal that in countries with high EPS, the EUI has a relatively greater impact on REN than in countries with low EPS and vice versa. In general, the EUI promotes REN, but its positive impacts can either be moderated by increasing GEPU (moderator role) or intensified by increasing EPS (catalyst role) in developed countries. Therefore, in light of the increased uncertainty related to energy markets (EUI), policymakers should refocus their efforts on reducing uncertainty related to economic policy and on designing and implementing clean ecological strategies to stimulate REN.

5. Robustness Check

As part of the robustness tests, technological innovation (LnTINV) was added as a control variable to estimate baseline Equation (1) following Refs. [8,9]. To gauge the development of the financial market, we also used the "stock market turnover ratio" (LnSMT) as a new alternative measurement. We obtained the data from the World Bank database. Furthermore, we employ panel quantile and FE methods to confirm the accuracy and coherence of the findings. To find out if the estimated model depends on other models, the CD post-estimation test [45] is used. Moreover, by Refs. [9,12], we estimate Equation (1) by the use of the dynamic panel data technique (SYS-GMM) to assess the dependability of the results in the event that endogeneity concerns may arise. It is interesting to note that many tests, including the Sargan, Hansen, and serial correlation tests, are used by SYS-GMM to verify the correctness of the calculated equations.

The robustness test results in Table 9 corroborate the above findings presented in Tables 7 and 8. The findings stress the beneficial role of LnSMT, LnFDI, LnREMIT, LnEUI, and LnEPS in promoting REN. Meantime, the results show that LnTINV positively impacts REN. This finding supports the prior research (e.g., [8,9,13]) and indicates that ecological technology, by increasing energy efficiency and accelerating replacing fossil fuels with RENEs, has a significant role in reducing carbon emissions and attaining ecological quality [58]. However, Table 9 reveals that $LnCO_2$, LnTNRR, LnGDPC, and lnGEPU have an adverse effect and diminish REN. This indicates that increasing CO_2, TNRR, GDPC, and GEPU results in lessening REN in developed countries.

Table 9. Robustness test.

Independent Variables	Quantile Estimated Coefficients				FE	GMM-SYS
	Q.25	Q.50	Q.75	Q.95	Coefficients	Coefficients
Lag dependent variable	---	---	---	---	---	0.138
	---	---	---	---	---	(1.33)
LnSMT	0.147 *	0.093	0.219 **	0.185 ***	0.066 **	0.244 ***
	(4.46)	(1.24)	(2.05)	(1.73)	(2.13)	(1.69)
LnFDI	0.013	0.074 **	0.138 *	0.105	0.042 ***	0.028 *
	(0.55)	(2.02)	(4.56)	(0.94)	(1.71)	(3.63)
LnREMIT	0.262	0.087	0.066 *	0.138 ***	0.075	0.163 **
	(0.88)	(1.11)	(5.58)	(1.68)	(1.37)	(2.03)
$LnCO_2$	−0.242 *	−0.009	−0.356 ***	−0.118 **	−0.007	−0.115
	(−5.33)	(−0.46)	(−1.69)	(−2.16)	(−1.22)	(−0.83)
LnTNRR	−0.063	−0.124 **	−0.252 **	−0.153	−0.337 *	−0.078
	(−1.03)	(−2.05)	(−2.22)	(−1.41)	(−4.67)	(−1.43)
LnGDPC	−0.233 *	−0.141	−0.473 **	−0.126	−0.351 *	−0.094
	(−5.12)	(−1.57)	(−2.06)	(−0.77)	(−6.33)	(−1.26)
LnEUI	0.058 *	0.342*	0.151 ***	0.276 **	0.128 *	0.304 **
	(3.66)	(4.72)	(1.73)	(2.08)	(5.31)	(2.24)
LnGEPU	−0.362 *	−0.453 **	−0.278 *	−0.541 ***	−0.342 *	−0.248 **
	(−4.26)	(−2.11)	(−5.43)	(−1.73)	(−4.55)	(−2.13)
LnEPS	0.362 *	0.441	0.426 *	0.251 **	0.133	0.425 **
	(4.43)	(1.06)	(4.77)	(2.13)	(1.16)	(2.19)
LnTINV	0.238 *	0.344 **	0.179 **	0.212	0.286	0.166 ***
	(4.22)	(2.06)	(2.13)	(1.17)	(0.88)	(1.69)
CD-test (*p*-value)	---	---	---	---	(0.428)	---
M_1-test	---	---	---	---	---	(0.026)
M_2-test	---	---	---	---	---	(0.451)
Sargan-test	---	---	---	---	---	(0.366)
Hansen-test	---	---	---	---	---	(0.477)
FC dummy	✓	✓	✓	✓	✓	✓
Time dummy	✓	✓	✓	✓	✓	✓
Country dummy	✓	✓	✓	✓	✓	✓

Note: Table 9 presents the robustness test results. T-values are presented for the quantile and fixed effect in the parentheses while Z-values reported for the SYS-GMM. *, **, and *** denote the significance level at 1%, 5%, and 10%, respectively.

6. Conclusions

Although many studies have focused on exploring the determinants of environmental sustainability, less attention has been paid by scholars to scrutinizing the drivers of RENE. Particularly, limited studies have attempted mainly to delve into the impact of the EUI on REN in general and advanced economies in particular. Furthermore, there is a lack of research in the literature on the potential effects of EPS and GEPU changes on the EU–REN nexus. Thus, this research endeavors to fill this gap by testing particularly the EUI–REN relationship by considering the traditional control variables. We also aim to examine whether EPS and GEPU attenuate or intensify the effect of the EUI on REN.

The results underscore that the EUI significantly impacts REN, suggesting that higher uncertainties related to energy markets lead to promoting REN. Furthermore, the interaction (EUI × EPS) findings underline that EPS has a favorable role in increasing the positive effect of the EUI on REN in sample developed countries while (EUI × GEPU) has a detrimental impact. Remarkably, the findings underscore that the effect of the EUI on REN is more positive in high-EPS countries and that the positive impact of the EUI is more moderate when GEPU is high. This finding indicates that by soaring EUI, countries should establish stricter environmental policies (EPS) and decrease uncertainties related to economic policies to be able to promote REN and attain climate change-alleviating targets. Interestingly, as discussed in Ref. [9], the strengthening of EPS is not only a useful channel to promote REN, but it helps to some extent to control the adverse effect of GEPU on REN. Therefore, enhancing environmental policies could be a beneficial approach to stimulate REN particularly when energy and economic uncertainties are high.

The findings also reveal that the STV, FDI, REMIT, and EPS positively promote REN while CO_2, TNRR, GDPC, and GEPU have an unfavorable impact. The results also stress that developed countries, to attain energy and ecological sustainability targets (SDG 7, SDG 13) and mitigate climate change, should replace conventional energies by promoting REN, particularly by focusing on inflowing FDI and REMIT, STV, scheming effective EPS, improving TINV, and reducing TNRR. The results, which are based on several measurements and approaches, are reliable and provide a significant contribution to the literature on sustainability and green energy.

6.1. Policy Suggestions

The findings suggest numerous policy recommendations. First, the findings of the traditional determinants emphasize the importance of internal and external financing to promote REN, suggesting that policymakers in developed countries should take steps forward to develop the financial market, inflow FDI (by increasing a country's competitiveness [59,60], and encourage personal remittances to enable investors and households to have easier access to borrowing funds. This causes conventional energies to be gradually replaced with RENEs and persuades consumers to spend more on RENE developments, which ultimately results in attaining SDG 7 and SDG 13. In addition, the findings stress that policymakers in advanced nations, to achieve energy and ecological sustainability goals (SDG 7, SDG 13) and reduce climate change, should promote REN by designing effective EPS, enhancing ecological innovation, reducing uncertainties related to economic policies, and decreasing total natural resources rents. To achieve a clean environment, governments in developed economies should also regulate CO_2 emissions.

Second, the positive interaction effect (EUIxEPS) recommends that policymakers, by increasing uncertainties related to energy markets, should focus on scheming and developing effective clean ecological policy instruments through market-based plans (e.g., taxes on CO_2), non-market-based plans (e.g., performance standards), and high-tech support plans (e.g., R&D support, feed-in tariffs) to be able to replace RENE and promote REN. Particularly, for the non-market-based plans, policymakers can also focus on socio-economic factors (e.g., education, income) to improve and achieve stricter environmental strategies. Having stricter environmental policies (high EPS) causes the beneficial impact of the EUI on REN to intensify in advanced countries compared to low EPS. Furthermore, the negative interaction effect (EUIxGEPU) recommends that policymakers should take steps forward to reduce economic instability and uncertainties related to economic policies to be able to promote REN and attain climate change mitigation plans when the EUI rises. All in all, enhancing EPS and reducing GEPU lead to promoting REN and intensifying the positive effect of the EUI on REN in advanced economies. To sum up, our discussion of the important potential and obstacles in promoting REN helps policymakers and decision-makers better understand how to support REN, which ultimately helps to reduce climate change and achieve the energy and ecological sustainability targets (SDG 7, SDG 13).

6.2. Study Limitations and Future Directions

It would be helpful to investigate the impact of the EUI on REN for emerging economies in future studies. It would also be worth scrutinizing the effect of other moderators such as the country's political instability, financial instability, and institutional quality on the EUI–REN nexus. In addition, further research can focus on probing the effect of the EUI on REN in the short and long term in developed and developing countries. Likewise, future studies could also test the impact of other potential factors such as monetary policy, economic complexity, GPR, sovereign ESG [61,62], and climate policy uncertainty [63] on REN. Moreover, wavelet and time-varying Granger causality (e.g., [64]) can be used in future research to determine the direction of causality between the variables and determine whether a non-linearity relationship exists.

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Abbreviations

REN	Renewable energy consumption
RENE	Renewable energy
EUI	Energy-related uncertainty index
EPS	Environmental policy stringency
GEPU	Global economic policy uncertainty
SDGs	Sustainable development goals
GPR	Geopolitical risk
CPU	Climate policy uncertainty
FE	Fixed effects
CD	Cross-sectional dependence

Appendix A

Table A1. List of samples of developed economies and the average of variables (2000–2020).

Sample Economies	Ln(REN)	Ln(STV)	Ln(FDI)	Ln(REMIT)	Ln(CO_2)	Ln(TNRR)	Ln(GDPC)	Ln(EUI)	Ln(EPS)
Australia	2.115	4.302	1.250	−1.957	12.845	1.554	10.660	2.682	0.767
Belgium	1.564	3.106	2.740	0.724	11.529	−3.492	10.581	2.972	0.924
Canada	3.079	4.379	0.901	−2.574	13.209	0.807	10.597	2.913	0.820
Denmark	3.062	3.379	0.581	−1.017	10.674	−0.033	10.854	2.792	1.187
France	2.433	4.088	0.537	−0.234	12.737	−3.075	10.499	3.329	1.195
Germany	2.301	3.875	0.817	−1.096	13.545	−2.108	10.564	3.145	1.053
Greece	2.434	2.636	−0.588	−0.738	11.317	−2.099	9.932	3.024	0.793
Ireland	1.634	1.761	2.938	−1.531	10.606	−2.726	10.871	3.218	0.817
Italy	2.380	3.955	−0.146	−1.145	12.871	−2.316	10.366	3.102	1.100
Japan	1.612	4.439	−1.418	−3.244	13.976	−3.736	10.575	3.052	1.196
Netherlands	1.389	4.457	3.040	−1.649	11.979	−0.691	10.713	3.049	1.011
Korea	0.379	4.759	−0.141	−0.608	13.202	−2.950	10.010	3.103	0.944
Spain	2.493	4.389	1.034	−1.934	12.551	−2.997	10.176	3.056	0.801
Sweden	3.796	4.500	0.979	−0.628	10.695	−0.560	10.769	2.964	1.192
United Kingdom	1.151	4.419	1.179	−1.606	13.031	−0.374	10.599	3.241	0.971
United States	2.005	5.366	0.479	−3.287	15.477	−0.264	10.806	3.162	0.671

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Do Environmental Tax and Energy Matter for Environmental Degradation in the UK? Evidence from Novel Fourier-Based Estimators

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Abstract: Currently, the UK has ambitious plans to reach net zero by 2050, despite other countries such as Russia and India targeting 2060 and 2070, respectively. Assuming that the UK emissions unceasingly decline at a given rate annually towards achieving net zero by 2050, its economy would need to ensure a reduction of 105 MtCO2 per year of its emissions from the current 2021 levels. Given that global greenhouse gas emissions have not peaked and continue to rise, the UK seeks to implement costly and aggressive emission reduction policies towards fulfilling commitments under the 2021 Glasgow Climate Pact. This paper investigates the effect of environmental taxes on environmental degradation in the UK between 2000Q1 and 2019Q4 using novel Fourier approaches. Using the novel Fourier ARDL estimator, the long-run equilibrium estimates indicate that gross domestic product and environmental tax cause a fall in carbon emissions. However, in trade and primary energy use, a unit change caused rising carbon emissions in the UK. Especially, the results indicate that environmental taxes have a negative effect on environmental degradation in the UK, and ecological tax policy could be considered as an effective channel to attain environmental sustainability. The outcome provides the following policy insights: (i) The government of the UK should support international environmental tax coordination mechanisms, especially on carbon pricing, to avoid relocation of carbon-intensive investments. (ii) The UK government must note that imposing more taxes to encourage emissions reductions could bring complexity to the tax system and unnecessarily bring costly ways to deal with climate change. Higher domestic electricity prices could disproportionately hit low-income households and create distributional cost concerns, which require benefit payouts or compensation schemes. (iii) Switching to electric vehicles simultaneously requires investments in charging infrastructure and battery technologies. To avoid this chicken-and-egg problem, the government of the UK could play a coordinating role, including deploying targeted subsidies, regulations, direct government involvement, or setting higher carbon prices in special cases.

Keywords: environmental tax; environmental degradation; Fourier; UK

1. Introduction

Historically, the relationship between the growing economic activity of nations and environmental degradation has been an undisputed fact relative to production structure [1]. Theoretically, this relationship is rooted in the environmental Kuznets curve, particularly when linked to fossil fuel use [2,3]. Ecological degradation is generally explained to refer to damage to the quality and quantity of naturally endowed resources to humanity, such as air, forest, water, and land. Economists (under the Pigouvian Framework, [4]) claim this environmental damage arises once the marginal social cost of consuming environmental resources surpasses the marginal social benefits [5]. In recent times, environmental economists have recognized that environmental damage relates directly to rising global warming, a critical existential global crisis largely found to be caused by energy-related greenhouse gas (GHG) emissions [6,7]. These greenhouse gas (GHG) emissions are observed through vehicles and factories' emissions of poisonous gasses into the air, waste generation, deforestation for agriculture, and chemical use for fishing. The consequential effects include global warming and climate change, poor agricultural output, various weather conditions, flooding, and poor human health [7].

Globally, the United Nations has, in contemporary decades, led the campaign for the reduction in carbon emissions that cause global warming. To achieve this goal, the United Nations urges the global economy to urgently take policy actions that promote low-carbon economies. Although existing global environmental initiatives, such as the Kyoto Protocol, the Paris Agreement, and the United Nations Framework Convention on Climate Change, have made significant gains, some environmentalists and scientists have observed that global initiatives cannot sufficiently deliver global climate change mitigation and emissions reduction goals due to disagreements on important policy issues. Accordingly, the United Nations urges economies to implement sustainable policy actions through administrative orders, economic incentives, and environmental taxes. While several experts claim that administrative orders and environmental regulations tend to be rigid and ineffective, economic incentive policies are relatively useful only in some economic cycles [8].

Recently, several scholarly studies have cited and proposed environmental taxes as having the best potential to reduce environmental degradation and mitigate the effects of global warming, notwithstanding the role of renewables and financial innovation [9–12]. Theoretically, environmental pollution occurs due to corporations' or individuals' failure to account for environmental harm created by others through their decision making [4]. Environmental taxes are generally hinged on principles of precaution, polluters pay, risk prevention, public participation, and integration of decision making. Experts claim environmental tax gains are needed for revenue-recycling benefits and energy gains [9,10]. Figure 1 is an illustration of Pigourian environmental theory and social effects [4]. If emissions tax revenues are not used to increase economic efficiency through cutting distortionary taxes (or through funding socially desirable spending), the net benefits from emissions taxes are greatly reduced (e.g., [9,13,14]). The case for using environmental taxes on cost-effectiveness grounded on regulatory approaches (e.g., emissions standards) can be substantially undermined (e.g., [14]). Environmental taxes tend to have a bigger impact on energy prices than regulatory policies (because the former involves the pass-through of tax revenue into prices), and the revenue-recycling benefit is needed to offset the effect of these greater energy price increases on exacerbating factor tax distortions. Although several economists traditionally argue that environmental regulations increase corporate costs and affect the competitiveness of the local industry if policy variations exist across countries [9,14], however, many others claim that environmental regulations could foster innovations in environmental technologies and leadership towards increased economic growth [4,13].

The question that continues rumbling in the ears of environmental economists is whether environmental taxes can truly reduce environmental degradation. To answer this continuously echoing academic question on the role of an environmental tax on carbon emissions, the economy of the United Kingdom of Great Britain (UK) presents an inspiring case for investigation. After leaving the EU, the UK passed the Environment Act in 2021 to empower the government with powers to establish new environmentally friendly binding targets on air quality, water, biodiversity, and waste reduction. The new Environment Act also established the Office for Environmental Protection (OEP), replacing existing EU environmental oversight functions and other regulations that were expiring at the end of 2023. Additionally, the country has an ambitious climate policy of net zero by 2050. Historically, the UK's attempt to develop environmental policies has conflicted with competing interests and perspectives of different groups in society, especially industry and local communities. Throughout history, the UK has been a signatory of several global agreements on the environment, e.g., the Convention for the Preservation and Protection of Fur Seals with the United States, Japan, and Russia (1911); the Convention for the Protection of Migratory Birds (1916) with the United States which was later extended to Mexico; and Convention on Preservation of Fauna and Flora (also referred to as London Convention of 1933).

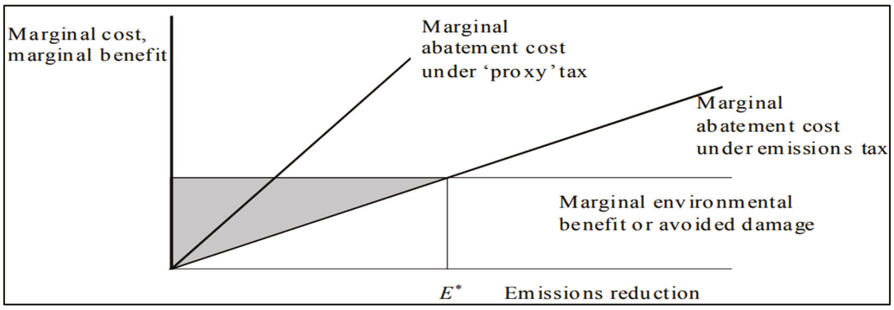

Figure 1. Social effects of environmental taxes under the Pigouvian framework (source: [4]).

According to [15], public advocacy on environmental taxation in the UK originated from the Minority Report of the Royal Commission on Environmental Pollution in 1972. This report set the British political and environmental agenda in 1989 when environmental taxes were presented through a meeting for a revenue-neutral carbon regulatory action. Environmental taxation in the UK was eventually influenced by the introduction of carbon taxes in Nordic countries during the 1990s but received a blow with the introduction of VAT on domestic energy in 1993. In 2001, the UK implemented the Climate Change Levy—a downstream tax on corporate energy use to promote energy efficiency and renewable energy development. In general, the UK's environmental taxes have covered energy, transport, pollution, and commercial exploitation of natural resources. Available data from the UK's Office of National Statistics (May 2023) indicate that, by using the internationally agreed framework, the UK's environmental tax revenue increased by 6.9% from GBP 44.3 billion in 2021 to GBP 47.4 billion in 2022 for energy (74.7%), transport (22.3%), and pollution and resource use (3.0%). This represented 1.9% of gross domestic product (GDP) in 2022, the lowest record since 1997. To disincentivize emissions from waste disposal, the UK government imposed landfill taxes, with consistent rate increases since its introduction. Between 2004 and 2021, the landfill taxes increased from GBP 15 to GBP 96.70 per ton. Figure 2 presents the tax types in the UK.

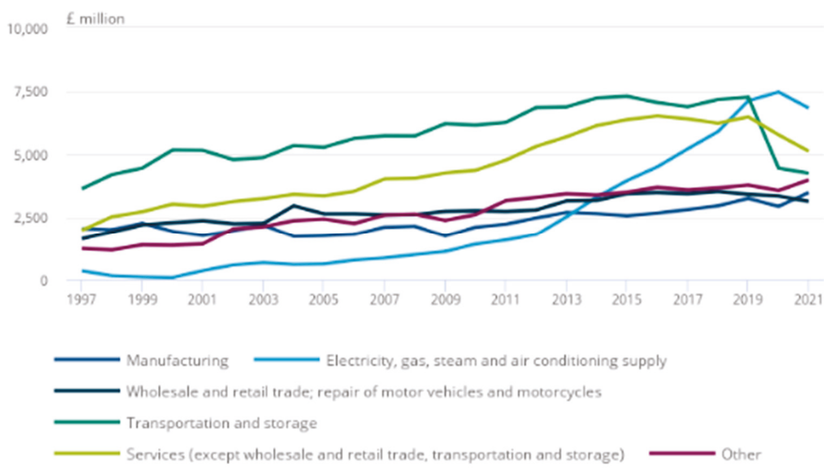

Figure 2. Tax types in the UK (source: [16]).

These notwithstanding, the UK has been urged by experts to do more to reduce carbon emissions as it lags behind several European economies [17]. Given that very limited studies have been conducted on environmental taxes on carbon emissions, this paper fills the gap and brings clarity to relevant arguments on environmental taxes using novel Fourier autoregressive distributive lag econometric approaches. The study is motivated by the Pigourian tax [4] and the cap-and-trade theoretical system of environmental tax by [18].

The paper progresses as follows: The next section reviews the relevant literature for conceptual frames and to construct the assumptions for the empirical study. This is followed by separate sections for methodology and empirical outcomes. The last section deals with conclusions and policy recommendations.

2. Brief Literature Review: The Environmental Tax–CO_2 Emissions Nexus

Several studies have explored the determinants of CO_2. For example, [19] uncovered that economic growth intensified CO_2 emissions, though green energy, remittances, and globalization decreased CO_2 emissions. [20] revealed that gross domestic product (GDP), urbanization, and globalization increased CO_2 emissions in China, while hydroelectricity consumption lessened CO_2 emissions. Recently, some studies have also discussed environmental sustainability by probing the determinants of renewable energy (e.g., [21–23]) and exploring the importance of firm and sovereign environmental, social, and governance sustainability activities [24,25].

Particularly, the relationship between environmental taxation and environmental degradation has been a matter of intense debate among researchers, policymakers, and economists over the past decades. This section systematically reviews relevant studies for insights into crafting a conceptual framework and positioning the study for empirical analysis.

Environmental taxes are an efficient policy instrument to decrease carbon emissions. [26] found that environmental taxes generally seek to decrease carbon emissions by influencing a fall in fossil fuel demand. They are ultimately implemented to achieve global environmental delivery targets of the Kyoto Protocol and the Paris Climate Agreement. Historically, environmental taxes (e.g., carbon taxes) have been implemented by several economies and sub-national governments. Globally, two waves of enactments of environmental taxes have occurred, beginning from the early 1990s (Denmark, Finland, Norway, and Sweden), and in the 2000s, countries such as Switzerland, Iceland, Ireland, Japan, Mexico, and Portugal enacted such laws.

Theoretically, the basis of environmental taxes is severely documented as improving social welfare if the consumption or production of particular goods results in a negative externality [12,27]. Environmental degradation has been generally classified as problematic due to the failure of corporations or individuals to damage control in their decision making to fully price resources for production or consumption. Given the divergence between private and social costs of pollution, [4] claimed that taxing pollution equates to social marginal damage and private costs while ensuring efficient market outcomes. Critics, however, argue that no consensus globally exists on the optimal effectiveness of energy and carbon taxes, subsidies, and transfers. They claim that environmental taxes may tend to be regressive against poorer households that could be compelled to purchase cheaper and less energy-efficient appliances [28].

Similarly, environmental taxes are distortionary, given the narrow tax base, and create double taxation on both intermediate input and final output [29,30]. As an alternate theory, others have recommended a cap-and-trade system, given that the carbon tax places costs on CO_2 pollution and permits markets to determine pollution. A cap-and-trade system rather caps pollution, allowing markets to have the right to pollute. In this case, politicians do not directly set prices [18]. However, [18] argues about three factors favoring carbon taxes over cap-and-trade systems. First, he argues that a cap-and-trade system allows price variations with changing market conditions, leading to price volatility and uncertainty, since corporations cannot plan for long-lived, capital-intensive projects. Second, the cap-and-trade system is administratively complex, requiring new administrative structures for tracking, holding auctions, and developing rules to avoid fraud and abuse. Finally, the cap-and-trade system has the potential for adverse policy interactions, which could be counterproductive [31].

Empirically, several studies investigating the effect of environmental taxes on pollution control have found it to be positive [32–34]. Ref. [35] found that environmental taxes significantly reduce carbon emissions. Furthermore, the outcomes of the investigation indicated that environmental taxes are instrumental in facilitating the development of renewable energy technologies and could help reduce energy demands. [36] investigated EU policies on carbon emissions mitigation and found environmental taxes to be a very effective approach to carbon emission reduction across member economies. A similar investigation by [37] on the effects of international competitiveness of environmental taxes in European countries indicated that environmental taxes are very effective in promoting the welfare of economies and market competitiveness. Another study by [38] examined the effects of carbon taxes on economic growth and energy intensity in China. The results indicated increases in carbon tax have negative effects on energy intensity and carbon emissions. However, some experts in their investigations found environmental taxes to have very little effect on reducing carbon emissions [39,40]. For example, [41] claimed environmental taxes could only protect environmental quality if investments in energy and environmental technologies could be prioritized. Using data from 1995 to 2005 on 25 European economies, [42] investigated the long-run effects of environmental taxes on energy use. The outcomes indicated that environmental taxes have little effect on energy consumption in the studied countries.

Based on the above review, the effects of environmental taxes on pollution vary, and the findings are inconclusive. Accordingly, the study seeks to bring clarity to the arguments on the effects of an environmental tax on pollution using the UK as a case study. To achieve the stated objectives, the paper gives the following hypothesis:

Hypothesis 1 (H1). *Environmental taxes have negative effects on environmental degradation in the UK.*

3. Methodology

3.1. Data

This paper aims to capture the effect of an environmental tax on environmental degradation in the UK between 2000Q1 and 2019Q4. To achieve the established objectives of the paper, economic growth, primary energy consumption, and trade in the UK are controlled. All variables are in the log form to avoid scaling [43]. Data were sourced on (i) carbon dioxide emissions (as a proxy variable for environmental degradation) from UNFCC. Carbon dioxide emissions are determined in kt (kiloton). Carbon dioxide (CO2) is a gas produced from the burning of carbon and the respiration of living organisms and is measured in parts-per-million (ppm) [44]. (ii) Data on environmental tax were sourced from OECD. (iii) Data were sourced from gross domestic product (GDP) as a proxy variable for economic growth. (iv) Data were sourced on primary energy consumption from OECD. Primary energy measures a country's total energy demand. (v) Data on trade were sourced from the IMF. Trade involves voluntary exchanges of goods or services between economic actors. Trade is measured by the difference between a country's exports and imports of goods. Figure 3 presents the analysis flowchart.

3.2. Control Variables

Towards achieving the objectives of the study, economic growth, trade, and primary energy consumption are controlled to assess the pollution effect of environmental tax in the case of the UK. First, for several decades, the UK's energy market has been largely driven by coal, fossil energy, nuclear, and renewables. With increasing renewable use, fossil energy has halved, while coal generation in the UK is expected to be phased out by 2024. Gas supply has largely been supplied locally (54% in 2022), while the remaining was imported from Norway, Netherlands, Qatar, Algeria, Belgium, and, to some extent, Russia before the ban in 2023 due to the Ukraine invasion [45]. Electricity generation from nuclear sources stood at 15% in 2022. In general, according to ESO's analysis, the energy mix for the UK from 2022 is made up of gas—38.5%; wind—26.8%; nuclear—15.5%; biomass—5.2%; coal—1.5%; solar—4.4%; imports—5.5%; hydro—1.8%; and energy storage—0.9%.

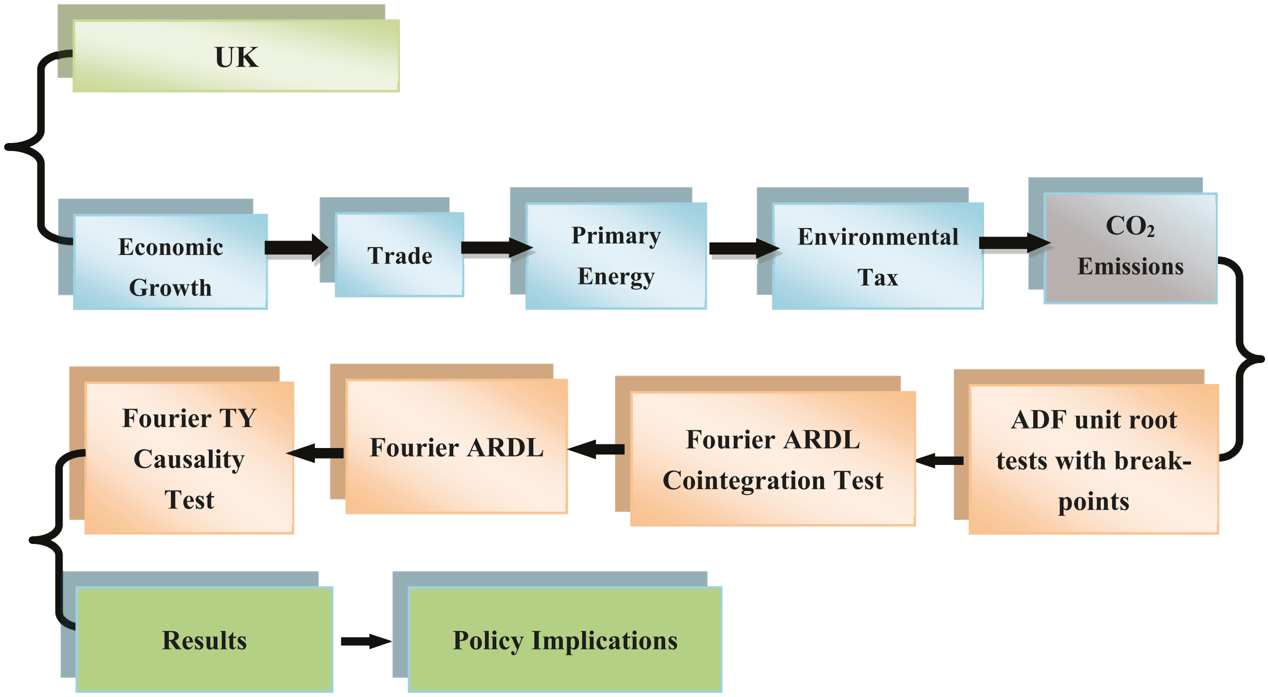

Figure 3. Analysis flowchart.

Hypothesis 2 (H2). *Based on these, an assumption is made for this paper that primary energy use in the UK positively moderates CO_2 emissions (H2), i.e.,* $\vartheta_2 = \frac{\vartheta LCO_2E}{\partial LPECit} > 0$*; where* ϑ *represents the interest parameter; LPEC signifies the natural log of primary energy use; LCO_2E is the natural log of CO_2 emissions (as a proxy for environmental degradation).*

For economic growth, the UK has, for several years, committed to the cause of climate change with several policies. After the 2008 climate action, which helped the economy sustain reductions in GHG emissions, the UK 2019 enacted an ambitious new law to further commit itself to reaching net zero greenhouse gas emissions by 2050. Accordingly, in 2021, the UK government adopted the sixth carbon budget to drastically cut emissions by 78% by the close of 2035. Being the pioneer of the Climate Act, the economy's climate actions have set the pace and as a model for climate legislation in several countries, including Denmark, France, Germany, Ireland, Mexico, New Zealand, and Sweden. Notwithstanding the 2007 peaking of emissions in the UK, due to a combination of environmental policies and a transition to less carbon-intensive service-based industries, the UK has witnessed imported emissions mainly from China and the neighboring EU countries. Critics have argued that the increasing proportion of the UK's economy to the higher-value services sector raises emissions through international trade flows and exaggerates apparent declining records in territory-based emissions. According to this view, there is the need for rethinking the EKC theory [46] on growth and carbon emissions.

Hypothesis 3 (H3). *Based on these, this study hypothesizes that rising economic growth in the UK significantly causes CO_2 emissions to be reduced, i.e., (H3)* $=\vartheta_3 = \frac{\vartheta LCO_2\,E}{\vartheta LGDPit} < 0$*; where* ϑ *is linked to the interest parameter; LGDP is the natural log of gross domestic product (GDP) (a proxy variable for the UK's economic growth); LCO_2E is the natural log of the UK's carbon dioxide emissions.*

Another factor considered as a determinant of carbon emissions in the UK is trade. In 2020, carbon dioxide emissions represented approximately 79% of the UK's total GHG emissions. However, records from the [47] indicate that the United Kingdom witnessed rising consumption-based emissions, suggesting that historically falling rates in total emissions were offset by rising consumption-based emissions. UK's exports of goods and services in 2022 amounted to GBP 834 billion. The country also imported a total of GBP 902 billion in goods and services, with the EU alone accounting for 47% of the total in 2022. Theoretically, the environmental effects of output in trade lends are explained by the pollution haven hypothesis—a framework that claims to reallocate dirty industries by corporations to economies with less strict environmental regulations [47]. Despite the negative effects of trade, several scholars argue that trade could provide knowledge and technology transfer, which helps to eventually improve environmental performance [48,49].

Hypothesis 4 (H4). *Based on the arguments, the authors of this paper hypothesize that the trade increases environmental degradation in the UK, i.e., (H4)* $=\vartheta_4=\frac{\vartheta LCO_2E}{\vartheta LTRAit} > 0$*; where* ϑ *is the interest parameter; LTRA is a log of trade; and* LCO_2E *is a log of carbon dioxide emissions in the UK.*

3.3. Model

Theoretically, productive and efficient energy use can promote environmental quality [50]. With growing global concerns about energy use for growth, environmental degradation, and global warming, new policy pathways are required for successful energy transformation. One major policy pathway for dealing with increasing environmental degradation is environmental tax [11]. Despite major critiques, [4] claimed that, with the divergence between private and social costs of pollution, taxing pollution equates social marginal damage and private costs, while ensuring efficient market outcomes. To estimate the nexus between environmental degradation, environmental tax, economic growth, trade, and primary energy consumption, the study employs the Stokey framework, which can establish how environmental pollution and abatement affect the regulation [51]. Similarly, the study is motivated by a balanced growth model, the role of abatement and technological progress towards improving growth and environmental quality over time, although the growth rate of output could equally be lowered, given the strength of scale, composition, and technique effects as espoused by the EKC hypothesis [52]. The Stokey framework highlights how rapidly increasing population and economic growth could eliminate any possibility of sustainable growth. It also highlights how convergence is demonstrated across countries involved in trade and pollution abatement, justifying how environmental taxes can level variations across countries and facilitate induced innovation in energy use, growth, pollution abatement, and general technological progress. Accordingly, the empirical model for this study is as follows:

$$CO_2\mathbf{E} = f(GDP,\ PEC,\ TRA,\ ETAX) \tag{1}$$

where CO_2E is carbon dioxide emissions (as a proxy for environmental degradation in the UK); GDP is gross domestic product (as a proxy for economic output); PEC is primary energy use; TRA is trade; and ETAX is environmental tax.

Next, by logging variables, the model is specified as follows:

$$LCO_2\mathbf{E} = f(LGDP + LPE + LTRA + LETAX + e_t) \tag{2}$$

where LCO_2E is a log of carbon dioxide emissions (as a proxy for environmental degradation in the UK); GDP is GDP output; and LPEC is primary energy use; LTRA is a log of trade; LETAX is a log of environmental tax; and e_t is the error term.

3.4. ADF Unit Root Test with Breakpoint

Next, after descriptive statistical assessments, the paper checks the integration order of variables using Augmented Dickey–Fuller (ADF) unit root tests with breakpoints. In the field of econometrics, when variables are integrated to varying degrees, it makes models not testable for cointegration using the conventional cointegration methods. This paper adopts the novel ADF unit root tests with breakpoints, which provide better and more reliable information for cointegration assessment despite integration order. To estimate the unit roots for ADF with breaks, the model used is as follows:

$$x_t = \mu + \rho x_{t-1} + e_t \quad (3)$$

here x_t refers to variables of interest; μ is the constant term; and e_t is the error term. By unit differencing, the model becomes $\Delta x_{t\,=}\ \mu + e_{t;}$ where $\Delta = (1 - B)$; ρ refers to parameter slopes for lagged variables and becomes 1 whenever there occurs a unit root. The study illustrates the alternative unit root for ADF with breaks in Equations (4) as follows:

$$x_t = \mu + \beta_t \delta DU_t + \theta D(T_B) + e_t \quad (4)$$

The re-specifications of error correction form; and after applying the augmentation factor, ADF with breaks equation is estimated as follows:

$$\Delta x_t = \mu + \beta_t + \gamma_1 \sin\left(\frac{2\pi k_t}{N}\right) + \gamma_2 \cos\left(\frac{2\pi k_t}{N}\right) + (\rho - 1)x_{1-1} + \sum\nolimits_{i-1}^{p} C_i \Delta x_{i-1} + \varepsilon \quad (5)$$

here *c* refers to the slope parameter of the augmented parts; *p* is the lag length with minimum information criteria values in the augmentation process; *k* is Fourier regularity; structural break date is $T_{B;}$ and break fraction refers to λ.

3.5. Fourier ARDL Cointegration Analysis

The traditional ARDL cointegration approach has historically been employed extensively by researchers for decades [53]. The limitation of this estimator is that it is unable to detect hidden long-term nonlinear relationships among variables. Accordingly, in this paper, the Fourier ARDL estimator is employed to estimate long-run equilibrium relations among interest variables. The estimators can detect the existence of unknown structural breaks, time, and structures related to the variables. In essence, the Fourier-based ARDL long-run estimator can provide more robust outcomes than the traditional ARDL approach [54,55]. The Fourier function is modeled in Equation (6).

$$\boldsymbol{d(t)} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{n}} \boldsymbol{a}_{\mathrm{k}} \mathbf{sin}\left(\frac{\boldsymbol{2\pi kt}}{\boldsymbol{T}}\right) + \sum_{\boldsymbol{k=1}}^{\boldsymbol{n}} \boldsymbol{b}_{\mathrm{k}} \mathbf{cos}\left(\frac{\boldsymbol{2\pi kt}}{\boldsymbol{T}}\right) \quad (6)$$

where *n* indicates the number of frequencies, π = 3.14, *k* is the number of special frequencies selected, *t* is the trend, and T is the sample size. A single frequency value is suggested [56,57] as in Equation (7).

$$\boldsymbol{d(t)} = \gamma_1 \boldsymbol{sin}\left(\frac{\boldsymbol{2\pi kt}}{\boldsymbol{T}}\right) + \gamma_2 \boldsymbol{cos}\left(\frac{\boldsymbol{2\pi kt}}{\boldsymbol{T}}\right) \quad (7)$$

The FARDL model for this study is shown in Equation (8).

$$\begin{aligned} \Delta \boldsymbol{LCO2E}_{\mathrm{t}} = {} & \boldsymbol{\beta}_0 + \gamma_1 \boldsymbol{sin}\left(\tfrac{\boldsymbol{2\pi kt}}{\boldsymbol{T}}\right) + \gamma_2 \boldsymbol{cos}\left(\tfrac{\boldsymbol{2\pi kt}}{\boldsymbol{T}}\right) + \boldsymbol{\beta}_1 \boldsymbol{LTRA}_{\mathrm{t}-1} + \boldsymbol{\beta}_2 \boldsymbol{LGDP}_{t-1} \\ & + \boldsymbol{\beta}_3 \boldsymbol{LPEC}_{t-1} + \boldsymbol{\beta}_4 \boldsymbol{LETAX}_{t-1} + \sum_{\boldsymbol{i-1}}^{\boldsymbol{\rho-1}} \boldsymbol{\varphi}_i{}' \Delta \boldsymbol{LCO2E}_{t-i} \\ & + \sum_{\boldsymbol{i-1}}^{\boldsymbol{\rho-1}} \delta_i{}' \Delta \boldsymbol{LTRA}_{t-i} + \sum_{\boldsymbol{i-1}}^{\boldsymbol{\rho-1}} \varnothing_i{}' \Delta \boldsymbol{LGDP}_{t-i} + \sum_{\boldsymbol{i-1}}^{\boldsymbol{\rho-1}} \boldsymbol{\vartheta}_i{}' \Delta \boldsymbol{LPEC}_{t-i} \\ & + \sum_{\boldsymbol{i=1}}^{\boldsymbol{\rho-1}} \boldsymbol{\vartheta}_i{}' \Delta \boldsymbol{LETAX}_{t-i} \\ & + \boldsymbol{e}_t \end{aligned} \quad (8)$$

Several experts apply the frequency value to the minimum sum of squared residuals [55,58,59]. In addition, the study employs the Fourier TY Causality Test to support the outcomes of the Fourier ARDL test.

4. Empirical Outcomes

In this paper, the effect of an environmental tax on environmental degradation in the case of the UK is investigated using data from 2000Q1 to 2019Q4. To achieve this objective, economic progress, trade, and primary energy consumption are controlled positions. Table 1 is a statistical description of the variables examined.

Table 1. Descriptive statistics.

	LCO_2E	**LGDP**	**LETAX**	**LPEC**	**LTRA**
	Production-Based CO_2 Emissions	**GDP (Constant 2015 USD)**	**Environmental Taxes**	**Primary Energy Consumption**	**Trade**
Mean	5.680814	12.40656	0.883805	3.394797	12.10137
Median	5.718796	12.42153	0.883395	3.407255	12.14079
Maximum	5.737927	12.50671	0.941662	3.432993	12.28227
Minimum	5.535779	12.27547	0.821466	3.324600	11.81647
Std. Dev.	0.063209	0.063380	0.032983	0.033321	0.125218
Skewness	−0.971417	−0.440579	0.118102	−0.557668	−0.648029
Kurtosis	2.508673	2.263405	2.149941	1.785334	2.420849
Jarque–Bera	17.40268	5.715721	3.373034	11.78403	8.732460
Probability	0.000166	0.057391	0.185163	0.002761	0.012699
Observation	80	80	80	80	80

Based on the outcomes of the descriptive analysis (Table 1), it is apparent that there are no outliers in the dataset. Similarly, the results suggest all variables are distributed normally. This suggests that further estimation action could proceed.

It is noteworthy to highlight that, historically, structural breaks have been overlooked in econometric studies, causing biases in unit root estimates. Before carrying out estimations to observe the integration order of interest variables, the paper conducted the Broock, Dechert, and Scheinkman (BDS) test [60] for any existence of stochastic hidden and nonlinear patterns (i.e., dependence or independence). The BDS test can also guide against any model misspecification and judgmental errors. The model for this econometric application is as follows (9):

$$\boldsymbol{BDS_{mT}}(\varepsilon) = \boldsymbol{T^{1/2}}[\boldsymbol{C_{m,T}}(\varepsilon) - \boldsymbol{C}_{1,\boldsymbol{T}}(\varepsilon)^{\mathrm{m}}\ ]/\boldsymbol{\delta_{mT}}(\varepsilon) \tag{9}$$

where T is the sample size, ε is the randomly adopted proximity parameter, and δ_mTˆ (ε) is the standard deviation of the numerator which varies with dimension "m" [61].

Based on the BDS estimates (Table 2), hidden nonlinear patterns exist in the time series data since variables have significant dimensional critical values higher than their respective BDS estimates. These outcomes imply nonlinear correlations between the interest variables.

The outcomes of the ADF unit root test with breakpoint (Table 3) indicate the interest variables. LGDP is integrated at level (i.e., I(0) with a breakpoint at 2009Q1 at a 10% significance level). However, while LCO_2E, LPEC, LTRA, and LRTAX are integrated at order ONE (i.e., I(1) with several breakpoints in 1996Q1, 2009Q1, 1996Q1, and 1997Q1, respectively, at a 5% significance level). The outcomes of the unit root analysis demonstrate that the time series variables integrate in a mixed order.

The next step involves investigating cointegration properties among the interest variables using the Fourier ARDL Cointegration estimator. This helps to ascertain how LETAX, LGDP, LPEC, and TRAL individually and collectively impact LCO_2E in the case of the UK. Table 4 shows the Fourier ARDL cointegration analysis.

Table 2. BDS test.

		LCO_2E		
Dimension	**BDS Statistic**	**Std. Error**	**Z-Statistic**	**Prob.**
2	0.189814	0.008048	23.58658	0.0000
3	0.315299	0.012877	24.48520	0.0000
4	0.398736	0.015439	25.82620	0.0000
5	0.455943	0.016203	28.14013	0.0000
6	0.496496	0.015733	31.55727	0.0000
		LETAX		
Dimension	BDS Statistic	Std. Error	Z-Statistic	Prob.
2	0.180957	0.005157	35.09075	0.0000
3	0.301061	0.008204	36.69570	0.0000
4	0.377348	0.009776	38.60040	0.0000
5	0.422836	0.010194	41.48058	0.0000
6	0.447332	0.009834	45.48929	0.0000
		LPEC		
Dimension	BDS Statistic	Std. Error	Z-Statistic	Prob.
2	0.184377	0.005693	32.38848	0.0000
3	0.305464	0.009069	33.68316	0.0000
4	0.385017	0.010821	35.58063	0.0000
5	0.437600	0.011300	38.72657	0.0000
6	0.473069	0.010917	43.33401	0.0000
		LGDP		
Dimension	BDS Statistic	Std. Error	Z-Statistic	Prob.
2	0.207899	0.005438	38.23326	0.0000
3	0.352709	0.008651	40.76968	0.0000
4	0.454483	0.010309	44.08579	0.0000
5	0.526880	0.010751	49.00911	0.0000
6	0.578796	0.010372	55.80252	0.0000
		LTRA		
Dimension	BDS Statistic	Std. Error	Z-Statistic	Prob.
2	0.205597	0.006003	34.25065	0.0000
3	0.349311	0.009585	36.44176	0.0000
4	0.450381	0.011465	39.28194	0.0000
5	0.521916	0.012002	43.48589	0.0000
6	0.573000	0.011624	49.29533	0.0000

Table 3. ADF unit root test with breakpoint.

Variables	**ADF with Breakpoint**
LCO_2E	−2.276 (2013Q1)
LETAX	−3.510 (2002Q1)
LGDP	−5.062 *** (2009Q1)
LPEC	−2.145 (2006Q4)
LTRA	−3.881 (1994Q4)
$DLCO_2E$	−6.406 (1996Q1) **
DLETAX	−6.011 (2009Q1) **
DLGDP	NA
DLPEC	−6.790 (1996Q1) **
DLTRA	−5.391 (1997Q1) **

Note: ** and *** denote 5% and 1% significance levels, respectively.

The Fourier ARDL Cointegration estimates (ARDL Bounds test) indicate the F-stats are significantly higher in value than the target critical values. This outcome suggests that both the dependent and independent variables possess long-term equilibrium relationships. This means the Fourier ARDL long-run cointegration test (Table 5) could be used since the estimator could detect any hidden information.

Table 4. Fourier ARDL Cointegration Analysis.

Model		Frequency	Min AIC
LCO_2E = f(LETAX, LGDP, LTRA, LPEC)	−7.853977	0.6	−3.572768

Table 5. Fourier ARDL long-run form.

Variables	Coefficient	Std. Error	t-Statistic	Prob.
LGDP	−2.198802	0.521931	−4.212819	0.0001
LTRA	0.737557	0.303497	2.430194	0.0183
LETAX	−0.395106	0.153661	−2.571279	0.0128
LPEC	1.645885	0.429862	3.828864	0.0003
C	1.757406	0.279609	6.285216	0.0000
@TREND	8.31×10^{-5}	1.49×10^{-5}	5.561438	0.0000
SIN	0.000710	0.000249	2.849281	0.0061
COS	0.000104	0.000270	0.383857	0.7025
CointEq(-1) ***	−0.093755	0.014914	−6.286291	0.0000

Note: *** denote statistical significance at the 1% level.

Based on the long-run Fourier ARDL estimates, LGDP has negative coefficients with a significant statistical value. The LGDP has a coefficient of −2.198802, signifying that unit change in LGDP causes a fall in LCO_2E by −2.198802% in the UK. This outcome validates hypothesis 3 (H3) established for the study and supports [62]. Theoretically, increasing economic growth creates environmental degradation as a direct result of more demand for energy and material resources for production. According to the EKC framework, the initial phase of economic growth culminates in environmental destruction until a time when environmental regulatory and technological effects set in to correct the anomaly. This outcome suggests that the UK's economy is currently beyond the EKC threshold, where rising GDP generates falling carbon due to increased technology application. This growth and environmental theory have been extensively validated by other growth frameworks such as the Source-and-Sink framework [63], Solow model [64], and Smulders and Stokey's AK theoretical model [51].

Similarly, LETAX has a negative coefficient with a significant statistical value. From the estimates (Table 5), the coefficient of −0.395106 signifies that a unit change in LETAX causes a fall in LCO_2E by −0.395106% in the UK. This estimate validates hypothesis 1 (H1) established in the paper. The result also confirms similar outcomes of the study by [65] for the case of Sweden. For policy insight, the UK government needs to use regulatory measures such as environmental tax to facilitate the delivery of globally agreed-upon nationally determined contributions. According to [66], while the government of the UK could continue imposing environmental taxes, such action must be coherent and fittingly adjusted within the tax system.

Further, the long-run Fourier ARDL estimates (Table 5) indicate that both LTRA have positive coefficients with a significant statistical value. The LTRA has a coefficient of 0.737557, signifying that unit change in LTRA causes a rise in LCO_2E by 0.737557% in the UK. It must be noted that the result validates hypothesis 4 (H4) established for the study and aligns with [67]. It is instructive to note that, in 2020, carbon dioxide emissions amounted to an estimated 79% of the UK's total GHG emissions. According to investigations by [68], the United Kingdom has witnessed increasing demand-based carbon emissions in recent years, suggesting that rising consumption-based emissions actually offset the historically falling rates in UK's total emissions. Available data show, in 2022, that the UK's exports of goods and services amounted to GBP 834 billion. While its imports totaled GBP 902 billion in goods and services. In theory, the environmental impact of trade lends support to the pollution haven hypothesis.

Furthermore, the coefficient of LPEC is positive and significant (Table 5). Based on Table 5, LPEC has a coefficient of 1.645885, signifying that unit change in LPEC causes an increase in LCO_2E by 1.645885% in the UK. This finding validates hypothesis 2 (H2) established in the paper. The estimate suggests that Russia's invasion of Ukraine, together with subsequent sanctions leading to rising energy costs, have led to the increasing use of coal in electricity production in the UK. Although the UK is committed to increasing the consumption of renewable energy, total primary energy consumption in 2019 was 141,951 ktoe (1651 TWh), largely from fossil fuels: petroleum products (44%) and natural gas (31%) (BEIS, 2020). It is not surprising that a unit change in primary energy use causes a whopping 1.645885% upward adjustment relative to carbon emissions in the UK for the period under study. It must, however, be noted that 2019 was equally a milestone when the UK heralded sourcing more energy from non-carbon resources than fossil fuels. It is no wonder why the economy has committed immensely to a net-zero emissions target by 2050. Between 1990 and 2019, the UK drastically reduced carbon emissions by 40%, making it the country with the largest carbon reductions among the OECD and G20 member countries.

Model Diagnostic Tests

Historically, scientists have considered model stability and residual diagnostic tests very essential in empirical research. Towards reducing LCO_2E in the UK, the coefficient values in the error-correction model must be stable to enable policy decisions on them to be reliable relative to the behavior of economic output, primary energy use, trade, and environmental taxes. Accordingly, the paper captures model stability using the cumulative stability test (CUSUM and CUSUM of squares estimators) of [69]; the estimates of both CUSUM and CUSUM of squares indicate the statistical figures are within acceptable limits. Figure 4 shows the CUSUM and CUSUM of squares estimators.

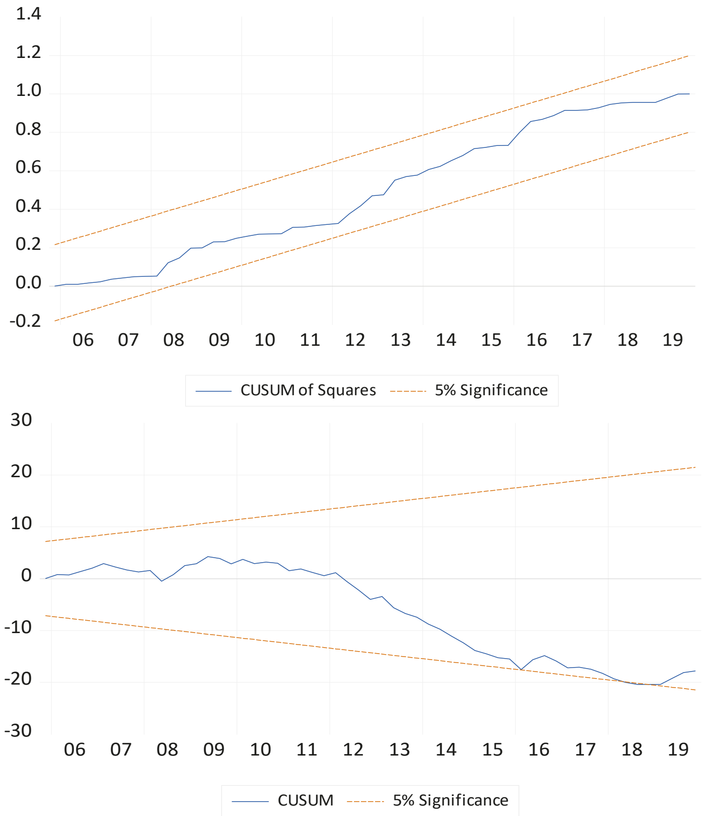

Figure 4. Model stability using the cumulative stability test (CUSUM and CUSUM of squares estimators).

Similarly, the paper checks if the model is free from heteroskedasticity and serial correlation issues using both the Breusch–Godfrey serial correlation LM test and residual diagnostic test, respectively. The results (Table 6) indicate the model is free from both heteroskedasticity and serial correlation. This means the outcomes of the Fourier ARDL long-run equilibrium model could be used to provide policy recommendations.

Table 6. Heteroskedasticity test and serial correlation LM tests.

	Breusch–Pagan–Godfrey		
F-statistic	0.790948	Prob. F(39,57)	0.7790
	Breusch–Godfrey Test		
F-statistic	0.371832	Prob. F(6,51)	0.8935

To further support the outcomes of the Fourier ARDL model, the Fourier Toda Yamamoto Causality Test was carried out. The estimates indicate that LGDP, LTRA, LETAX, and LPEC individually and unidirectionally cause LCO_2E in the UK. Table 7 shows the Fourier TY Causality Test results. Overall, Figure 5 shows the Summary of empirical findings with methods.

Table 7. Fourier TY Causality Test.

		T-Stat	*p*-Value
Ho_1	LGDP does not cause LCO_2E	16.88529 **	0.031326
Ho_2	LTRA does not cause LCO_2E	25.33331 ***	0.000662
Ho_3	LETAX does not cause LCO_2E	16.94006 **	0.017787
Ho_4	LPEC does not cause LCO_2E	10.85399 *	0.07612

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

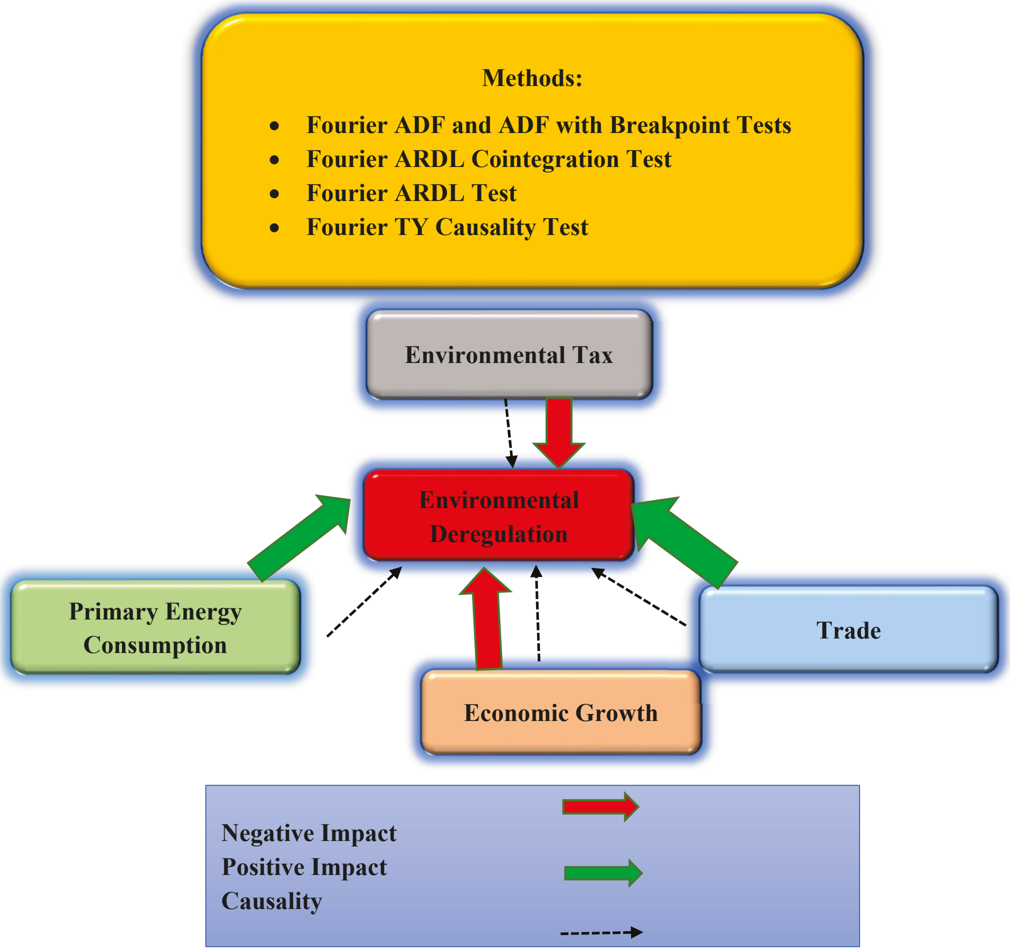

Figure 5. Summary of empirical findings with methods.

5. Conclusions

In response to the Paris Agreement, the United Kingdom is a part of developed economies committed to reducing domestic greenhouse gas emissions. They have historically achieved broad political consensus on policy initiatives on energy transition towards reaching net-zero emissions by 2050. The government seeks policy pathways toward achieving stated emissions targets. In this paper, the authors investigated the effect of an environmental tax on environmental degradation in the UK between 2000Q1 and 2019Q4. To achieve this objective, economic progress, trade, and primary energy consumption are controlled positions. Using the novel Fourier ARDL estimator, the long-run equilibrium estimates indicate that both LGDP and LETAX cause a fall in carbon emissions. However, in the case of both LTRA and LPEC, a unit change caused rising carbon emissions in the UK.

5.1. Policy Recommendations

These outcomes have profound environmental policy insight as follows: First, in periods requiring policy response to environmental degradation, the UK economy could safely deploy environmental tax to discourage pollution-intensive activities. It is conceivable to equally deploy environmental taxes on corporate managers to spur growth in green innovation, increase output, and assure environmental quality. Corporations that invest hugely in green production could derive environmental tax advantages over other pollution-intensive enterprises in terms of cost savings and subsequent competitive edge on product pricing.

Second, the UK government must simplify the environmental tax system while ensuring an equitable incentive system to bring relief to vulnerable households. This study has noted that the current UK environmental policy landscape has many overlapping and complex policy cases, especially in the energy sector, where incentives to abate vary across sectors, fuel types, and consumers. This inconsistency within environmental taxes eventually increases the costs of transitioning to net zero. Policy simplification could entail ensuring uniform, effective environmental tax rates and regulatory guidelines. Additionally, the UK government should continue seeking broad-based policy consensus to assure policy stability, as this helps corporations and households to plan. Third, for purposes of the emissions effect of trade, the government of the UK should support international environmental tax coordination efforts, such as those on carbon pricing towards avoiding relocation of carbon-intensive investments. For local coordination, the government of the UK could play a coordinating role, including deploying targeted subsidies and regulations, direct government involvement, or setting higher carbon prices in specific sectors. It is noteworthy that switching to electric vehicles simultaneously requires investments in charging infrastructure and battery technologies to avoid chicken-and-egg situations. Fourth, contrary to some other G7 economies, the United Kingdom does not track support measures with potential environmental impacts. This makes it difficult to accurately quantify the extent of support and failure in the delivery of policy objectives. Moreover, ring-fencing corporate income tax to exclude them from environmental tax is not entirely helpful since, generally, corporations fully deduct decommissioning expenses from profits.

Fifth, the UK government could offer improved private incentives for researching, developing, and deploying new green technologies. The government could recycle environmental tax revenue to support developing clean technologies and infrastructure. This will increase popular support for environmental policies and direct carbon pricing instruments. Essentially, this will require allocating portions of carbon pricing revenue to public and private investments in green infrastructure, research, development, and deployment of green technologies, including carbon capture and storage.

5.2. Limitations and Future Research

Currently, data on environmental subsidies are not fully captured within the environmental tax systems in the UK, and this affects the quality of the research outcomes. Essentially, the broad measure of environmental revenues fails to capture the effect of subsidies and compensation payments. Future studies could consider using data that capture the complete picture of the UK's environmental tax revenues and subsidies to accurately determine their impact on environmental degradation.

Additionally, the study focuses only on the UK economy. However, due to contextual and policy differences across economies, it would be better to conduct such a study across several economies to be able to accurately capture the true effect of environmental taxes on environmental degradation. It is instructive to note that environmental policy objectives for developing economies will be quite different from developed nations. With such variations, environmental tax development and implementation may quite likely differ in their effects on pollution and environmental quality. Future scholars should take a cue from this limitation.

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Simulation Model of a Unified Energy System for Different Scenarios of Planned Disturbances

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Abstract: The study established that the application of graph theory enables the creation of a model of a country's power system structure in the form of a tiered graph. This allows complex structural elements of the system, such as generating units, electrical substations, and power transmission lines, to be represented as nodes and edges in simulation models that can be used for analysis, dispatch control, and optimization of system operation. A simulation model of the unified power system has been developed to analyze operational efficiency and performance under various planned disturbance scenarios. To solve the given task, it is necessary to develop a model of the power system in the form of a tiered graph, where the nodes are generating equipment stations, transmission system substations with voltages from 330 kV to 750 kV, and distribution system substations with voltages from 110 kV to 220 kV, and the edges are power transmission lines with voltages from 110 kV to 750 kV. The model takes into account the generated and transmitted power, the nominal capacity and the number of transformers at the substations, the cross-section and maximum throughput of the power transmission lines, which made it possible to determine complex interconnections between its nodes and integrate the equipment into a unified power system for efficiency and performance analysis.

Keywords: graph-based modeling; planned disturbances; simulation model; unified energy system

1. Introduction

In today's high-tech world, reliable and uninterrupted power supply is becoming critically important across various areas of life [1,2]. Studying models and methods for analyzing the efficiency and operability of electric power systems is of utmost significance [3,4]. The management of fuel element cladding lifetime under variable loading conditions in nuclear reactors presents challenges that are particularly relevant in the context of energy system reliability. The complexity of ensuring a safe and prolonged operation of nuclear fuel cladding is underscored by studies on VVER-1000 reactors, which outline principles for controlling cladding lifetime in fluctuating operational environments [5]. Additionally, effective predictive models are crucial for managing the risk of cladding failure, especially in scenarios involving multiple cyclic reactor power changes, which can impact the overall reliability and safety of power systems [6]. This research underscores the need for robust simulation models that can accurately predict the operational efficiency and reliability of power systems under diverse disturbance scenarios. The substantial number of electricity consumers and the ever-growing demand for new technologies put serious pressure on the energy infrastructure [7]. This pressure necessitates continuous adaptation to new challenges, ensuring the highest levels of efficiency and operability.

The advancement of modern technologies in the energy sector demands constant refinement of analytical and predictive methods [8,9]. This enables prompt responses to changes within the system and maximizes resource management efficiency to meet consumer needs [10–12]. Such an approach helps ensure the stability of the power supply, reduces the likelihood of outages, and promotes efficient use of energy resources within environmental dimensions.

The development and implementation of advanced technologies and equipment, as well as socio-economic and political transformations aimed at achieving sustainable development, lead to gradual changes in the methods and means of managing energy systems. Moving away from centralized or vertically hierarchical models, energy systems are transitioning to decentralized or multi-level approaches. Under these conditions, the issue of effective management and ensuring reliability in the operation of energy systems at the distribution and transmission levels becomes particularly relevant [13]. The application of modern management methods and technologies allows for optimizing energy transmission systems, enhancing productivity, ensuring stability, and reducing the risk of emergency situations.

A literature review on the topic revealed a scientific–technical contradiction: current energy systems incorporate models and methods that regulate the amount of electricity generated during normal operating modes or planned disturbances [14–17]. The arguments in such models include the amount of electricity generated, electricity quality, transmission and distribution losses, and technological expenses [18–21]. However, current energy system models [22–25] and methods [26–28] do not account for scenarios in which, under consumer management conditions, the consumer orders only the necessary volume of electricity [22,29,30], or the unified energy system is subject to random disturbances [17,28,31,32]. Recent advancements in modeling disturbed power systems include the use of Markov Jump Systems to model and control inverter-fed weak grids [33] and distributed secondary control for AC microgrids under non-uniform delays [34]. While these approaches focus on specific challenges, such as control optimization and handling delays, the proposed graph-based model emphasizes structural analysis, providing insights into reliability, operability, and energy flow optimization under varying disturbance scenarios.

This contradiction lies in the discrepancy between the supply and consumption volume needed for critical infrastructure operation and the inability to adapt to various random disturbances. Resolving this contradiction is possible by developing a simulation model and methods for assessing the efficiency and operability of the unified energy system.

Thus, the purpose of this study is to develop a simulation model of a unified power system that can effectively analyze operational efficiency and performance under various planned disturbance scenarios. The goal is to understand the interconnections and dependencies between different system components, from generation units to distribution substations, and to optimize system responses during disturbances.

To achieve this goal, it is necessary to consistently solve the following tasks:

- develop a simulation model of the unified power system in the form of a layered graph.
- identify the nodes representing generation stations, transmission substations with voltages ranging from 330 kV to 750 kV, and distribution substations with voltages from 110 kV to 220 kV.
- analyze the model to assess operational efficiency and performance under planned disturbance scenarios.

2. Materials and Methods

Graph-based modeling is the process of creating mathematical models that represent graphs, where nodes (vertices) are objects and edges are connections between them [35,36]. Such models can be used to analyze and forecast various systems and processes where objects and their interconnections are significant. Examples of the application of graph-based modeling include modeling social networks, road networks, genetic networks, and many others [37–40].

Graph theory provides tools for analyzing graph models, such as measuring vertex centrality, finding the shortest path between two vertices, and detecting communities in a graph [39]. These tools can be used to predict system behavior and evaluate the effect of changing parameters on the system.

Various approaches can be used to create graph models, including topological, stochastic, probabilistic, and others. Graph models can be constructed as either static or dynamic, where connections between vertices change over time [41–43].

Graph-based modeling has many applications in the power industry. Graph theory is an important tool for analyzing and modeling power supply systems. Graphs help represent the complex network of power system components, such as generators, transformers, transmission lines, and consumers, in the form of nodes (vertices) and connections (edges) between them.

The main concepts of graph theory applied to power supply systems include the following:

1. Network Representation. The power supply system can be represented as a complex network of various elements that interact to transmit electricity. Graph theory helps depict this network as a graph, where nodes represent different elements of the system, and edges represent the connections between them. The main elements of the power supply system that can be represented as graph vertices include:
    (a) Power plants. Graph vertices can represent various types of power plants, such as thermal, hydroelectric, wind, or solar power plants. Each vertex corresponds to a specific power plant and contains information about its electricity production.
    (b) Substations. Substations used for the transmission of electricity between different system elements can also be represented as graph vertices. These may include substations of different voltage levels that provide connections between power plants, transformers, and consumers.
    (c) Transformers. Graph vertices can represent transformers used to change the voltage level between different sections of the power supply system. Transformers are usually used to step down the voltage during electricity transmission from production to consumers and to step up the voltage during transmission from substations to remote sections.
    (d) Transmission lines. Graph edges represent transmission lines that connect different elements of the power supply system. These can include high-voltage transmission lines, cables, towers, and other means of electricity transmission.
2. Connection Analysis. Connection analysis in power supply systems using graph theory involves identifying existing connections between different elements and determining their dependencies. For this purpose, breadth-first search (BFS) and depth-first search (DFS) algorithms are used, which help determine power transmission paths and the hierarchy of dependencies among system elements. Main tasks include:
    (a) Finding power transmission paths. Applying BFS or DFS to a power supply system graph allows for finding all possible electricity transmission paths from production sources (power plants) to consumers. The algorithms traverse graph vertices, exploring all possible paths from one vertex to another. This helps determine which system elements are connected to power plants and how electricity is transmitted through the system.
    (b) Determining dependencies between elements. BFS and DFS algorithms also help identify dependencies among different power supply system elements. For instance, when applying BFS from a particular vertex, all vertices that can be reached from that vertex will have a distance of 1 from it. Thus, it is possible

to determine which elements are directly dependent on a specific element. DFS also helps reveal the depth of dependency among elements, as it explores the graph deeply.

Connection analysis helps understand how the elements of the power supply system interact and how changes in one element can affect others. This helps solve issues related to network optimization, identifying weak points, and developing management and maintenance strategies for the power supply system.

3. Reliability Analysis. Reliability analysis of power supply systems using graph theory involves analyzing reliability and identifying critical elements that impact the continuity of electricity supply. Graph representation allows for modeling the disconnection or failure of individual system elements by removing graph vertices or edges. Key tasks include:
   (a) Modeling disconnections. Graph representation of the power supply system allows for the isolation of individual graph vertices or edges corresponding to elements that may fail or be disconnected. Removing a vertex means disconnecting the respective element, such as a power plant, substation, or transformer, from the system. Removing an edge reflects disconnecting a transmission line or link between elements.
   (b) Impact analysis of disconnections. After modeling disconnections, the impact on the power supply system can be analyzed. This may include determining elements dependent on disconnected vertices or edges and identifying critical power transmission paths that may be severed in the event of disconnections.
   (c) Determining reliability and critical elements. Graph theory helps determine the reliability of the power supply system and identify critical elements that have the greatest impact on the continuity of electricity supply. Critical elements may be vertices whose disconnection leads to an interruption in power supply to key consumers or edges that represent vulnerable transmission lines.

Reliability analysis of the power supply system using graph theory helps solve issues related to preventing disconnections, planning redundancy, and improving the system's structure to ensure uninterrupted power supply.

4. Network Optimization. Power supply network optimization using graph theory involves applying various algorithms to find optimal power transmission routes, minimize energy losses, and ensure efficient system operation. The main algorithms that can be used include shortest path search, maximum flow, and the traveling salesman problem. Main tasks include:
   (a) Finding shortest paths: Shortest path search algorithms, such as Dijkstra's algorithm or the Bellman–Ford algorithm, help find the shortest routes for power transmission between different system elements. This helps optimize energy transmission paths, reduce energy losses, and ensure more efficient electricity distribution.
   (b) Maximum flow: Maximum flow algorithms, such as the Ford–Fulkerson algorithm or the Edmonds–Karp algorithm, help determine the maximum volume of electricity that can be transmitted through the power supply system. This allows for identifying overloaded sections of the network and finding an optimal operating mode for the system with maximum use of available capacity.
   (c) Traveling salesman problem: The traveling salesman problem involves finding the shortest path that passes through all elements of the power supply system and returns to the starting point. Applying algorithms that solve this problem helps optimize the sequence of traversing network elements, reducing time and energy consumption for movement.

Using these algorithms and graph theory methods ensures optimal functioning of the power supply system, reduces energy losses, improves reliability, and ensures efficient use of resources. Network optimization is a crucial step to increase the productivity and stability of the power supply system.

5. Development Planning. Power supply system development planning using graph theory allows for analyzing the network structure and identifying opportunities to improve its efficiency and reliability. Key aspects that can be considered in the context of development planning include identifying weak points, and redundant elements, and assessing the impact of new technologies. Main tasks include:
   (a) Identifying weak points. Graph structure analysis helps identify weak points in the power supply system, such as areas with high energy losses, insufficient capacity, or limited throughput. Identifying these weak points helps plan network expansion or improve existing elements to enhance system efficiency and reliability.
   (b) Redundant elements. Graph analysis also helps identify redundant elements in the power supply system, such as alternative power transmission routes or backup power sources. Using redundant elements ensures reliability and reduces the risk of system failure in the event of problems in one of the elements.
   (c) Impact assessment of new technologies. Applying graph theory allows for assessing the impact of introducing new technologies into the power supply system. New technologies, such as renewable energy sources, energy-efficient solutions, or smart grids, may require changes in the network structure and operation. Graph analysis helps determine optimal locations for implementing new technologies and assess their impact on system performance and reliability.

Planning the development of the power supply system using graph theory allows for making informed decisions about network expansion, implementing new technologies, and improving system efficiency, thereby ensuring reliable power supply.

Graphs are an effective tool for visualizing the structure of power grids, providing a clear representation of the network topology, as well as the relationships between nodes and transmission lines. However, their application extends far beyond visual analysis. Leveraging the mathematical foundation of graphs enables the development of sophisticated models for analyzing and forecasting network performance.

An adjacency matrix is used to describe the connections between nodes in the network, such as substations or distribution points, indicating the presence of transmission lines between them. An incidence matrix further links nodes with transmission lines, reflecting the network's topological features. These data structures, combined with the characteristics of nodes (e.g., load, generation, degree of connectivity) and lines (e.g., resistance, capacity, length), serve as the foundation for constructing stochastic models.

Stochastic modeling of power grids accounts for random changes and uncertainties, such as daily, seasonal, or random fluctuations due to disturbances, emergency line outages, changes in generation capacity, or the unpredictable behavior of renewable energy sources. This approach enables detailed analysis of system behavior under various scenarios and the development of measures to enhance its reliability and efficiency.

The simulation model of the power system can be represented as a layered graph. A layered graph (also known as a hierarchical or level graph) is a type of graph in which nodes are grouped into levels or layers based on their hierarchical or structural relationships. Each level represents a certain degree of importance or detail of the system components.

This graph structure allows for a visual representation of the system's hierarchy and organization and reveals its complex interrelationships. A layered graph is often used to model hierarchical structures, such as organizational structures, information systems, technical networks, management systems, power supply systems, etc.

One of the main types of layered graphs is the top-down graph, where nodes are arranged in layers from top to bottom, from the upper layer to the lower layer. The opposite type is the bottom-up graph, where nodes are arranged in layers from bottom to top, from the lower layer to the upper one. Figure 1 shows an example of a layered graph.

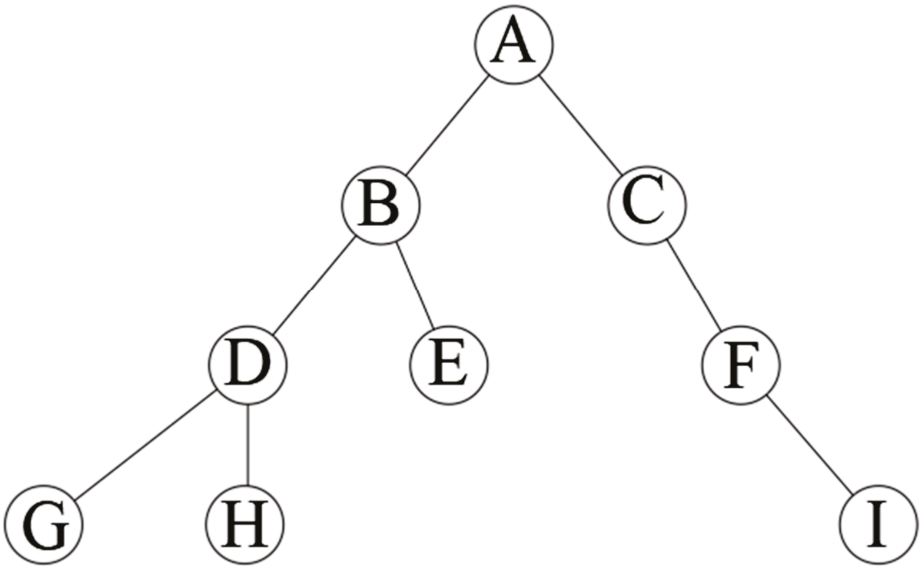

Figure 1. Example of a layered graph.

The layered graph has its advantages and disadvantages that should be considered when applying it, namely:

- a layered graph allows for the visual representation of the hierarchical structure of a system or organization. This makes it easy to distinguish different levels of importance and dependencies between components.
- the graphical representation as a layered graph is highly intuitive and easy to comprehend. It helps to quickly navigate the structure of the system and the relationships between its components.
- a layered graph conveniently facilitates tracking and analyzing interrelationships between system components.
- the layered graph can be easily extended or modified by adding new nodes or levels, allowing for convenient consideration of the system's development or changes in its structure.
- for very large systems with a significant number of components and interrelationships, a layered graph may become difficult to understand and analyze due to the large number of nodes and connections.
- a layered graph provides a general overview of the system's structure but may be limited in accurately depicting details and relationships between components.
- the layered graph may be less flexible compared to other types of graphs since it is constrained by a specific hierarchical structure and dependencies between levels.
- a large number of components and connections in the system may lead to the loss of some detail when represented in a layered graph.

3. Research Results

For creating the simulation model of the power system, a layered graph $G = (V,\ E)$ was used, which included:

Set $V = \{v1,\ v2, \ldots, vn\}$—the set of vertices;

Set $E = \{e1, 2, e2, 3, \ldots, ei, j\}$—the set of edges or arcs of the graph.

At the top layer, "generation level," are the vertices that represent the main power-generating stations or energy sources, such as thermal power plants, cogeneration plants, nuclear power plants, hydroelectric power plants, and pumped-storage power plants.

Table 1 provides detailed information about the vertices at the "generation level". The properties of each vertex at this level include an identifier, name, generating capacity, and type of power plant.

Table 1. Set of vertices V at the top layer "generation level".

Vertex Identifier	Vertex Name	Generating Capacity (MW)	Type of Power Plant
V1	Gen1	3000	Nuclear
V2	Gen2	6000	Nuclear
V3	Gen3	2000	Nuclear
V4	Gen4	2835	Nuclear
V5	Gen5	1800	Thermal
V6	Gen6	302	Pumped-storage
V7	Gen7	500	Thermal
V8	Gen8	700	Thermal
V9	Gen9	1825	Thermal
V10	Gen10	972	Pumped-storage
V11	Gen11	702	Hydro
V12	Gen12	482.5	Hydro
V13	Gen13	2351	Thermal
V14	Gen14	510	Thermal
V15	Gen15	636.2	Thermal
V16	Gen16	2079	Thermal
V17	Gen17	910	Thermal
V18	Gen18	1532	Thermal
V19	Gen19	2850	Thermal
V20	Gen20	2265	Thermal
V21	Gen21	3600	Thermal
V22	Gen22	1270	Thermal

Source: created by the authors based on data [44,45].

The next layer contains the vertices representing 750 kV transmission substations. Table 2 provides detailed information about the vertices at the "750 kV transmission substations" level. The properties of each vertex at this level include an identifier, name, number of transformers, nominal transformer capacity, and substation load.

The next layer contains the vertices representing 500 kV transmission substations. Table 3 provides detailed information about the vertices at the "500 kV transmission substations" level. The properties of each vertex at this level include an identifier, name, number of transformers, nominal transformer capacity, and substation load.

The next layer contains the vertices representing 400 kV transmission substations. Table 4 provides detailed information about the vertices at the "400 kV transmission substations" level. The properties of each vertex at this level include an identifier, name, number of transformers, nominal transformer capacity, and substation load.

The next layer contains the vertices representing 330 kV transmission substations. Table 5 provides a fragment of detailed information about the vertices at the "330 kV transmission substations" level. The complete list of vertices at this layer is provided in Appendix A. The properties of each vertex at this level include an identifier, name, number of transformers, nominal transformer capacity, and substation load.

Table 2. Set of vertices *V* at the top layer "750 kV transmission substations".

Vertex Identifier	Vertex Name	Number of Transformers	Nominal Transformer Capacity (MW)	Substation Load (kW)
V30	PS_750_1	3	333	125,999
V31	PS_750_2	3	250	600
V32	PS_750_3	2	999	1598
V33	PS_750_4	2	1250	3600
V34	PS_750_5	2	999	1598
V35	PS_750_6	2	250	600
V36	PS_750_7	1	999	799
V37	PS_750_8	2	999	1500
V38	PS_750_9	3	999	2398
V39	PS_750_10	Foreign Substation	-	-

Source: created by the authors based on data [44,45].

Table 3. Set of vertices *V* at the top layer "500 kV transmission substations".

Vertex Identifier	Vertex Name	Number of Transformers	Nominal Transformer Capacity (MW)	Substation Load (kW)
V40	PS_500_1	2	200	320
V41	PS_500_2	2	200	400

Source: created by the authors based on data [44,45].

Table 4. Set of vertices *V* at the top layer "400 kV transmission substations".

Vertex Identifier	Vertex Name	Number of Transformers	Nominal Transformer Capacity (MW)	Substation Load (kW)
V42	PS_400_1	2	200	980

Source: created by the authors based on data [44,45].

Table 5. Set of vertices *V* at the top layer "330 kV transmission substations".

Vertex Identifier	Vertex Name	Number of Transformers	Nominal Transformer Capacity (MW)	Substation Load (kW)
V43	PS_330_1	3	250	600
V44	PS_330_2	2	125	200
V45	PS_330_3	Transit	-	-
V46	PS_330_4	2	325	488
V47	PS_330_5	2	200	320
V48	PS_330_6	3	200	500
V49	PS_330_7	2	125	200
V50	PS_330_8	2	250	600
V51	PS_330_9	1	200	160
V52	PS_330_10	2	125	360
V53	PS_330_11	2	125	200
V54	PS_330_12	3	125	300

Source: created by the authors based on data [44,45].

The next layer contains the vertices representing 220 kV transmission substations. Table 6 provides a fragment of detailed information about the vertices at the "220 kV transmission substations" level. The complete list of vertices at this layer is provided in Appendix A. The properties of each vertex at this level include an identifier, name, number of transformers, nominal transformer capacity, and substation load.

Table 6. Set of vertices *V* at the top layer "220 kV transmission substations".

Vertex Identifier	Vertex Name	Number of Transformers	Nominal Transformer Capacity (MW)	Substation Load (kW)
V132	PS_220_1	2	63	101
V133	PS_220_2	2	63	105
V134	PS_220_3	2	125	200
V135	PS_220_4	2	125	200
V136	PS_220_5	2	125	200
V137	PS_220_6	2	63	101
V138	PS_220_7	2	200	320
V139	PS_220_8	2	125	200
V140	PS_220_9	2	125	200
V141	PS_220_10	2	200	320

Source: created by the authors based on data [44,45].

The next layer contains the vertices representing 150 kV distribution substations. Table 7 provides a fragment of detailed information about the vertices at the "150 kV distribution substations" level. The complete list of vertices at this layer is provided in Appendix A. The properties of each vertex at this level include an identifier, name, number of transformers, nominal transformer capacity, and substation load.

Table 7. Set of vertices *V* at the top layer "150 kV transmission substations".

Vertex Identifier	Vertex Name	Number of Transformers	Nominal Transformer Capacity (MW)	Substation Load (kW)
V167	PS_150_1	1	16	12
V168	PS_150_2	1	25	19
V169	PS_150_3	2	40	168
V170	PS_150_4	2	25	40
V171	PS_150_5	1	200	160
V172	PS_150_6	2	25	40
V173	PS_150_7	2	25	40
V174	PS_150_8	2	40	64
V175	PS_150_9	2	40	64
V176	PS_150_10	2	40	64

Source: created by the authors based on data [44,45].

The next layer contains the vertices representing 110 kV distribution substations. Table 8 provides a fragment of detailed information about the vertices at the "110 kV distribution substations" level. The complete list of vertices at this layer is provided in Appendix A. The properties of each vertex at this level include an identifier, name, number of transformers, nominal transformer capacity, and substation load.

Table 8. Set of vertices *V* at the top layer "110 kV transmission substations".

Vertex Identifier	Vertex Name	Number of Transformers	Nominal Transformer Capacity (MW)	Substation Load (kW)
V200	PS_110_1	2	16	26
V201	PS_110_2	2	25	40
V202	PS_110_3	2	10	17
V203	PS_110_4	2	32	50
V204	PS_110_5	2	25	40
V205	PS_110_6	2	32	48
V206	PS_110_7	3	10	25
V207	PS_110_8	1	40	53
V208	PS_110_9	2	25	40
V209	PS_110_10	2	40	64

Source: created by the authors based on data [44,45].

After defining the graph's vertices, it is necessary to define the connections or dependencies between them, i.e., determine the graph's edges. The edges represent physical or functional connections between the components of the power supply system, which allows for revealing various aspects of the system's functioning.

Physical connections between components include the transmission of electricity through cable or overhead power lines, which connect generating stations, substations, and consumers. Identifying the graph's edges allows for the creation of a complete simulation model of the power supply system, in which each graph edge represents important connections between components.

Table 9 presents detailed information and properties of the set of edges EEE of the layered graph. The properties of each edge include an identifier, length, redundancy, maximum line losses, cost per kilometer, and line voltage.

Table 9. Set of edges *E* of the layered graph.

Edge Identifier	Length (km)	Cross-Section	Redundancy	Maximum Losses (kW)	Cost per km (UAH/km)	Line Voltage (kV)
e (36,37)	126	4 × AC-500/64	–	7410	4 × 270,000	750
e (36,37)	162	2 × AC-300/39	330 kV backup	164,023	2 × 220,000	330
e (3,36)	261	5 × AC-400/51	–	4339	5 × 230,000	750
e (33,40)	198	2 × AC-400	–	2975	4 × 230,000	500
e (13,42)	197	2 × ACO-500	–	34,954	4 × 270,000	400
e (5,43)	132	2 × AC-300/39	–	21,468	2 × 220,000	330

Source: created by the authors based on data [44,45].

Figure 2 shows a fragment of the layered graph of the country's power supply system.

The complete graph consists of various levels, with each level corresponding to a specific voltage class and hierarchy.

- Level 0 represents power generation stations.
- Levels 1–5 correspond to transmission system operator substations with voltage levels ranging from 220 kV to 750 kV.
- Levels 6–7 represent distribution system operator substations with voltage levels of 110–150 kV.

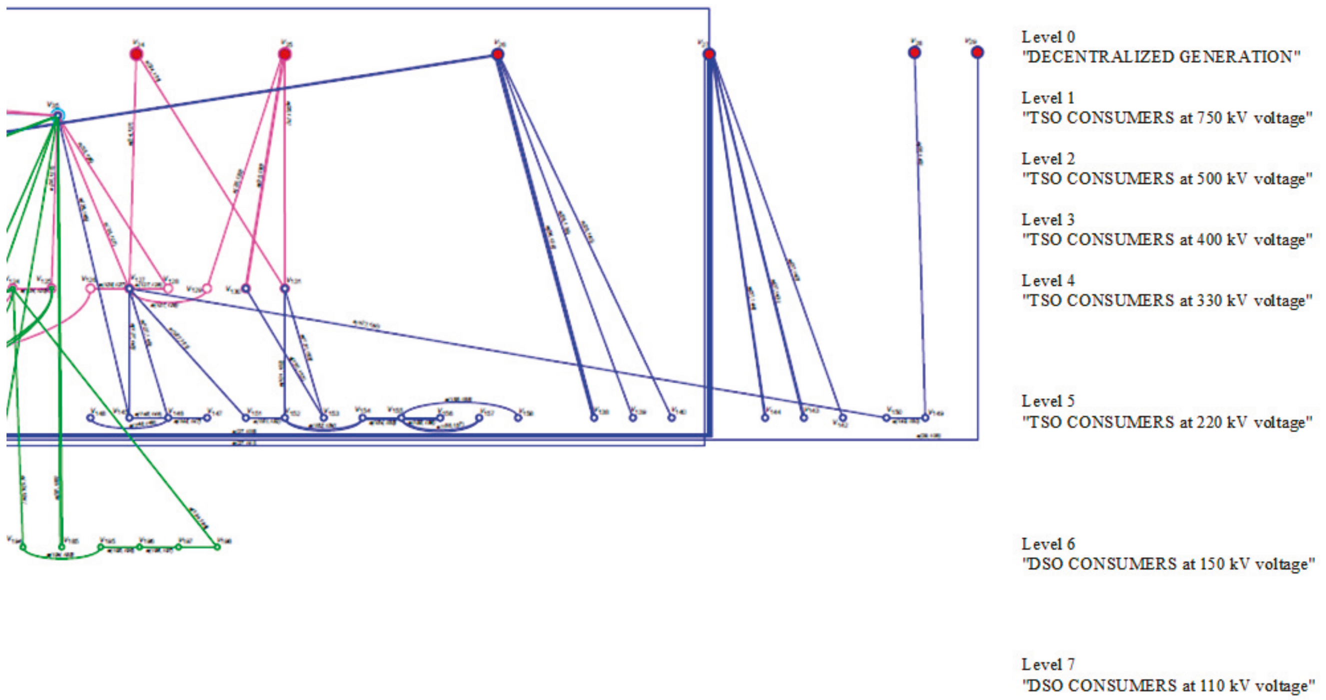

Figure 2. Fragment of the layered graph of the power system of the country (constructed by the authors). Legend: green lines: 150 kV power lines; blue lines: 220 kV power lines; magenta lines: 330 kV power lines.

Each node in the graph represents either a power generation station or an individual substation of various voltage classes.

Overall, the simulation model in the form of a layered graph consists of 385 vertices and 626 connections (edges).

A circular layered graph is a type of graph that has specific properties. It consists of vertices and edges, where each vertex is connected to two neighboring vertices by an edge, and each pair of vertices is also connected by an edge. The feature of the circular layered graph is that it can be represented as a circle, where the vertices are positioned along the circumference, and the edges are like radii connecting the center of the circle to the vertices.

The main properties of the circular graph include:

- The circular layered graph consists of vertices and edges. The vertices are represented by points on the circle, and the edges are segments connecting these vertices.
- Each vertex in the graph is connected by an edge to two neighboring vertices. This creates a closed loop encompassing all the vertices of the graph.
- Since the vertices are positioned on a circle, geometric properties of the circle can be used for analyzing and studying the graph.
- Circular layered graphs can be used to model various situations, such as electronic circuits, where vertices can represent components and edges can represent connections between them.

The main advantages of the circular graph include:

- A simple and intuitive structure, which makes it easy to study and analyze.
- Due to the simple structure and closed loop of the circular layered graph, analysis of its properties, such as diameter, radius, and other metrics, can be performed quite easily.
- The ability to represent a circular layered graph as a circle allows for easy visualization of its structure and interconnections between vertices.

The main disadvantages of the circular graph include:

- The number of edges in a circular layered graph increases proportionally to the number of vertices, which can lead to increased data volume and processing complexity.

- In cases where the graph has a large number of vertices and edges, the circular layered graph may require significant memory to store its structure.
- In some cases, the structure of a circular layered graph may be too simple for adequately modeling complex systems or analyzing intricate interrelationships.

Figure 3 shows an example of a circular graph.

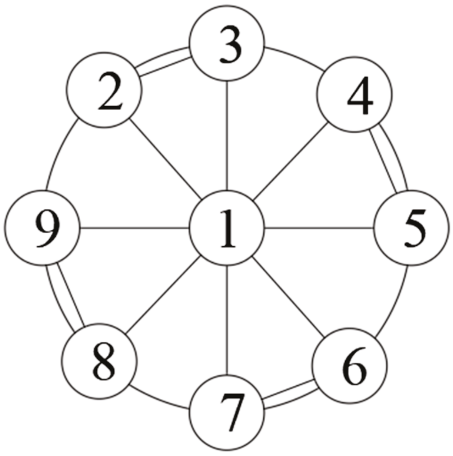

Figure 3. Example of a circular graph of a system (constructed by the authors).

Figure 4 shows a fragment of the circular layered graph of the power system simulation model.

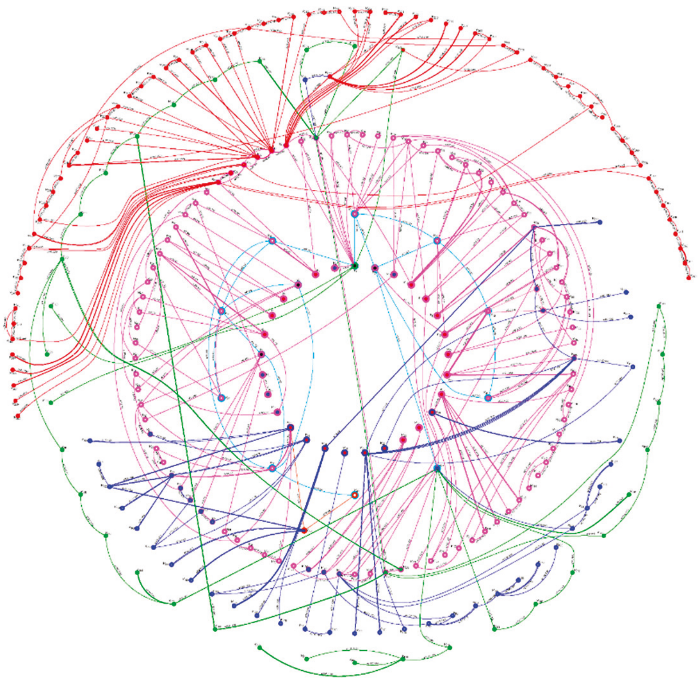

Figure 4. Fragment of the circular layered graph of the power system simulation model (constructed by the authors). Legend: red lines (110 kV) represent lower voltage transmission lines; green lines (150 kV) represent medium voltage lines at the distribution level; blue lines (220 kV) are transmission lines operating at a higher voltage; magenta lines (330 kV) represent high voltage transmission lines.

Another way to represent a graph is in the form of an adjacency matrix AG. This method is used when working with a graph on a computer. The simulation model consists of 385 vertices, so the adjacency matrix AG will be of size 385 $\times$ 385, containing the set of elements $AG = (aij)$. In this matrix, the indices i, j vary from one to n, and the value aij is one if there is an edge between the corresponding vertices Vi, Vj, or zero if no such edge exists.

$$a_{i,j} = \left[(v_i, v_j) \in E \right] = \begin{cases} 1, (v_i, v_j) \in E \\ 0, (v_i, v_j) \notin E \end{cases}. \tag{1}$$

To automate the construction of the adjacency matrix, a VBA program code was developed and embedded in Microsoft Excel (Algorithm 1). The input data for constructing the adjacency matrix is the database of edges, which is provided in Appendix A.

Algorithm 1 VBA code for constructing the adjacency matrix

```
Sub matrix_sm()
    Dim v As Integer, e As Integer, i As Integer, j As Integer
    Worksheets("v").Cells.Clear
    v = Worksheets("e").Cells(2, 12)
    MsgBox ("Number of graph vertices–" and v)
    e = Worksheets("e").Cells(3, 12)
    MsgBox ("Number of graph edges–" and e)
    Worksheets("v").Cells(2, 2) = "V"
    For i = 1 To v
        For j = 1 To v
            Worksheets("v").Cells(2, 2 + i) = i
            Worksheets("v").Cells(2 + i, 2) = i
            Worksheets("v").Cells(2 + j, 2 + i) = 0
        Next j
    Next i
    For i = 1 To e
        e1 = Worksheets("e").Cells(1 + i, 2)
        e2 = Worksheets("e").Cells(1 + i, 3)
        Worksheets("v").Cells(2 + e1, 2 + e2) = Worksheets("v").Cells(2 + e1, 2 + e2) + 1
        Worksheets("v").Cells(2 + e2, 2 + e1) = Worksheets("v").Cells(2 + e2, 2 + e1) + 1
    Next i
End Sub
```

The main disadvantages of the incidence matrix include the fact that for graphs with a large number of vertices and edges, the incidence matrix can require a significant amount of memory, especially in the case of sparse graphs where most edges are absent. The incidence matrix can also be challenging to read and edit, particularly for large graphs, as it contains many zero values, which complicates determining the connections between vertices and edges.

Figure 5 shows a fragment of the adjacency matrix of the simulation model.

The incidence matrix BG connects the vertices and edges in graph G. Like the adjacency matrix, this method is used when working with graphs on a computer. Each element of the matrix $BG = (bij)$ takes the value 1 if vertex vi is an endpoint of edge eij, and takes the value 0 if this condition is not met.

To automate the construction of the incidence matrix, a VBA program code was developed and embedded in Microsoft Excel (Algorithm 2). The input data for constructing the incidence matrix is the database of edges, provided in Appendix B.

V	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
6	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
31	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0
34	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	1	1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
43	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0

Figure 5. Fragment of the incidence matrix AG = (a*ij*) (constructed by the authors).

Algorithm 2 VBA code for constructing the incidence matrix

```
Sub matrix_inc()
    Dim v As Integer, e As Integer, i As Integer, j As Integer
    Dim e1 As String, e2 As String
    v = Worksheets("e").Cells(2, 12)
    MsgBox ("Number of graph vertices–" and v)
    e = Worksheets("e").Cells(3, 12)
    MsgBox ("Number of graph edges–" and e)
    Worksheets("inc").Cells(2, 2) = "V"
    For i = 1 To v
        For j = 1 To e
            Worksheets("inc").Cells(2 + i, 2) = i
            e1 = Worksheets("e").Cells(1 + j, 2)
            e2 = Worksheets("e").Cells(1 + j, 3)
            Worksheets("inc").Cells(2, 2 + j) = e1 and "-" and e2
            Worksheets("inc").Cells(2 + i, 2 + j) = 0
        Next j
    Next i
    For i = 1 To e
        e1 = Worksheets("e").Cells(1 + i, 2)
        e2 = Worksheets("e").Cells(1 + i, 3)
        Worksheets("inc").Cells(2 + e1, 2 + i) = 1
        Worksheets("inc").Cells(2 + e2, 2 + i) = 1
    Next i
End Sub
```

The main disadvantage of the incidence matrix is that for graphs with a large number of vertices and edges, the incidence matrix can require a significant amount of memory, especially in the case of sparse graphs where most edges are absent. The incidence matrix can also be difficult to read and edit, particularly for large graphs, since it contains many zero values, which complicates identifying the connections between vertices and edges.

Figure 6 shows a fragment of the incidence matrix for the simulation model.

V	1-167	1-168	1-169	1-30	1-31	1-43	1-49	1-50	1-6	1-81	1-81	1-83	10-11	10-53	10-80	100-101	101-102	105-141	106-119	106-120	106-123	107-109	108-109	109-110	110-111	111-112	111-115	112-113	112-114	115-116
1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 6. Fragment of the incidence matrix $BG = (b_{i,j})$ (constructed by the authors).

4. Discussion and Conclusions

Based on the conducted research, the scientific novelty of the study can be formulated as the proposed simulation model of the unified power system in the form of a layered graph. The nodes of this graph represent the generation equipment stations, transmission system substations with voltage levels from 330 kV to 750 kV, and distribution system substations with voltage levels from 110 kV to 220 kV. The edges represent power transmission lines with voltage levels from 110 kV to 750 kV. The model takes into account the generated and transmitted power, the nominal capacity, and the number of transformers at the substations, as well as the cross-section and maximum transmission capacity of the power lines. This approach to the results obtained allowed for the identification of complex interconnections between its nodes and the integration of equipment into a unified power system for analyzing operational efficiency and performance.

The proposed layered graph model differs significantly from recent graph-theoretic approaches in its scope and application. For instance, Biswas et al. (2021) [17] introduced a graph-theoretic method for identifying saturated cut-sets in meshed power networks during multiple outages. This approach focuses on real-time vulnerability assessment and situational awareness, optimizing solution time for critical contingency management. In contrast, our model emphasizes the structural analysis of hierarchical power systems, enabling the evaluation of energy transmission paths and reliability under a wide range of disturbance scenarios. While the method by [17] provides actionable insights for operational decision-making in real-time, our model offers a more holistic representation, capable of simulating energy flow disruptions across multiple voltage tiers and identifying optimal pathways for energy delivery. This distinction highlights our model's utility in long-term planning and analysis of system-wide resilience.

Werho et al. (2016) [21] developed a network flow algorithm to monitor power system connectivity in real-time, which determines the maximum flow between two nodes in a directed graph. Their method identifies system vulnerabilities by analyzing the minimum number of branches required to disconnect specific nodes. This approach is particularly useful for operational decision-making during major disturbances, such as the 2008 island formation in the Entergy power system. In contrast, our model emphasizes long-term structural analysis of hierarchical power systems. While Werho et al.'s method offers critical insights for real-time network visualization and situational awareness, our model focuses on evaluating system-wide reliability and operability under a variety of scenarios, such as stochastic disturbances or planned outages. Moreover, the layered graph structure of our model enables multi-tiered analysis of voltage classes, which provides a broader scope for planning and optimization in large-scale energy systems.

In contrast to [25], our model focuses on a layered graph representation, which captures the hierarchical structure of power systems and provides a detailed analysis of energy transmission paths. While Zhang et al.'s approach excels in evaluating immediate vulnerabilities and resilience at the topological level, our model offers a broader scope for long-term planning, including stochastic disturbance scenarios and optimization of energy delivery across multiple voltage tiers. These complementary approaches highlight the diversity in applying graph theory to power system analysis, with our model particularly suited for planning and system-wide structural analysis.

In comparison to [28], the proposed layered graph model focuses on a multi-tier representation of energy systems, analyzing energy transmission paths and system operability under disturbances. While Beyza et al.'s method excels in evaluating immediate structural vulnerabilities and cascading failures, our model offers a broader scope, incorporating voltage tier hierarchies and enabling long-term planning for reliability and optimization. These methods complement each other, with our model designed for system-wide analysis and strategic decision-making, while Beyza et al.'s approach emphasizes rapid assessment in operational contexts.

The proposed layered graph model differs from existing methods in its focus on structural analysis of hierarchical power systems. Unlike the Markov Jump System approach [33], which models weak grids and addresses specific control challenges, our model provides a holistic representation of energy transmission paths, enabling the analysis of system-wide reliability and efficiency. Similarly, while the distributed secondary control method [34] is tailored to microgrids, the proposed model is designed for larger power systems, accommodating multiple voltage tiers and their interconnections.

The newest research [46] introduced a data-driven graph modeling approach for electric power transmission networks (EPTNs) using synchrophasor measurements. Their method constructs graph models based on real-time data from substations, bypassing the need for prior knowledge of network connectivity. The approach leverages an exhaustive search algorithm and evaluates the accuracy of Transmission Network Graph Models (TNGMs) under varying power plant operating conditions, achieving an average error margin within 2%.

In contrast, the proposed layered graph model focuses on the hierarchical representation of energy systems, analyzing structural reliability and energy transmission paths under disturbances. While Venayagamoorthy et al.'s method excels in providing real-time situational awareness and connectivity analysis, our model offers a broader scope for long-term strategic planning and optimization. These methods complement each other, with the data-driven approach suited for operational decision-making and our model tailored for planning and system-wide analysis.

Unlike these methods, our model integrates a hierarchical representation of power systems, enabling detailed evaluation of energy transmission reliability across multiple voltage tiers. This long-term focus positions our model as a strategic planning tool, complementary to operational approaches like those by [46], which are optimized for real-time monitoring and network reconfiguration.

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Appendix A. Properties of the Set of Vertices of the Tiered Graph

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v1	Gen 1			3000			generation
v2	Gen 2			6000			generation
v3	Gen 3			2000			generation
v4	Gen 4			2835			generation
v5	Gen 5			1800			generation
v6	Gen 6			302			generation
v7	Gen 7			500			generation
v8	Gen 8			700			generation
v9	Gen 9			1825			generation
v10	Gen 10			972			generation
v11	Gen 11			702			generation
v12	Gen 12			4825			generation
v13	Gen 13			2351			generation
v14	Gen 14			510			generation
v15	Gen 15			6362			generation
v16	Gen 16			2079			generation
v17	Gen 17			910			generation
v18	Gen 18			1532			generation
v19	Gen 19			2850			generation
v20	Gen 20			2265			generation
v21	Gen 21			3600			generation
v22	Gen 22			1270			generation
v23	Gen 23			880			generation
v24	Gen 24			2010			generation
v25	Gen 25			275			generation
v26	Gen 26			470			generation
v27	Gen 27			470			generation
v28	Gen 28			68			generation
v29	Gen 29			1220			generation

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v30	PS_750_1	3 2	333 125	999	3 × 621 2 × 375	3 × 1011 2 × 310	750 kV
v31	PS_750_2	3	250	600	3 × 463	3 × 600	750 kV
v32	PS_750_3	2	999	1598	2 × 1860	2 × 2730	750 kV
v33	PS_750_4	2 2	1250 999	3600	2 × 3400 2 × 1860	2 × 3100 2 × 2730	750 kV
v34	PS_750_5	2	999	1598	2 × 1860	2 × 2730	750 kV
v35	PS_750_6	2 1	250 300	600	2 × 463 1 × 510	2 × 600 1 × 950	750 kV
v36	PS_750_7	1	999	799	1860	1 × 2730	750 kV
v37	PS_750_8	2	999	1500	2 × 1860	2 × 2730	750 kV
v38	PS_750_9	3	999	2398	3 × 1860	3 × 2730	750 kV
v39	PS_750_10						Foreign State Substation
v40	PS_500_1	2	200	320	2 × 380	2 × 560	500 kV
v41	PS_500_2	2 1	200 100	400	2 × 380 1 × 210	2 × 560 2 × 300	500 kV
v42	PS_400_1	2 2	200 400	980	2 × 380 2 × 590	2 × 560 2 × 870	400 kV
v43	PS_330_1	3	250	600	3 × 470	3 × 410	330 kV
v44	PS_330_2	2	125	200	2 × 352	2 × 230	330 kV
v45	PS_330_3						transit
v46	PS_330_4	2	325	488	2 × 600	2 × 560	330 kV
v47	PS_330_5	2	200	320	2 × 534	2 × 410	330 kV
v48	PS_330_6	3	200	500	3 × 534	3 × 410	330 kV
v49	PS_330_7	2	125	200	2 × 352	2 × 230	330 kV
v50	PS_330_8	2 1	250 300	600	2 × 470 1 × 520		330 kV
v51	PS_330_9	1	200	160	1 × 534	1 × 410	330 kV
v52	PS_330_10	2 1	125 200	360	2 × 352 1 × 534	2 × 230 1 × 410	330 kV
v53	PS_330_11	2	125	200	2 × 352	2 × 230	330 kV
v54	PS_330_12	3	125	300	3 × 352	3 × 230	330 kV
v55	PS_330_13	2	125	200	2 × 352	2 × 230	330 kV
v56	PS_330_14	2	200	320	2 × 534	2 × 410	330 kV
v57	PS_330_15	3	200	480	3 × 534	3 × 410	330 kV
v58	PS_330_16	2	125	200	2 × 352	2 × 230	330 kV
v59	PS_330_17	2	200	320	2 × 534	2 × 410	330 kV
v60	PS_330_18	2	200	320	2 × 534	2 × 410	330 kV
v61	PS_330_19	2	125	200	2 × 352	2 × 230	330 kV
v62	PS_330_20	2	200	320	2 × 534	2 × 410	330 kV
v63	PS_330_21	2	200	320	2 × 534	2 × 410	330 kV

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v64	PS_330_22	2	200	320	2 × 534	2 × 410	330 kV
v65	PS_330_23	2	125	200	2 × 352	2 × 230	330 kV
v66	PS_330_24	2	125	200	2 × 352	2 × 230	330 kV
v67	PS_330_25	2 2	200 125	520	2 × 534 2 × 352	2 × 410 2 × 230	330 kV
v68	PS_330_26	2	125	200	2 × 352	2 × 230	330 kV
v69	PS_330_27	2	125	200	2 × 352	2 × 230	330 kV
v70	PS_330_28	1	200	160	1 × 534	1 × 410	330 kV
v71	PS_330_29	2 2 2	125 200 240	904	2 × 352 2 × 534 2 × 580	2 × 230 2 × 410 2 × 430	330 kV
v72	PS_330_30	2 1	200 125	420	2 × 534 1 × 352	1 × 230	330 kV
v73	PS_330_31	3	200	480	3 × 534	3 × 410	330 kV
v74	PS_330_32	1 2	200 125	360	1 × 534 2 × 352	2 × 230	330 kV
v75	PS_330_33	1 1	200 125	260	1 × 534 1 × 352	1 × 230	330 kV
v76	PS_330_34	4	125	400	4 × 352	4 × 230	330 kV
v77	PS_330_35	3	125	300	3 × 352	3 × 230	330 kV
v78	PS_330_36	2	125	200	2 × 352	2 × 230	330 kV
v79	PS_330_37	2	125	200	2 × 352	2 × 230	330 kV
v80	PS_330_38	2	200	320	2 × 534	2 × 410	330 kV
v81	PS_330_39	2	250	400	2 × 470	2 × 430	330 kV
v82	PS_330_40	2	125	200	2 × 352	2 × 230	330 kV
v83	PS_330_41	2	200	320	2 × 534	2 × 410	330 kV
v84	PS_330_42	1	250	200	1 × 470	1 × 430	330 kV
v85	PS_330_43	3 2	250 63	700	3 × 470 2 × 180	3 × 430 2 × 120	330 kV
v86	PS_330_44	2	250	400	2 × 470	2 × 430	330 kV
v87	PS_330_45	2 1	250 63	450	2 × 470 1 × 180	2 × 430 2 × 120	330 kV
v88	PS_330_46	2	250	400	2 × 470	2 × 430	330 kV
v89	PS_330_47	4	250	800	4 × 470	4 × 430	330 kV
v90	PS_330_48	4	250	800	4 × 470	4 × 430	330 kV
v91	PS_330_49	4	250	800	4 × 470	4 × 430	330 kV
v92	PS_330_50	2	125	200	2 × 352	2 × 230	330 kV
v93	PS_330_51	3	250	600	3 × 470	3 × 430	330 kV
v94	PS_330_52	2	125	200	2 × 352	2 × 230	330 kV
v95	PS_330_53	5	250	1000	5 × 470	5 × 430	330 kV
v96	PS_330_54	2	125	200	2 × 352	2 × 230	330 kV

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v97	PS_330_55	2	125	200	2 × 352	2 × 230	330 kV
v98	PS_330_56	2	125	200	2 × 352	2 × 230	330 kV
v99	PS_330_57	2	125	200	2 × 352	2 × 230	330 kV
v100	PS_330_58	2	125	200	2 × 352	2 × 230	330 kV
v101	PS_330_59	2	125	200	2 × 352	2 × 230	330 kV
v102	PS_330_60	2	125	200	2 × 352	2 × 230	330 kV
v103	PS_330_61	2	200	320	2 × 534	2 × 410	330 kV
v104	PS_330_62	2	125	200	2 × 352	2 × 230	330 kV
v105	PS_330_63	2	200	320	2 × 534	2 × 410	330 kV
v106	PS_330_64	2	125	200	2 × 352	2 × 230	330 kV
v107	PS_330_65	2	125	200	2 × 352	2 × 230	330 kV
v108	PS_330_66	2	200	320	2 × 534	2 × 410	330 kV
v109	PS_330_67	1	999	800	1 × 1620	1 × 2120	330 kV
v110	PS_330_68	2 1	125 200	360	2 × 352 2 × 534	2 × 230 1 × 410	330 kV
v111	PS_330_69	2 1	125 200	360	2 × 352 1 × 534	2 × 230 1 × 410	330 kV
v112	PS_330_70	3	125	300	3 × 352	3 × 230	330 kV
v113	PS_330_71	3	125	300	3 × 352	3 × 230	330 kV
v114	PS_330_72	2	200	320	2 × 534	2 × 410	330 kV
v115	PS_330_73	3	200	480	3 × 534	3 × 410	330 kV
v116	PS_330_74	2	200	320	2 × 534	2 × 410	330 kV
v117	PS_330_75	2	125	200	2 × 352	2 × 230	330 kV
v118	PS_330_76	2	125	200	2 × 352	2 × 230	330 kV
v119	PS_330_77	2	125	200	2 × 352	2 × 230	330 kV
v120	PS_330_78	2	125	200	2 × 352	2 × 230	330 kV
v121	PS_330_79	2 2	250 63	500	2 × 470 2 × 180	2 × 410 2 × 120	330 kV
v122	PS_330_80	2	200	320	2 × 534	2 × 410	330 kV
v123	PS_330_81	2	200	320	2 × 534	2 × 410	330 kV
v124	PS_330_82	2	250	375	2 × 470	2 × 430	330 kV
v125	PS_330_83	2	250	375	2 × 470	2 × 430	330 kV
v126	PS_330_84	3 3	250 63	751	3 × 470 2 × 180	3 × 430 3 × 120	330 kV
v127	PS_330_85	2	200	320	2 × 534	2 × 410	330 kV
v128	PS_330_86	2	125	200	2 × 352	2 × 230	330 kV
v129	PS_330_87	2	125	200	2 × 352	2 × 230	330 kV
v130	PS_330_88	2	125	200	2 × 352	2 × 230	330 kV
v131	PS_330_89	2	200	320	2 × 534	2 × 410	330 kV
v132	PS_220_1	2	63	101	2 × 180	2 × 110	220 kV

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v133	PS_220_2	2	63	105	2 × 180	2 × 110	220 kV
v134	PS_220_3	2	125	200	2 × 270	2 × 190	220 kV
v135	PS_220_4	2	125	200	2 × 270	2 × 190	220 kV
v136	PS_220_5	2	125	200	2 × 270	2 × 190	220 kV
v137	PS_220_6	2	63	101	2 × 180	2 × 110	220 kV
v138	PS_220_7	2	200	320	2 × 400	2 × 350	220 kV
v139	PS_220_8	2	125	200	2 × 270	2 × 190	220 kV
v140	PS_220_9	2	125	200	2 × 270	2 × 190	220 kV
v141	PS_220_10	2	200	320	2 × 400	2 × 350	220 kV
v142	PS_220_11	2	125	200	2 × 270	2 × 190	220 kV
v143	PS_220_12	2	200	320	2 × 400	2 × 350	220 kV
v144	PS_220_13	2	125	200	2 × 270	2 × 190	220 kV
v145	PS_220_14	2	125	200	2 × 270	2 × 190	220 kV
v146	PS_220_15	2	200	320	2 × 400	2 × 350	220 kV
v147	PS_220_16	2	125	200	2 × 270	2 × 190	220 kV
v148	PS_220_17	2	200	320	2 × 400	2 × 350	220 kV
v149	PS_220_18	2	63	101	2 × 180	2 × 110	220 kV
v150	PS_220_19	2	125	200	2 × 270	2 × 190	220 kV
v151	PS_220_20	2	200	320	2 × 400	2 × 350	220 kV
v152	PS_220_21	2	200	320	2 × 400	2 × 350	220 kV
v153	PS_220_22	2	125	200	2 × 270	2 × 190	220 kV
v154	PS_220_23	2	125	200	2 × 270	2 × 190	220 kV
v155	PS_220_24	2	200	320	2 × 400	2 × 350	220 kV
v156	PS_220_25	2	125	200	2 × 270	2 × 190	220 kV
v157	PS_220_26	2	125	200	2 × 270	2 × 190	220 kV
v158	PS_220_27	2	125	200	2 × 270	2 × 190	220 kV
v159	PS_220_28	2	125	200	2 × 270	2 × 190	220 kV
v160	PS_220_29	2	250	400	2 × 450	2 × 380	220 kV
v161	PS_220_30	2	250	400	2 × 450	2 × 380	220 kV
v162	PS_220_31	2	250	400	2 × 450	2 × 380	220 kV
v163	PS_220_32	2	200	320	2 × 400	2 × 350	220 kV
v164	PS_220_33	2	125	200	2 × 270	2 × 190	220 kV
v165	PS_220_34	2	250	400	2 × 450	2 × 380	220 kV
v166	PS_220_35	2	63	101	2 × 180	2 × 110	220 kV
v167	PS_150_1	1	16	12	1 × 87	1 × 20	150 kV
v168	PS_150_2	1	25	19	1 × 120	1 × 28	150 kV

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v169	PS_150_3	2 1 1	40 90 25	168	2 × 171 1 × 340 1 × 120	2 × 48 1 × 110 1 × 28	150 kV
v170	PS_150_4	2	25	40	2 × 120	2 × 28	150 kV
v171	PS_150_5	1	200	160	1 × 270	1 × 210	150 kV
v172	PS_150_6	2	25	40	2 × 120	2 × 28	150 kV
v173	PS_150_7	2	25	40	2 × 120	2 × 28	150 kV
v174	PS_150_8	2	40	64	2 × 171	2 × 47	150 kV
v175	PS_150_9	2	40	64	2 × 171	2 × 47	150 kV
v176	PS_150_10	2	40	64	2 × 171	2 × 47	150 kV
v177	PS_150_11	2	40	64	2 × 171	2 × 47	150 kV
v178	PS_150_12	2	63	95	2 × 242	2 × 75	150 kV
v179	PS_150_13	2	63	95	2 × 242	2 × 75	150 kV
v180	PS_150_14	2	32	52	2 × 150	2 × 38	150 kV
v181	PS_150_15	2	40	64	2 × 171	2 × 47	150 kV
v182	PS_150_16	2	16	40	2 × 87	2 × 20	150 kV
v183	PS_150_17						transit
v184	PS_150_18	2	25	40	2 × 120	2 × 28	150 kV
v185	PS_150_19	2 2	63 25	141	2 × 242 2 × 120	2 × 80 2 × 28	150 kV
v186	PS_150_20	2	40	64	2 × 171	2 × 47	150 kV
v187	PS_150_21	2	25	40	2 × 120	2 × 28	150 kV
v188	PS_150_22	1	40	32	2 × 171	2 × 47	150 kV
v189	PS_150_23	2	40	64	2 × 171	2 × 47	150 kV
v190	PS_150_24	2	40	64	2 × 171	2 × 47	150 kV
v191	PS_150_25	1	32	26	1 × 150	2 × 38	150 kV
v192	PS_150_26	2	25	40	2 × 120	2 × 28	150 kV
v193	PS_150_27	2	40	64	2 × 171	2 × 47	150 kV
v194	PS_150_28	2	25	34	2 × 120	2 × 28	150 kV
v195	PS_150_29	2	16	25	2 × 87	2 × 20	150 kV
v196	PS_150_30	2	25	40	2 × 120	2 × 28	150 kV
v197	PS_150_31	3	32	76	3 × 150	2 × 38	150 kV
v198	PS_150_32	2	25	40	2 × 120	2 × 28	150 kV
v199	PS_150_33	2	25	40	2 × 120	2 × 28	150 kV
v200	PS_110_1	2	16	26	2 × 87	2 × 20	110 kV
v201	PS_110_2	2	25	40	2 × 120	2 × 28	110 kV
v202	PS_110_3	2	10	17	2 × 66	2 × 13	110 kV
v203	PS_110_4	2	32	50	2 × 150	2 × 38	110 kV

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v204	PS_110_5	2	25	40	2 × 120	2 × 28	110 kV
v205	PS_110_6	2	32	48	2 × 150	2 × 38	110 kV
v206	PS_110_7	3	10	25	2 × 66	2 × 12	110 kV
v207	PS_110_8	1 1	40 25	53	1 × 171 1 × 120	1 × 48 1 × 28	110 kV
v208	PS_110_9	2	25	40	2 × 120	2 × 28	110 kV
v209	PS_110_10	2	40	64	2 × 171	2 × 48	110 kV
v210	PS_110_11	1 1	40 25	53	1 × 171 1 × 120	1 × 48 1 × 28	110 kV
v211	PS_110_12	2	25	40	2 × 120	2 × 28	110 kV
v212	PS_110_13	2	10	16	2 × 66	2 × 12	110 kV
v213	PS_110_14	3	40	96	3 × 171	2 × 48	110 kV
v214	PS_110_15	2	25	40	2 × 120	2 × 28	110 kV
v215	PS_110_16	2	25	40	2 × 120	2 × 28	110 kV
v216	PS_110_17	2	80	140	2 × 332	2 × 110	110 kV
v217	PS_110_18	2	40	64	2 × 171	2 × 48	110 kV
v218	PS_110_19	2	16	25	2 × 87	2 × 20	110 kV
v219	PS_110_20	2 1	20 40	64	2 × 110 1 × 171	2 × 22 1 × 48	110 kV
v220	PS_110_21	2	16	26	2 × 87	2 × 20	110 kV
v221	PS_110_22	2	16	26	2 × 87	2 × 20	110 kV
v222	PS_110_23	2	16	26	2 × 87	2 × 20	110 kV
v223	PS_110_24	2	40	64	2 × 171	2 × 48	110 kV
v224	PS_110_25	2	25	40	2 × 120	2 × 28	110 kV
v225	PS_110_26	2	25	40	2 × 120	2 × 28	110 kV
v226	PS_110_27	2	40	64	2 × 171	2 × 48	110 kV
v227	PS_110_28	2	25	40	2 × 120	2 × 28	110 kV
v228	PS_110_29	2	16	26	2 × 87	2 × 20	110 kV
v229	PS_110_30	2	16	26	2 × 87	2 × 20	110 kV
v230	PS_110_31	2	63	103	2 × 242	2 × 80	110 kV
v231	PS_110_32	2	40	64	2 × 171	2 × 48	110 kV
v232	PS_110_33	2	40	64	2 × 171	2 × 48	110 kV
v233	PS_110_34	2	25	40	2 × 120	2 × 28	110 kV
v234	PS_110_35	2	25	40	2 × 120	2 × 28	110 kV
v235	PS_110_36	1	16	13	1 × 87	1 × 20	110 kV
v236	PS_110_37	2	16	26	2 × 87	2 × 20	110 kV
v237	PS_110_38	2	10	16	2 × 66	2 × 12	110 kV
v238	PS_110_39	2	16	26	2 × 87	2 × 20	110 kV
v239	PS_110_40	2	25	40	2 × 120	2 × 28	110 kV
v240	PS_110_41	2	16	26	2 × 87	2 × 20	110 kV

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v241	PS_110_42	2	25	40	2 × 120	2 × 28	110 kV
v242	PS_110_43	1	7,5	6	2 × 56	2 × 8	110 kV
v243	PS_110_44	2	25	40	2 × 120	2 × 28	110 kV
v244	PS_110_45	2	25	40	2 × 120	2 × 28	110 kV
v245	PS_110_46	2	16	26	2 × 87	2 × 20	110 kV
v246	PS_110_47	2	40	64	2 × 171	2 × 48	110 kV
v247	PS_110_48	2	25	40	2 × 120	2 × 28	110 kV
v248	PS_110_49	2	16	24	2 × 87	2 × 20	110 kV
v249	PS_110_50	2	16	24	2 × 87	2 × 20	110 kV
v250	PS_110_51	2	63	105	2 × 242	2 × 80	110 kV
v251	PS_110_52	2	16	26	2 × 87	2 × 20	110 kV
v252	PS_110_53	2	16	26	2 × 87	2 × 20	110 kV
v253	PS_110_54	2	6,3	11	2 × 50	2 × 7,5	110 kV
v254	PS_110_55	2	10	16	2 × 66	2 × 12	110 kV
v255	PS_110_56	2	16	24	2 × 87	2 × 20	110 kV
v256	PS_110_57	2	40	64	2 × 171	2 × 48	110 kV
v257	PS_110_58	2	16	26	2 × 87	2 × 20	110 kV
v258	PS_110_59	2	25	40	2 × 120	2 × 28	110 kV
v259	PS_110_60	2	20	32	2 × 110	2 × 22	110 kV
v260	PS_110_61	2	16	26	2 × 87	2 × 20	110 kV
v261	PS_110_62	2	25	40	2 × 120	2 × 28	110 kV
v262	PS_110_63						transit
v263	PS_110_64	2	10	16	2 × 66	2 × 12	110 kV
v264	PS_110_65	2	10	16	2 × 66	2 × 12	110 kV
v265	PS_110_66	2	40	64	2 × 171	2 × 48	110 kV
v266	PS_110_67	2	25	40	2 × 120	2 × 28	110 kV
v267	PS_110_68	2	25	40	2 × 120	2 × 28	110 kV
v268	PS_110_69	2	40	64	2 × 171	2 × 48	110 kV
v269	PS_110_70	2	40	64	2 × 171	2 × 48	110 kV
v270	PS_110_71	2	10	16	2 × 66	2 × 12	110 kV
v271	PS_110_72	2	10	16	2 × 66	2 × 12	110 kV
v272	PS_110_73	2	40	64	2 × 171	2 × 48	110 kV
v273	PS_110_74	2	25	40	2 × 120	2 × 28	110 kV
v274	PS_110_75	2	25	40	2 × 120	2 × 28	110 kV
v275	PS_110_76	2	40	64	2 × 171	2 × 48	110 kV
v276	PS_110_77	2	40	64	2 × 171	2 × 48	110 kV
v277	PS_110_78	2	10	16	2 × 66	2 × 12	110 kV
v278	PS_110_79	2	10	16	2 × 66	2 × 12	110 kV
v279	PS_110_80	2	40	64	2 × 171	2 × 48	110 kV
v280	PS_110_81	2	25	40	2 × 120	2 × 28	110 kV

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v281	PS_110_82	2	25	40	2 × 120	2 × 28	110 kV
v282	PS_110_83	2	40	64	2 × 171	2 × 48	110 kV
v283	PS_110_84	2	40	64	2 × 171	2 × 48	110 kV
v284	PS_110_85	2	25	40	2 × 120	2 × 28	110 kV
v285	PS_110_86	2	40	64	2 × 171	2 × 48	110 kV
v286	PS_110_87	2	40	64	2 × 171	2 × 48	110 kV
v287	PS_110_88	2	10	16	2 × 66	2 × 12	110 kV
v288	PS_110_89	2	10	16	2 × 66	2 × 12	110 kV
v289	PS_110_90	2	40	64	2 × 171	2 × 48	110 kV
v290	PS_110_91	2	25	40	2 × 120	2 × 28	110 kV
v291	PS_110_92	2	25	40	2 × 120	2 × 28	110 kV
v292	PS_110_93	2	40	64	2 × 171	2 × 48	110 kV
v293	PS_110_94	2	40	64	2 × 171	2 × 48	110 kV
v294	PS_110_95	2	25	40	2 × 120	2 × 28	110 kV
v295	PS_110_96	2	40	64	2 × 171	2 × 48	110 kV
v296	PS_110_97	2	40	64	2 × 171	2 × 48	110 kV
v297	PS_110_98	2	10	16	2 × 66	2 × 12	110 kV
v298	PS_110_99	2	25	40	2 × 120	2 × 28	110 kV
v299	PS_110_100	2	40	64	2 × 171	2 × 48	110 kV
v300	PS_110_101	2	40	64	2 × 171	2 × 48	110 kV
v301	PS_110_102	2	10	16	2 × 66	2 × 12	110 kV
v302	PS_110_103	2	25	40	2 × 120	2 × 28	110 kV
v303	PS_110_104	2	40	64	2 × 171	2 × 48	110 kV
v304	PS_110_105	2	40	64	2 × 171	2 × 48	110 kV
v305	PS_110_106	2	10	16	2 × 66	2 × 12	110 kV
v306	PS_110_107	2	40	64	2 × 171	2 × 48	110 kV
v307	PS_110_108	2	40	64	2 × 171	2 × 48	110 kV
v308	PS_110_109	2	25	40	2 × 120	2 × 28	110 kV
v309	PS_110_110	2	40	64	2 × 171	2 × 48	110 kV
v310	PS_110_111	2	40	64	2 × 171	2 × 48	110 kV
v311	PS_110_112	2	10	16	2 × 66	2 × 12	110 kV
v312	PS_110_113	2	25	40	2 × 120	2 × 28	110 kV
v313	PS_110_114	2	40	64	2 × 171	2 × 48	110 kV
v314	PS_110_115	2	40	64	2 × 171	2 × 48	110 kV
v315	PS_110_116	2	10	16	2 × 66	2 × 12	110 kV
v316	PS_110_117	2	25	40	2 × 120	2 × 28	110 kV
v317	PS_110_118	2	40	64	2 × 171	2 × 48	110 kV
v318	PS_110_119	2	40	64	2 × 171	2 × 48	110 kV
v319	PS_110_120	2	10	16	2 × 66	2 × 12	110 kV

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v320	PS_110_121	2	40	64	2 × 171	2 × 48	110 kV
v321	PS_110_122	2	40	64	2 × 171	2 × 48	110 kV
v322	PS_110_123	2	25	40	2 × 120	2 × 28	110 kV
v323	PS_110_124	2	40	64	2 × 171	2 × 48	110 kV
v324	PS_110_125	2	40	64	2 × 171	2 × 48	110 kV
v325	PS_110_126	2	10	16	2 × 66	2 × 12	110 kV
v326	PS_110_127	2	25	40	2 × 120	2 × 28	110 kV
v327	PS_110_128	2	40	64	2 × 171	2 × 48	110 kV
v328	PS_110_129	2	40	64	2 × 171	2 × 48	110 kV
v329	PS_110_130	2	10	16	2 × 66	2 × 12	110 kV
v330	PS_110_131	2	25	40	2 × 120	2 × 28	110 kV
v331	PS_110_132	2	40	64	2 × 171	2 × 48	110 kV
v332	PS_110_133	2	40	64	2 × 171	2 × 48	110 kV
v333	PS_110_134	2	10	16	2 × 66	2 × 12	110 kV
v334	PS_110_135	2	40	64	2 × 171	2 × 48	110 kV
v335	PS_110_136	2	40	64	2 × 171	2 × 48	110 kV
v336	PS_110_137	2	25	40	2 × 120	2 × 28	110 kV
v337	PS_110_138	2	40	64	2 × 171	2 × 48	110 kV
v338	PS_110_139	2	40	64	2 × 171	2 × 48	110 kV
v339	PS_110_140	2	10	16	2 × 66	2 × 12	110 kV
v340	PS_110_141	2	25	40	2 × 120	2 × 28	110 kV
v341	PS_110_142	2	40	64	2 × 171	2 × 48	110 kV
v342	PS_110_143	2	40	64	2 × 171	2 × 48	110 kV
v343	PS_110_144	2	10	16	2 × 66	2 × 12	110 kV
v344	PS_110_145	2	25	40	2 × 120	2 × 28	110 kV
v345	PS_110_146	2	40	64	2 × 171	2 × 48	110 kV
v346	PS_110_147	2	40	64	2 × 171	2 × 48	110 kV
v347	PS_110_148	2	10	16	2 × 66	2 × 12	110 kV
v348	PS_110_149	2	40	64	2 × 171	2 × 48	110 kV
v349	PS_110_150	2	40	64	2 × 171	2 × 48	110 kV
v350	PS_110_151	2	25	40	2 × 120	2 × 28	110 kV
v351	PS_110_152	2	40	64	2 × 171	2 × 48	110 kV
v352	PS_110_153	2	40	64	2 × 171	2 × 48	110 kV
v353	PS_110_154	2	10	16	2 × 66	2 × 12	110 kV
v354	PS_110_155	2	25	40	2 × 120	2 × 28	110 kV
v355	PS_110_156	2	40	64	2 × 171	2 × 48	110 kV
v356	PS_110_157	2	40	64	2 × 171	2 × 48	110 kV
v357	PS_110_158	2	10	16	2 × 66	2 × 12	110 kV

Vertex	Vertex Name	Number of Transformers	Power (MVA)	Load (MW)	Transformer Losses (kW)	Cost per 1 kW (UAH/kW)	Note
v358	PS_110_159	2	25	40	2 × 120	2 × 28	110 kV
v359	PS_110_160	2	40	64	2 × 171	2 × 48	110 kV
v360	PS_110_161	2	40	64	2 × 171	2 × 48	110 kV
v361	PS_110_162	2	10	16	2 × 66	2 × 12	110 kV
v362	PS_110_163	2	40	64	2 × 171	2 × 48	110 kV
v363	PS_110_164	2	40	64	2 × 171	2 × 48	110 kV
v364	PS_110_165	2	25	40	2 × 120	2 × 28	110 kV
v365	PS_110_166	2	40	64	2 × 171	2 × 48	110 kV
v366	PS_110_167	2	40	64	2 × 171	2 × 48	110 kV
v367	PS_110_168	2	10	16	2 × 66	2 × 12	110 kV
v368	PS_110_169	2	25	40	2 × 120	2 × 28	110 kV
v369	PS_110_170	2	40	64	2 × 171	2 × 48	110 kV
v370	PS_110_171	2	40	64	2 × 171	2 × 48	110 kV
v371	PS_110_172	2	10	16	2 × 66	2 × 12	110 kV
v372	PS_110_173	2	25	40	2 × 120	2 × 28	110 kV
v373	PS_110_174	2	40	64	2 × 171	2 × 48	110 kV
v374	PS_110_175	2	40	64	2 × 171	2 × 48	110 kV
v375	PS_110_176	2	10	16	2 × 66	2 × 12	110 kV
v376	PS_110_177	2	40	64	2 × 171	2 × 48	110 kV
v377	PS_110_178	2	40	64	2 × 171	2 × 48	110 kV
v378	PS_110_179	2	25	40	2 × 120	2 × 28	110 kV
v379	PS_110_180	2	40	64	2 × 171	2 × 48	110 kV
v380	PS_110_181	2	40	64	2 × 171	2 × 48	110 kV
v381	PS_110_182	2	10	16	2 × 66	2 × 12	110 kV
v382	PS_110_183	2	25	40	2 × 120	2 × 28	110 kV
v383	PS_110_184	2	40	64	2 × 171	2 × 48	110 kV
v384	PS_110_185	2	40	64	2 × 171	2 × 48	110 kV
v385	PS_110_186	2	10	16	2 × 66	2 × 12	110 kV

Appendix B. Properties of the Set of Edges of the Tiered Graph

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (1,30)	289	4 × ACS-400		9407	4 × 230,000	750
e (1,31)	222	4 × AS-400/93		2600	4 × 230,000	750
e (2,31)	130	3 × ALS-500/336		1634	4 × 270,000	750
e (2,32)	190	5 × AS-400/51		12,645	5 × 230,000	750
e (31,32)	136	4 × AS-400/51		11,350	4 × 230,000	750
e (32,33)	138	4 × AS-400/51		58,467	4 × 230,000	750
e (33,34)	213	5 × AS-300/66		18,995	5 × 220,000	750

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (2,34)	273	5 × AS-300/66		24,341	5 × 220,000	750
e (2,35)	213	2 × AS-400/51		4985	2 × 230,000	750
e (30,36)	177	5 × AS-400/51		2950	5 × 230,000	750
e (36,37)	126	4 × AS-500/64		7410	4 × 270,000	750
e (36,37)	162	2 × AS-300/39	reserve of 330 kV	164,023	2 × 220,000	330
e (3,36)	261	5 × AS-400/51		4339	5 × 230,000	750
e (4,36)	345	5 × AS-400/51		5742	5 × 230,000	750
e (3,38)	228	4 × AS-500/64		34,401	4 × 270,000	750
e (4,38)	282	5 × AS-400/51		42,323	5 × 230,000	750
e (30,38)	361	4 × ACS-400		67,534	4 × 230,000	750
e (38,39)	278	4 × AS-400/93		3256	4 × 230,000	750
e (33,40)	198	2 × AS-400		2975	4 × 230,000	500
e (33,41)	35	2 × AS-400		812	2 × 230,000	500
e (40,41)	138	2 × AS-400		3228	2 × 230,000	500
e (39,42)	54	3 × ASS-400		7912	3 × 230,000	400
e (13,42)	197	2 × ASS-500		34,954	4 × 270,000	400
e (1,6)	8	2 × AS-600/72		156	2 × 300,000	330
e (1,43)	81	2 × AS-400/51		9846	2 × 230,000	330
e (5,43)	132	2 × AS-300/39		21,468	2 × 220,000	330
e (5,30)	77	2 × ASS-400		25,950	2 × 230,000	330
e (5,30)	77	2 × ASS-400	reserve	25,950	2 × 230,000	330
e (5,44)	111	2 × AS-400/51		1495	2 × 230,000	330
e (44,45)	147	2 × ASS-300		2649	2 × 220,000	330
e (45,46)	104	2 × AS-300/39		11,219	2 × 220,000	330
e (45,47)	45	2 × ASS-300		2080	2 × 220,000	330
e (45,48)	64	2 × AS-500/64		4301	2 × 270,000	330
e (47,48)	36	2 × ASS-400		3043	2 × 230,000	330
e (48,49)	33	2 × ASS-300		596	2 × 220,000	330
e (1,49)	156	2 × AS-400/51		2104	2 × 230,000	330
e (49,50)	94	2 × ASS-300		15,338	2 × 220,000	330
e (30,51)	83	2 × ASS-300		956	2 × 220,000	330
e (51,52)	160	2 × ASS-300		9349	2 × 220,000	330
e (9,52)	72	2 × ASS-300		4227	2 × 220,000	330
e (30,53)	68	2 × ASS-300		1227	2 × 220,000	330
e (10,53)	85	2 × AS-400/51		1148	2 × 230,000	330
e (10,11)	22	2 × ASS-400		3642	2 × 230,000	330
e (53,54)	102	2 × ASS-300		4131	2 × 220,000	330
e (3,54)	119	2 × AS-400/51		3614	2 × 230,000	330

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (37,55)	44	2 × AS-300/51		789	2 × 220,000	330
e (37,56)	135	2 × AS-300/39		6238	2 × 220,000	330
e (56,57)	73	2 × ASS-300		7622	2 × 220,000	330
e (9,57)	172	2 × ASS-300		17,927	2 × 220,000	330
e (9,12)	91	2 × ASS-300		9520	2 × 220,000	330
e (36,58)	77	2 × ASS-300		1394	2 × 220,000	330
e (36,58)	77	2 × ASS-300	reserve	1394	2 × 220,000	330
e (7,58)	28	2 × ACS-300		496	2 × 220,000	330
e (7,59)	45	2 × ASS-300		2070	2 × 220,000	330
e (59,60)	95	2 × ASS-300		4372	2 × 220,000	330
e (60,61)	107	2 × AS-400/51		1436	2 × 230,000	330
e (55,61)	41	2 × AS-400/51		549	2 × 230,000	330
e (36,62)	84	2 × ASS-300		3872	2 × 220,000	330
e (62,63)	34	2 × ASS-300		1576	2 × 220,000	330
e (8,62)	19	2 × ASS-300		883	2 × 220,000	330
e (8,59)	50	2 × AS-300/39		2306	2 × 220,000	330
e (9,62)	47	2 × ASS-300		2177	2 × 220,000	330
e (9,62)	47	2 × ASS-300	reserve	2177	2 × 220,000	330
e (12,64)	79	2 × ASS-300		3642	2 × 220,000	330
e (64,65)	18	2 × ASS-300		332	2 × 220,000	330
e (15,65)	124	2 × ASS-300		2235	2 × 220,000	330
e (57,66)	128	2 × ASS-300		2318	2 × 220,000	330
e (3,66)	49	2 × ASS-300		892	2 × 220,000	330
e (3,67)	69	2 × ASS-300		8360	2 × 220,000	330
e (4,67)	97	2 × AS-400/51		8827	2 × 230,000	330
e (38,67)	233	2 × AS-300/39		28,448	2 × 220,000	330
e (67,68)	176	2 × AS-300/39		3176	2 × 220,000	330
e (38,13)	42	2 × ASS-500		65,892	2 × 270,000	330
e (38,13)	42	2 × ASS-500	reserve	65,892	2 × 270,000	330
e (38,69)	54	2 × AS-300/39		966	2 × 220,000	330
e (69,70)	25	2 × AS-300/39		283	2 × 220,000	330
e (69,71)	23	2 × AS-300/39		8520	2 × 220,000	330
e (38,71)	48	2 × ASS-400		13,229	2 × 230,000	330
e (38,71)	48	2 × ASS-400	reserve	13,229	2 × 230,000	330
e (67,72)	11	2 × ASS-300		908	2 × 220,000	330
e (4,72)	85	2 × AS-400/51		5046	2 × 230,000	330
e (4,73)	88	2 × AS-400/51		6855	2 × 230,000	330
e (4,74)	92	2 × AS-400/51		4004	2 × 230,000	330
e (74,75)	77	2 × AS-300/39		2343	2 × 220,000	330
e (13,76)	22	2 × ASS-400		1190	2 × 230,000	330

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (54,76)	97	2 × ASS-400		5202	2 × 230,000	330
e (13,77)	38	2 × ASS-500		936	2 × 270,000	330
e (77,78)	26	2 × AS-240/39		596	2 × 170,000	330
e (78,79)	97	2 × AS-240/39		2184	2 × 170,000	330
e (79,80)	83	2 × AS-240/39		4777	2 × 170,000	330
e (10,80)	73	2 × ASS-300		3395	2 × 220,000	330
e (1,50)	108	2 × AS-500/26		10,538	2 × 270,000	330
e (16,50)	148	2 × AS-300/39		23,990	2 × 220,000	330
e (1,81)	122	2 × AS-400/51		6580	2 × 230,000	330
e (1,81)	122	2 × AS-400/51	reserve	6580	2 × 230,000	330
e (81,82)	77	2 × AS-300/39		1398	2 × 220,000	330
e (1,83)	148	2 × AS-400/51		5102	2 × 230,000	330
e (82,83)	136	2 × AS-400/51		4691	2 × 230,000	330
e (31,82)	46	2 × AS-500/64		495	2 × 270,000	330
e (31,84)	6	2 × AS-240/39		136	2 × 170,000	330
e (31,85)	53	2 × AS-400/51		8686	2 × 230,000	330
e (31,86)	97	2 × AS-300/39		7031	2 × 220,000	330
e (31,87)	46	2 × AS-400/51		3154	2 × 230,000	330
e (15,86)	55	2 × ASS-300		3972	2 × 220,000	330
e (15,85)	116	2 × AS-300/39		25,689	2 × 220,000	330
e (82,85)	17	2 × AS-400/51		2853	2 × 230,000	330
e (85,88)	36	2 × AS-400/51		1928	2 × 230,000	330
e (16,88)	47	2 × AS-400/51		2527	2 × 230,000	330
e (85,89)	41	2 × ASS-480		8786	2 × 240,000	330
e (85,89)	41	2 × ASS-480	reserve	8786	2 × 240,000	330
e (16,89)	35	2 × AS-400/51		7625	2 × 230,000	330
e (16,89)	35	2 × AS-400/51	reserve	7625	2 × 230,000	330
e (17,85)	126	AS-400/93		41,521	230,000	330
e (85,90)	116	2 × AS-300/39		33,553	2 × 220,000	330
e (17,90)	46	AS-400/93		19,618	230,000	330
e (87,90)	15	2 × AS-400/51		3127	2 × 230,000	330
e (16,91)	42	2 × AS-400/51		9111	2 × 230,000	330
e (16,91)	42	2 × AS-400/51	reserve	9111	2 × 230,000	330
e (90,92)	19	2 × AS-400/51		249	2 × 230,000	330
e (17,92)	46	2 × AS-300/39		822	2 × 220,000	330
e (32,92)	90	2 × AS-300/39		1628	2 × 220,000	330
e (32,93)	44	2 × AS-400/51		5331	2 × 230,000	330
e (32,93)	44	2 × AS-400/51	reserve	5331	2 × 230,000	330

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (93,94)	15	2 × AS-300/39		276	2 × 220,000	330
e (94,95)	65	2 × AS-300/39		29,458	2 × 220,000	330
e (16,95)	57	2 × AS-400/51		19,166	2 × 230,000	330
e (16,35)	63	2 × AS-400/51		7691	2 × 230,000	330
e (93,96)	94	2 × AS-300/39		1703	2 × 220,000	330
e (19,32)	178	2 × AS-500/64		122,993	2 × 270,000	330
e (18,32)	150	2 × AS-400/93		128,662	2 × 230,000	330
e (2,19)	5	3 × AS-600		5688	3 × 300,000	330
e (19,97)	34	2 × AS-500/64		371	2 × 270,000	330
e (19,97)	34	2 × AS-500/64	reserve	371	2 × 270,000	330
e (95,97)	12	2 × AS-600/72		110	2 × 300,000	330
e (95,97)	12	2 × AS-600/72	reserve	110	2 × 300,000	330
e (18,98)	29	ASS-500		631	270,000	330
e (18,98)	29	ASS-500	reserve	631	270,000	330
e (18,99)	56	2 × ASS-400		756	2 × 230,000	330
e (23,33)	56	2 × ASS-400		16,140	2 × 230,000	330
e (21,33)	18	2 × ASS-400		79,905	2 × 230,000	330
e (21,33)	18	2 × ASS-400		79,905	2 × 230,000	330
e (21,33)	18	2 × ASS-400	reserve	79,905	2 × 230,000	330
e (98,100)	4	2 × ASS-400		53	2 × 230,000	330
e (98,100)	4	2 × ASS-400	reserve	53	2 × 230,000	330
e (100,101)	37	2 × ASS-400		503	2 × 230,000	330
e (99,101)	60	2 × ASS-400		803	2 × 230,000	330
e (34,101)	22	2 × AS-400/51		302	2 × 230,000	330
e (34,101)	22	2 × AS-400/51	reserve	302	2 × 230,000	330
e (101,102)	14	2 × AS-300/39		126	2 × 220,000	330
e (34,102)	18	2 × AS-300/39		162	2 × 220,000	330
e (20,100)	4	2 × AS-500		22	2 × 270,000	330
e (20,103)	9	2 × AS-500		244	2 × 270,000	330
e (98,104)	4	2 × ASS-400		56	2 × 230,000	330
e (21,104)	72	2 × AS-400		970	2 × 230,000	330
e (21,105)	52	2 × AS-500		1429	2 × 270,000	330
e (21,106)	37	2 × AS-500		400	2 × 270,000	330
e (21,106)	37	2 × AS-500	reserve	400	2 × 270,000	330
e (22,107)	154	2 × ASS-300		2771	2 × 220,000	330
e (86,107)	89	2 × ASS-300/39		1600	2 × 220,000	330
e (86,108)	109	2 × AS-300/39		5056	2 × 220,000	330
e (107,109)	173	2 × AS-300/39		49,943	2 × 220,000	330

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (108,109)	89	2 × AS-300/39		25,737	2 × 220,000	330
e (109,110)	92	2 × AS-300/39		5393	2 × 220,000	330
e (110,111)	17	2 × AS-300/39		994	2 × 220,000	330
e (111,112)	132	2 × ASS-300		5370	2 × 220,000	330
e (112,113)	91	2 × AS-300/39		3692	2 × 220,000	330
e (112,114)	94	2 × ASS-300		4321	2 × 220,000	330
e (111,115)	153	2 × ASS-400		11,895	2 × 230,000	330
e (22,115)	61	2 × ASS-480		4700	2 × 240,000	330
e (22,115)	61	2 × ASS-480	reserve	4700	2 × 240,000	330
e (115,116)	71	2 × ASS-400		2436	2 × 230,000	330
e (22,116)	60	2 × ASS-400		2057	2 × 230,000	330
e (22,117)	61	2 × ASS-400		827	2 × 230,000	330
e (22,117)	61	2 × ASS-400	reserve	827	2 × 230,000	330
e (22,118)	38	2 × ASS-300		679	2 × 220,000	330
e (22,23)	38	2 × ASS-500		7888	2 × 270,000	330
e (118,119)	67	2 × AS-300/39		1202	2 × 220,000	330
e (106,119)	127	2 × AS-400/51		1711	2 × 230,000	330
e (106,120)	50	2 × ASS-400		670	2 × 230,000	330
e (120,121)	105	2 × AS-400/51		8837	2 × 230,000	330
e (17,121)	66	2 × ASS-300/48		7436	2 × 220,000	330
e (23,122)	97	2 × ASS-300		4488	2 × 220,000	330
e (23,123)	39	2 × ASS-500		1090	2 × 270,000	330
e (106,123)	24	2 × ASS-500		655	2 × 270,000	330
e (50,124)	41	2 × AS-300/39		2602	2 × 220,000	330
e (124,125)	76	2 × AS-300/39		4815	2 × 220,000	330
e (35,125)	55	2 × ASS-300		3831	2 × 220,000	330
e (19,96)	102	2 × AS-500/64		1107	2 × 270,000	330
e (126,127)	200	2 × AS-300/39		9257	2 × 220,000	330
e (19,35)	195	2 × AS-400/51		23,667	2 × 230,000	330
e (35,128)	137	2 × AS-400/51		1842	2 × 230,000	330
e (35,127)	153	2 × AS-400/51		5259	2 × 230,000	330
e (127,128)	14	2 × AS-400/51		183	2 × 230,000	330
e (127,129)	97	2 × AS-400/51		1312	2 × 230,000	330
e (25,129)	137	2 × AS-400/51		1842	2 × 230,000	330
e (25,130)	4	2 × AS-400/51		55	2 × 230,000	330
e (25,130)	4	2 × AS-400/51	reserve	61	2 × 230,000	330
e (25,131)	31	2 × AS-400/51		1058	2 × 230,000	330
e (24,127)	69	2 × ASS-400/51		2390	2 × 230,000	330
e (50,132)	95	2 × AS-300/39		979	2 × 220,000	220

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (132,133)	27	2 × AS-300/39		305	2 × 220,000	220
e (23,134)	23	ASS-400		1371	230,000	220
e (23,134)	23	ASS-400	reserve	1371	230,000	220
e (41,98)	106	2 × AS-400		3207	2 × 230,000	220
e (41,98)	106	2 × AS-400	reserve	3207	2 × 230,000	220
e (40,135)	39	2 × ASS-400		1184	2 × 230,000	220
e (40,136)	12	2 × ASS-400		373	2 × 230,000	220
e (27,40)	143	2 × ASS-400		11,061	2 × 230,000	220
e (41,105)	15	2 × AS-400		1134	2 × 230,000	220
e (98,137)	7	2 × ASS-400		55	2 × 230,000	220
e (98,137)	7	2 × ASS-400	reserve	55	2 × 230,000	220
e (26,98)	21	2 × 400/51		651	2 × 230,000	220
e (26,98)	21	2 × 400/51	reserve	651	2 × 230,000	220
e (26,138)	55	AS-400/51		8469	230,000	220
e (26,138)	55	AS-400/51		8469	230,000	220
e (26,138)	55	AS-400/51	reserve	8469	230,000	220
e (26,139)	47	2 × AS-400/51		1435	2 × 230,000	220
e (26,140)	18	2 × AS-400/51		541	2 × 230,000	220
e (27,105)	59	2 × AS-400/51		4555	2 × 230,000	220
e (27,105)	59	2 × AS-400/51		4555	2 × 230,000	220
e (27,105)	59	2 × AS-400/51	reserve	4555	2 × 230,000	220
e (27,105)	59	2 × AS-400/51	reserve	4555	2 × 230,000	220
e (27,40)	143	2 × AS-400		11,061	2 × 230,000	220
e (29,105)	33	2 × ASS-400		2590	2 × 230,000	220
e (105,141)	39	2 × AS-400		3055	2 × 230,000	220
e (27,142)	66	2 × ASS-400		950	2 × 230,000	220
e (27,143)	13	2 × AS-400		431	2 × 230,000	220
e (27,143)	13	2 × AS-400	reserve	431	2 × 230,000	220
e (27,144)	34	2 × AS-400		1025	2 × 230,000	220
e (27,144)	34	2 × AS-400	reserve	1025	2 × 230,000	220
e (127,145)	143	2 × AS-400		4339	2 × 230,000	220
e (35,145)	174	2 × AS-400		5282	2 × 230,000	220
e (145,146)	37	2 × ASS-400		2878	2 × 230,000	220
e (127,146)	63	2 × ASS-400		4870	2 × 230,000	220
e (146,147)	4	2 × AS-300/39		150	2 × 220,000	220
e (146,147)	4	2 × AS-300/39	reserve	150	2 × 220,000	220
e (146,148)	174	2 × ASS-400		13,525	2 × 230,000	220
e (28,149)	27	2 × ASS-300/39		564	2 × 220,000	220
e (149,150)	17	2 × AS-300/39		678	2 × 220,000	220

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (127,150)	13	2 × ASS-300/39		53	2 × 220,000	220
e (127,151)	13	2 × AS-400		1016	2 × 230,000	220
e (151,152)	27	2 × ASS-400		2075	2 × 230,000	220
e (131,152)	83	2 × ASS-400		6419	2 × 230,000	220
e (131,153)	20	2 × ASS-400		593	2 × 230,000	220
e (130,153)	14	2 × ASS-400		429	2 × 230,000	220
e (152,154)	27	2 × ASS-400		811	2 × 230,000	220
e (152,154)	27	2 × ASS-400	reserve	892	2 × 230,000	220
e (154,155)	85	2 × AS-400		6560	2 × 230,000	220
e (154,155)	85	2 × AS-400	reserve	6560	2 × 230,000	220
e (155,156)	24	2 × AS-400		718	2 × 230,000	220
e (155,156)	24	2 × AS-400	reserve	718	2 × 230,000	220
e (155,157)	25	2 × AS-400		766	2 × 230,000	220
e (155,157)	25	2 × AS-400	reserve	766	2 × 230,000	220
e (155,158)	32	2 × ASS-400		954	2 × 230,000	220
e (72,73)	58	2 × ASS-300		13,505	2 × 220,000	220
e (73,159)	20	ASS-400		1224	230,000	220
e (74,159)	81	ASS-240		8234	170,000	220
e (14,159)	91	ASS-400		5537	230,000	220
e (14,75)	63	ASS-400		5118	230,000	220
e (14,71)	64	ASS-500		64,155	270,000	220
e (14,71)	64	ASS-500	reserve	64,155	270,000	220
e (14,68)	75	ASS-300		6052	220,000	220
e (71,160)	26	AS-500		4993	270,000	220
e (71,160)	26	AS-500	reserve	4993	270,000	220
e (71,161)	36	AS-500		6982	270,000	220
e (71,161)	36	AS-500	reserve	6982	270,000	220
e (71,162)	62	AS-500		11,995	270,000	220
e (71,162)	62	AS-500	reserve	11,995	270,000	220
e (42,162)	146	AS-500		28,379	270,000	220
e (42,162)	146	AS-500	reserve	28,379	270,000	220
e (13,162)	60	ASS-500		11,741	270,000	220
e (13,162)	60	ASS-500	reserve	11,741	270,000	220
e (13,163)	31	AS-400/51		4738	230,000	220
e (13,163)	31	AS-400/51	reserve	4738	230,000	220
e (162,164)	42	ASS-400		2529	230,000	220
e (42,165)	42	ASS-500		8114	270,000	220
e (42,165)	42	ASS-500	reserve	8114	270,000	220

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (42,166)	81	ASS-300		1688	220,000	220
e (42,166)	81	ASS-300	reserve	1688	220,000	220
e (1,167)	34	AS-185		35	150,000	150
e (1,168)	63	AS-185		276	150,000	150
e (1,169)	37	2 × AS-185		7431	2 × 150,000	150
e (50,124)	121	AS-185	reserve of 150 kV	120,632	150,000	150
e (50,169)	66	AS-120		121	120,000	150
e (50,170)	64	AS-300		11	220,000	150
e (50,171)	69	AS-240		9698	170,000	150
e (170,171)	27	AS-150		6052	135,000	150
e (50,172)	24	AS-300		164	220,000	150
e (50,172)	24	AS-300	reserve	164	220,000	150
e (172,173)	36	AS-300		254	220,000	150
e (173,174)	9	AS-300		154	220,000	150
e (174,175)	5	AS-300		85	220,000	150
e (175,176)	16	AS-300		284	220,000	150
e (176,177)	24	AS-185		689	150,000	150
e (177,178)	29	AS-185		1848	150,000	150
e (125,178)	25	AS-300		974	220,000	150
e (125,178)	25	AS-300	reserve	974	220,000	150
e (178,179)	8	AS-185		505	150,000	150
e (178,180)	16	AS-185		311	150,000	150
e (180,181)	19	AS-185		557	150,000	150
e (181,182)	24	AS-185		275	150,000	150
e (182,183)	51	AS-185		576	150,000	150
e (183,184)	32	ASS-300		222	220,000	150
e (183,184)	32	ASS-300	reserve	222	220,000	150
e (35,183)	3	ASS-300		4890	220,000	150
e (35,183)	3	ASS-300	reserve	4890	220,000	150
e (35,185)	42	ASS-400		2701	230,000	150
e (35,185)	42	ASS-400	reserve	2701	230,000	150
e (35,186)	42	AS-185		1210	150,000	150
e (186,187)	57	AS-150		794	135,000	150
e (187,188)	64	AS-150		578	135,000	150
e (35,188)	60	AS-185		432	150,000	150
e (35,189)	44	AS-185		1268	150,000	150
e (189,190)	64	AS-185		1847	150,000	150
e (190,191)	47	AS-150		278	135,000	150
e (190,192)	35	AS-185		394	150,000	150

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (190,193)	39	AS-240		869	170,000	150
e (190,193)	39	AS-240		869	170,000	150
e (124,194)	52	AS-185		427	150,000	150
e (194,195)	24	AS-185		106	150,000	150
e (195,196)	45	AS-185		510	150,000	150
e (196,197)	24	AS-185		979	150,000	150
e (197,198)	62	AS-185		696	150,000	150
e (124,198)	11	AS-185		128	150,000	150
e (124,199)	24	AS-300		166	220,000	150
e (124,199)	24	AS-300	reserve	166	220,000	150
e (175,199)	8	AS-300		54	220,000	150
e (175,199)	8	AS-300	reserve	54	220,000	150
e (49,200)	45	AS-240		312	170,000	110
e (49,200)	45	AS-240	reserve	312	170,000	110
e (49,201)	20	ACS-120		659	120,000	110
e (49,201)	20	ACS-120	reserve	659	120,000	110
e (201,202)	4	ACS-120		24	120,000	110
e (201,202)	4	ACS-120	reserve	24	120,000	110
e (49,133)	15	ACS-240		1665	170,000	110
e (49,133)	15	ACS-240	reserve	1665	170,000	110
e (49,203)	12	ACS-120		604	120,000	110
e (133,203)	23	ACS-240		595	170,000	110
e (49,204)	12	ACS-120		381	120,000	110
e (49,205)	12	ACS-120		583	120,000	110
e (204,205)	1	ACS-120		42	120,000	110
e (133,204)	23	ACS-240		381	170,000	110
e (133,206)	7	AS-185		53	150,000	110
e (133,206)	7	AS-185	reserve	53	150,000	110
e (133,207)	2	AS-120		141	120,000	110
e (133,207)	2	AS-120	reserve	141	120,000	110
e (133,208)	8	AS-95		315	100,000	110
e (133,208)	8	AS-95	reserve	315	100,000	110
e (208,209)	9	AS-185		490	150,000	110
e (133,209)	5	AS-185		242	150,000	110
e (209,210)	4	AS-185		133	150,000	110
e (210,211)	1	AS-185		14	150,000	110
e (211,212)	3	ACS-185		8	150,000	110
e (48,212)	6	ACS-185		22	150,000	110

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (47,48)	46	AS-240		116,393	170,000	110
e (48,213)	6	ACS-185		741	150,000	110
e (48,213)	6	ACS-185	reserve	741	150,000	110
e (213,214)	5	AS-185		100	150,000	110
e (214,215)	1	AS-185		29	150,000	110
e (215,216)	4	AS-185		1156	150,000	110
e (216,217)	7	AS-185		350	150,000	110
e (48,217)	9	AS-185		509	150,000	110
e (217,218)	7	AS-185		56	150,000	110
e (48,218)	3	AS-185		22	150,000	110
e (48,219)	4	AS-120		300	120,000	110
e (48,219)	4	AS-120	reserve	300	120,000	110
e (219,220)	23	AS-120		319	120,000	110
e (47,220)	3	AS-150		35	135,000	110
e (48,221)	3	AS-150		163	135,000	110
e (48,221)	3	AS-150	reserve	36	135,000	110
e (221,222)	14	AS-150		155	135,000	110
e (221,222)	14	AS-150	reserve	155	135,000	110
e (47,222)	28	AS-240		195	170,000	110
e (47,222)	28	AS-240	reserve	195	170,000	110
e (48,223)	2	AS-185		84	150,000	110
e (223,224)	23	AS-185		480	150,000	110
e (224,225)	7	AS-185		144	150,000	110
e (47,225)	23	AS-240		373	170,000	110
e (48,226)	40	AS-120		3323	120,000	110
e (226,227)	27	AS-95		1095	100,000	110
e (47,227)	19	AS-185		410	150,000	110
e (47,228)	10	AS-150		114	135,000	110
e (47,229)	9	AS-120		119	120,000	110
e (47,229)	9	AS-120	reserve	119	120,000	110
e (47,230)	44	AS-185		6110	150,000	110
e (47,230)	44	AS-185	reserve	6110	150,000	110
e (230,231)	6	AS-185		344	150,000	110
e (230,231)	6	AS-185	reserve	344	150,000	110
e (216,231)	3	AS-185		180	150,000	110
e (216,232)	1	AS-185		38	150,000	110
e (232,233)	4	AS-185		94	150,000	110
e (230,233)	5	AS-185		106	150,000	110

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (47,234)	29	AS-185		601	150,000	110
e (234,235)	1	AS-120		2	120,000	110
e (235,236)	25	AS-120		344	120,000	110
e (236,237)	15	AS-185		49	150,000	110
e (227,237)	33	AS-185		112	150,000	110
e (227,238)	30	AS-185		270	150,000	110
e (45,238)	46	AS-185/24		410	150,000	110
e (46,238)	63	AS-185		558	150,000	110
e (238,239)	25	AS-120		826	120,000	110
e (239,240)	23	AS-120		316	120,000	110
e (240,241)	6	AS-150		165	135,000	110
e (241,242)	9	AS-150		6	135,000	110
e (242,243)	17	AS-120		543	120,000	110
e (243,244)	38	AS-120		1247	120,000	110
e (46,244)	30	AS-150		779	135,000	110
e (45,245)	19	AS-120		257	120,000	110
e (45,245)	19	AS-120	reserve	257	120,000	110
e (226,245)	52	AS-120		716	120,000	110
e (169,246)	10	AS-150		634	135,000	110
e (246,247)	36	AS-150		935	135,000	110
e (247,248)	14	AS-150		1,543,219	135,000	110
e (248,249)	17	AS-185		126	150,000	110
e (249,250)	34	AS-185		4976	150,000	110
e (250,251)	109	AS-185		965	150,000	110
e (45,251)	29	AS-185/24		258	150,000	110
e (251,252)	40	AS-150		439	135,000	110
e (248,253)	43	AS-185		68	150,000	110
e (253,254)	28	AS-185		94	150,000	110
e (254,255)	35	AS-185		261	150,000	110
e (255,256)	35	AS-120		2923	120,000	110
e (44,256)	28	AS-185		1495	150,000	110
e (46,257)	33	AS-185		293	150,000	110
e (257,258)	14	AS-120		464	120,000	110
e (258,259)	38	AS-120		785	120,000	110
e (259,260)	35	AS-120		484	120,000	110
e (260,261)	45	AS-150		1185	135,000	110
e (261,262)	10	AS-185		217	150,000	110
e (261,262)	10	AS-185	reserve	217	150,000	110

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (261,262)	10	AS-185		217	150,000	110
e (262,263)	29	AS-120		150	120,000	110
e (263,264)	35	AS-150		145	135,000	110
e (44,265)	36	AS-185		1921	150,000	110
e (44,266)	46	AS-185		972	150,000	110
e (44,267)	15	AS-120		472	120,000	110
e (44,267)	15	AS-120	reserve	472	120,000	110
e (44,268)	18	AS-150		1187	135,000	110
e (44,268)	18	AS-150	reserve	1187	135,000	110
e (44,269)	13	AS-120		1052	120,000	110
e (44,269)	13	AS-120	reserve	1052	120,000	110
e (43,264)	57	AS-150		238	135,000	110
e (51,270)	32	AS-150		133	135,000	110
e (51,270)	32	AS-150	reserve	133	135,000	110
e (52,271)	32	AS-150		133	135,000	110
e (52,271)	32	AS-150	reserve	133	135,000	110
e (53,272)	24	AS-150		1600	135,000	110
e (53,272)	24	AS-150	reserve	1600	135,000	110
e (54,273)	39	AS-185		820	150,000	110
e (54,273)	39	AS-185	reserve	820	150,000	110
e (55,274)	47	AS-185		988	150,000	110
e (274,275)	21	AS-120		1749	120,000	110
e (275,276)	36	AS-120		2998	120,000	110
e (58,276)	53	AS-185		2853	150,000	110
e (59,277)	10	AS-120		52	120,000	110
e (60,278)	44	AS-185		148	150,000	110
e (60,278)	44	AS-185	reserve	148	150,000	110
e (61,279)	19	AS-150		1267	135,000	110
e (62,280)	38	AS-185		799	150,000	110
e (62,280)	38	AS-185	reserve	799	150,000	110
e (63,281)	46	AS-150		1198	135,000	110
e (56,282)	31	AS-150		2067	135,000	110
e (56,282)	31	AS-150	reserve	2067	135,000	110
e (57,283)	28	AS-185		1507	150,000	110
e (283,284)	13	AS-120		423	120,000	110
e (283,284)	13	AS-120	reserve	423	120,000	110
e (64,285)	28	AS-185		1507	150,000	110
e (64,285)	28	AS-185	reserve	1507	150,000	110

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (65,286)	59	AS-185		3176	150,000	110
e (286,287)	11	AS-120		57	120,000	110
e (66,287)	49	AS-185		165	150,000	110
e (67,288)	37	AS-150		154	135,000	110
e (68,289)	44	AS-150		2934	135,000	110
e (289,290)	16	AS-120		520	120,000	110
e (69,290)	43	AS-150		1120	135,000	110
e (70,291)	39	AS-185		820	150,000	110
e (70,291)	39	AS-185	reserve	820	150,000	110
e (164,292)	41	AS-185		2207	150,000	110
e (292,293)	17	AS-120		1416	120,000	110
e (293,294)	22	AS-120		716	120,000	110
e (162,294)	35	AS-185		736	150,000	110
e (161,295)	38	AS-150		2534	135,000	110
e (161,295)	38	AS-150	reserve	2534	135,000	110
e (160,296)	29	AS-185		1561	150,000	110
e (160,296)	29	AS-185	reserve	1561	150,000	110
e (159,297)	23	AS-185		77	150,000	110
e (297,298)	13	AS-120		423	120,000	110
e (165,298)	23	AS-185		484	150,000	110
e (166,299)	64	AS-150		4268	135,000	110
e (166,299)	64	AS-150	reserve	4268	135,000	110
e (163,300)	38	AS-150		2534	135,000	110
e (163,300)	38	AS-150	reserve	2534	135,000	110
e (76,301)	50	AS-150		208	135,000	110
e (301,302)	13	AS-120		423	120,000	110
e (80,302)	39	AS-185		820	150,000	110
e (79,303)	47	AS-150		3134	135,000	110
e (303,304)	13	AS-120		1083	120,000	110
e (304,305)	13	AS-120		68	120,000	110
e (305,306)	13	AS-120		1083	120,000	110
e (78,306)	38	AS-185		2045	150,000	110
e (77,307)	35	AS-185		1884	150,000	110
e (77,307)	35	AS-185	reserve	1884	150,000	110
e (307,308)	15	AS-120		488	120,000	110
e (307,308)	15	AS-120	reserve	488	120,000	110
e (308,309)	13	AS-120		1083	120,000	110
e (308,309)	13	AS-120	reserve	1083	120,000	110

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (81,310)	24	AS-185		1292	150,000	110
e (310,311)	15	AS-120		78	120,000	110
e (82,311)	27	AS-185		91	150,000	110
e (83,312)	43	AS-150		1120	135,000	110
e (83,312)	43	AS-150	reserve	1120	135,000	110
e (84,313)	13	AS-120		1083	120,000	110
e (85,314)	11	AS-120		916	120,000	110
e (86,315)	11	AS-120		57	120,000	110
e (87,316)	27	AS-185		568	150,000	110
e (316,317)	18	AS-120		14,356	120,000	110
e (317,318)	26	AS-120		2165	120,000	110
e (88,318)	41	AS-185		2207	150,000	110
e (89,319)	43	AS-150		179	135,000	110
e (89,319)	43	AS-150	reserve	179	135,000	110
e (90,320)	34	AS-150		2267	135,000	110
e (90,320)	34	AS-150	reserve	2267	135,000	110
e (91,321)	28	AS-150		1867	135,000	110
e (91,321)	28	AS-150	reserve	1867	135,000	110
e (92,322)	16	AS-150		417	135,000	110
e (92,322)	16	AS-150	reserve	417	135,000	110
e (93,323)	18	AS-185		969	150,000	110
e (323,324)	31	AS-120		2581	120,000	110
e (324,325)	29	AS-120		151	120,000	110
e (94,325)	48	AS-185		161	150,000	110
e (95,326)	17	AS-120		553	120,000	110
e (96,327)	39	AS-185		2099	150,000	110
e (327,328)	43	AS-150		2868	135,000	110
e (97,328)	52	AS-185		2799	150,000	110
e (98,329)	9	AS-120		47	120,000	110
e (99,330)	7	AS-120		228	120,000	110
e (100,331)	26	AS-185		1399	150,000	110
e (331,332)	11	AS-150		734	135,000	110
e (101,332)	41	AS-185		2207	150,000	110
e (102,333)	26	AS-185		87	150,000	110
e (333,334)	11	AS-150		734	135,000	110
e (103,334)	41	AS-185		2207	150,000	110
e (104,335)	15	AS-150		1000	135,000	110
e (104,335)	15	AS-150	reserve	1000	135,000	110

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (106,336)	22	AS-150		573	135,000	110
e (106,336)	22	AS-150	reserve	573	135,000	110
e (107,337)	39	AS-150		2601	135,000	110
e (107,337)	39	AS-150	reserve	2601	135,000	110
e (108,338)	51	AS-150		3401	135,000	110
e (108,338)	51	AS-150	reserve	3401	135,000	110
e (109,339)	27	AS-185		91	150,000	110
e (339,340)	13	AS-150		339	135,000	110
e (110,340)	48	AS-185		1009	150,000	110
e (111,341)	37	AS-185		1991	150,000	110
e (341,342)	49	AS-150		3268	135,000	110
e (112,342)	58	AS-185		3122	150,000	110
e (113,343)	38	AS-185		128	150,000	110
e (113,343)	38	AS-185	reserve	128	150,000	110
e (114,344)	29	AS-185		610	150,000	110
e (344,345)	47	AS-150		3134	135,000	110
e (115,345)	13	AS-185		700	150,000	110
e (116,346)	27	AS-185		1453	150,000	110
e (116,346)	27	AS-185	reserve	1453	150,000	110
e (117,347)	46	AS-185		155	150,000	110
e (117,347)	46	AS-185	reserve	155	150,000	110
e (118,348)	18	AS-185		969	150,000	110
e (118,348)	18	AS-185	reserve	969	150,000	110
e (119,349)	59	AS-185		3176	150,000	110
e (119,349)	59	AS-185	reserve	3176	150,000	110
e (120,350)	34	AS-185		715	150,000	110
e (350,351)	46	AS-150		3068	135,000	110
e (121,351)	25	AS-185		1346	150,000	110
e (122,352)	17	AS-185		915	150,000	110
e (122,352)	17	AS-185	reserve	915	150,000	110
e (123,353)	51	AS-185		172	150,000	110
e (123,353)	51	AS-185	reserve	172	150,000	110
e (126,354)	34	AS-185		715	150,000	110
e (126,354)	34	AS-185	reserve	715	150,000	110
e (134,355)	63	AS-150		4201	135,000	110
e (134,355)	63	AS-150	reserve	4201	135,000	110
e (148,356)	24	AS-150		1600	135,000	110
e (148,356)	24	AS-150	reserve	1600	135,000	110

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (145,357)	34	AS-185		114	150,000	110
e (357,358)	46	AS-150		1198	135,000	110
e (146,358)	25	AS-185		526	150,000	110
e (147,359)	17	AS-150		1134	135,000	110
e (147,359)	17	AS-150	reserve	1134	135,000	110
e (151,360)	33	AS-185		1776	150,000	110
e (360,361)	49	AS-150		204	135,000	110
e (152,361)	41	AS-185		138	150,000	110
e (153,362)	39	AS-150		2601	135,000	110
e (153,362)	39	AS-150	reserve	2601	135,000	110
e (154,363)	18	AS-120		1499	120,000	110
e (363,364)	3	AS-120		98	120,000	110
e (128,365)	24	AS-150		1600	135,000	110
e (128,365)	24	AS-150	reserve	1600	135,000	110
e (155,366)	18	AS-120		1499	120,000	110
e (366,367)	3	AS-120		16	120,000	110
e (156,367)	24	AS-150		100	135,000	110
e (129,368)	33	AS-150		860	135,000	110
e (129,368)	33	AS-150	reserve	860	135,000	110
e (157,369)	41	AS-185		2207	150,000	110
e (369,370)	19	AS-120		1582	120,000	110
e (370,371)	10	AS-120		52	120,000	110
e (371,372)	14	AS-120		455	120,000	110
e (158,372)	28	AS-185		589	150,000	110
e (138,373)	38	AS-185		2045	150,000	110
e (373,374)	14	AS-120		1166	120,000	110
e (374,375)	19	AS-120		99	120,000	110
e (139,375)	57	AS-185		192	150,000	110
e (140,376)	21	AS-150		1400	135,000	110
e (140,376)	21	AS-150	reserve	1400	135,000	110
e (144,377)	35	AS-150		1724	135,000	110
e (144,377)	35	AS-150	reserve	2334	135,000	110
e (143,378)	51	AS-150		1329	135,000	110
e (143,378)	51	AS-150	reserve	1329	135,000	110
e (142,379)	7	AS-120		583	120,000	110
e (150,380)	29	AS-185		1561	150,000	110
e (380,381)	17	AS-120		88	120,000	110
e (381,382)	13	AS-120		423	120,000	110
e (382,383)	24	AS-120		1999	120,000	110

Edge	Length (km)	Cross-Section	Reservation	Maximum Losses in Line (kW)	Cost per 1 km (UAH/km)	Voltage in Line (kV)
e (149,383)	42	AS-185		2261	150,000	110
e (383,384)	13	AS-120		1083	120,000	110
e (383,384)	13	AS-120	reserve	1083	120,000	110
e (384,385)	28	AS-120		146	120,000	110
e (384,385)	28	AS-120	reserve	146	120,000	110

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Article

Analysis of Sustainable Energy and Environmental Policies in Agriculture in the EU Regarding the European Green Deal

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Abstract: The paper analyzes energy and environmental policies in agriculture in the context of the European Green Deal, emphasizing the contribution of the Common Agricultural Policy in supporting sustainability objectives. The study explores how Member States implement specific measures to reduce greenhouse gas emissions, conserve natural resources, and protect biodiversity by 2030. The analysis focuses on three main objectives: reducing emissions and adapting to climate and energy changes, managing natural resources sustainably and ensuring energy efficiency, and promoting organic farming and conserving biodiversity. Using a methodology that aligns Green Deal goals with CAP measures, this research involves a comparative analysis between Member States, highlighting disparities in policy implementation, particularly between Eastern and Western Europe, suggesting that a coordinated EU approach is needed to support equitable progress. The paper provides a detailed perspective on the progress made and offers recommendations for harmonizing agricultural policies in the EU, supporting farmers in adopting ecological and energy efficient practices, and ensuring a consistent approach in achieving Green Deal objectives by 2030.

Keywords: European Green Pact; sustainable agriculture; energy policies; environmental policies; ecological transition; climate targets

1. Introduction

European agriculture plays a central role in addressing energy, climate, and environmental issues. Over the years, sustainable development strategies and programs have been implemented to tackle these challenges. However, despite the correct orientation of these initiatives, they remain insufficient to meet the current needs of the agricultural sector. The 2003 reform of the EU Common Agricultural Policy [1] marked a significant change by providing direct and decoupled financial support to farmers, thus reducing their motivation to intensify production. Instead, the new support framework required farmers to adopt ecological cultivation methods [2], aimed at conserving environmental energy. Nevertheless, the energy and climate challenges associated with agricultural activities necessitate the implementation of sustainable and efficient practices. The European Environment Agency [3] highlights several essential areas for transitioning to a sustainable agricultural and economic system, including: (a) strengthening policy implementation and cohesion methods; (b) creating a long-term policy framework oriented towards sustainability; (c) promoting international cooperation for sustainable development; (d) supporting innovation through social actions; (e) increasing investments and reorienting finances; (f) managing risks and ensuring a fair transition; and (g) integrating knowledge into concrete actions.

In response to the deteriorating state of the natural environment in Europe, including the effects of climate change, the European Commission launched the European Green Deal in 2019 [4], with the aim of stimulating international actions to achieve economic objectives in balance with environmental protection, reaffirming the EU's commitment to addressing the energy, climate, and environmental crisis, considered the most pressing issues of society [5].

The European Green Deal is the growth strategy proposed by the European Union to transform the economy into a modern, resource-efficient, and competitive one [6], with the objective of zero net greenhouse gas emissions by 2050 [7]. Thus, through this strategy, the EU seeks to decouple economic growth from excessive use of natural resources, putting the economy and society on a sustainable trajectory that covers all sectors, including agriculture [8].

Countries with more developed economies, such as Germany and France, have access to more funds and advanced technologies, allowing them to implement carbon sequestration or pesticide use reduction measures more quickly, while Eastern European countries face challenges in accessing funds and adopting modern practices due to economic and infrastructural constraints [9]. Thus, the Green Pact promotes eco-schemes, which include voluntary measures to encourage farmers to adopt sustainable practices (e.g., growing legumes, maintaining fallow areas for biodiversity, using renewable energy) [10]. However, differences in participation rates between countries reflect varying levels of awareness and financial support [11]. According to the Green Pact, by 2030, 25% of the EU's agricultural land should be organic. Some countries, such as Austria, have already exceeded this target, while others, such as Romania, have more modest targets due to lack of demand and limited subsidies.

EU countries are implementing the Common Agricultural Policy 2023–2027 through customized national CAP strategic plans targeting local needs while supporting EU objectives and the European Ecological Pact. Thus, the European Green Pact policies and related strategies such as Farm to Fork and Biodiversity mark a significant transition towards more sustainable agriculture in the European Union [12]. These policies aim to address climate challenges, reduce negative environmental impacts, and improve the use of natural resources in the agricultural sector. The main action lines and impacts include [9] reducing environmental impacts; thus, pesticide sales have fallen by 7% between 2011 and 2019, representing progress in reducing risks to biodiversity and human health, and greenhouse gas emissions from agriculture have been reduced by 25% since 1990, in line with climate change mitigation targets.

In terms of the area of land used for organic farming, it increased annually by 5.5% between 2012–2019, reaching 13.8 million ha in 2019, and the 2030 target is to reach 25% of the agricultural area used. In addition, increasing the diversity of agricultural landscapes by keeping 10% of agricultural land for areas of high biodiversity contributes to the restoration of natural ecosystems and habitats [13], and Member States such as Denmark, Germany, and the Netherlands are leaders in the uptake of renewable energy sources, including biogas and solar energy. However, challenges of high upfront costs and limited infrastructure prevent the spread of these practices to all regions.

In terms of challenges to the objectives of the European Green Pact, around 50% of agricultural land in the EU is suffering from a shortage of pollination, droughts have led to annual economic losses of 9 billion EUR, and fragmentation of agricultural land and lack of modern infrastructure continue to be barriers for Eastern European Member States such as Romania and Bulgaria to adopt renewable energy and sustainable practices [14].

In terms of the role of support policies, the Common Agricultural Policy 2021–2027 allocates substantial funds for the green transition, including for organic farming, infrastructure investment, and support for small- and medium-sized farmers. These funds are essential for achieving the environmental objectives of the European Green Pact. Thus, the paper aims to analyze the implementation and effectiveness of sustainable energy and environmental policies in agriculture under the European Green Pact, with a special focus on the contribution of the Common Agricultural Policy to the achievement of the set environmental objectives. The goal is to highlight how these policies support the transition to sustainable agricultural practices and contribute to the reduction of greenhouse gas emissions, conservation of natural and energy resources, and protection of biodiversity.

The objectives of the analysis are as follows:

O1: Analysis of adaptation and emission reduction in agriculture: aims to evaluate the commitments of Member States to reduce emissions in the agricultural and live-stock sectors, examine investments and capacities for renewable energy production in agriculture to reduce dependence on fossil fuels, and identify differences between states in supporting farmers to reduce emissions and adapt to climate change.

O2: Evaluation of sustainable natural resource management: involves investigating measures to protect soil, water, and air quality through sustainable management policies, analyzing the adoption of sustainable water and pesticide use measures to reduce environmental impact, and identifying the role of sustainable nutrient and water resource management in the context of the European Green Deal and the transition to energy efficient and sustainable agricultural practices.

O3: Conservation of biodiversity and promotion of organic farming: involves analyzing support for organic farming and its impact on reducing pollution and protecting natural resources, investigating biodiversity and landscape conservation practices through the management of natural features and habitats in European agriculture, and evaluating the support provided to farmers for adopting organic practices and the need for additional measures to support the energy transition in the EU. The paper will provide an in-depth understanding of the efficiency and limitations of energy and environmental policies in agriculture, reflecting the commitments of Member States within the Green Deal, with targets set until 2030. The analysis will also offer recommendations for harmonizing agricultural policies at the EU level and propose support measures for equitable implementation of sustainable practices in all Member States.

2. European Green Deal: A Comprehensive Strategy for Implementing the 2030 Agenda and Transitioning to Sustainability

The European Green Deal supports the implementation of the UN's 2030 Agenda and the Sustainable Development Goals [9]; thus, the implementation of this pact requires significant changes in various policy areas, from energy and industry to agriculture and transport. The objectives include protecting ecosystems, the sustainable use of resources, and improving public health; thus, the interconnected areas of action require integrated policies and, in some cases, compromises between economic, environmental, and social objectives [15–17], and to achieve the pact's objectives [18], specific policies have been established to contribute to improving the natural environment and stabilizing the climate (Figure 1).

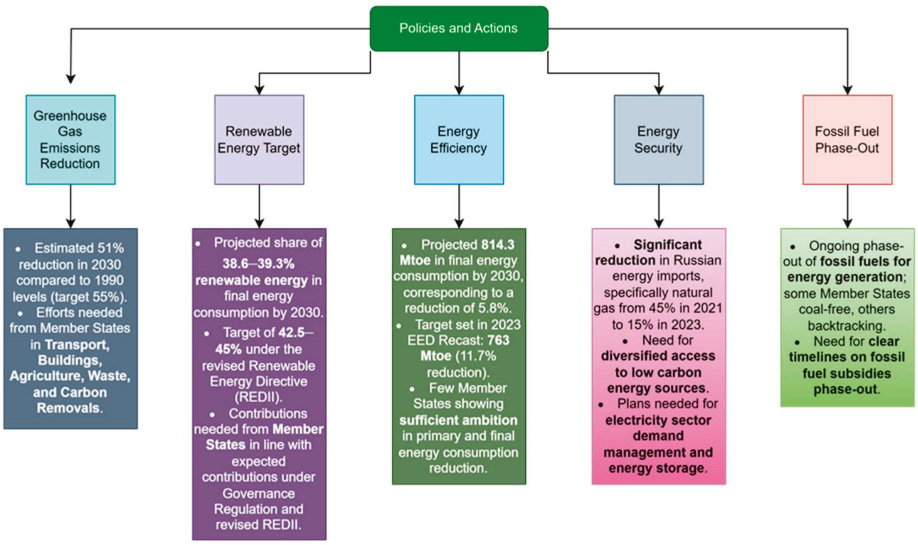


Figure 1. Political measures and actions to achieve energy and climate sustainability goals at the European Union level by 2030. Source: own interpretation based on Regulation (EU) 2018/1999 of the European Parliament and of the Council [19].

Between 2020 and 2021, the European Green Deal initiated multiple major actions to ensure the EU's transition to sustainability. In the agricultural sector, the "Farm to Fork" strategy was adopted, promoting a sustainable food system, reducing the use of pesticides and synthetic fertilizers, and supporting organic farming, while biodiversity was protected by expanding the protected area of EU lands and waters and strengthening the Natura 2000 network of protected areas.

To achieve ambitious climate objectives, the EU has set a goal of climate neutrality by 2050 and a 50–55% reduction in emissions by 2030, compared to 1990 levels [20]. In the energy sector, the focus has been on developing an energy system based on renewable sources, reducing coal, and encouraging the transition to low-carbon energy sources. Additionally, the "zero pollution" goal was established for a cleaner and healthier environment, and the circular economy was promoted to support the EU industry in adopting a sustainable growth model, prioritizing the reuse and recycling of materials [21]. In transport, a 90% reduction in emissions is targeted by 2050, supporting zero emission vehicles and charging infrastructure, with all these measures supporting the transition to a green and sustainable economy (Figure 2).

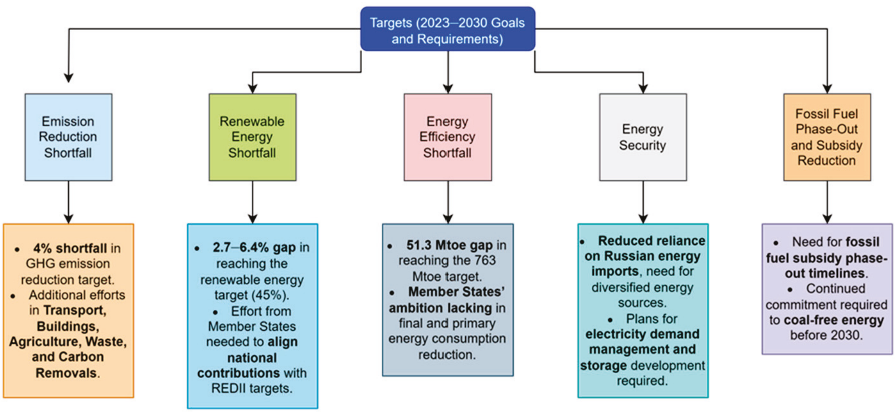


Figure 2. Objectives and requirements for achieving energy and climate sustainability goals in the European Union for the period 2023–2030. Source: own interpretation based on Regulation (EU) 2018/842 of the European Parliament and of the Council [21].

The European Green Deal is based on ambitious objectives and structural reforms that transform the European economy, addressing issues related to climate, energy, and biodiversity. This pact represents a major paradigm shift that will directly influence all sectors of the European economy in the coming decades, and the implementation of the European Green Deal strategy comes with a series of major challenges, both at the European level and in the Member States, challenges that can be grouped into four main categories:

1. Fundamental challenge related to the ambition of the European Green Deal objectives: Between 1990 and 2018, the EU reduced greenhouse gas emissions by 23% [22], while the economy grew by 61%. However, according to estimates, current policies would only ensure a 60% reduction in emissions by 2050, making it necessary to set more ambitious climate and energy objectives [23,24]. Achieving these, however, involves significant risks and requires radical solutions to transform economic sectors in a sustainable direction. To support this transformation, the EU will need to take measures in various areas: climate taxation, development of a circular and climate neutral economy, biodiversity restoration, digitization, and massive investments in new technologies [25] that require sustained effort to integrate these initiatives into a sustainable economic framework.
2. Administrative and legal challenges: The successful implementation of the Green Deal requires adapting the institutional and regulatory framework at European and national levels [26]. Member States must develop their own national energy and climate plans, as well as strategic plans for the Common Agricultural Policy, which

must be in line with European objectives. The European Commission is responsible for evaluating and monitoring the implementation of these plans [27], and Member States must achieve measurable results. Additionally, periodic review of progress in environmental protection will contribute to adjusting strategies and measures to achieve objectives [28].

3. Global challenges in the European context: The EU, being responsible for an increasingly smaller proportion of global emissions [29], needs similar measures from other regions to have a real impact on energy, climate, and the environment globally. The European Green Deal will influence geopolitics and economic and commercial interests, creating new challenges for Member States and international relations. Thus, the EU intends to collaborate with global partners to mitigate risks related to food security, conflicts, and forced migration, placing environmental and climate policy in a central position in common security policy [30].
4. Financial and social challenges: To achieve the ambitious objectives set [31], innovative solutions and massive investments are necessary, which involve significant costs. The question of who is responsible for these costs is essential, given that energy, the environment, and climate are common resources. The EU and Member States must coordinate international actions and attract private capital to support green initiatives [32], and from a social perspective, the success of the Green Deal depends on public support [33]. Although awareness of climate issues has increased, the level of willingness to cover the associated costs of these changes remains limited. Therefore, public education on the importance of the Green Deal and the negative effects of inaction must be intensified to ensure broad support [34]. A large part of the population adopts a passive approach, waiting for others to take the initiative, which reduces the effectiveness of energy and environmental policies and increases the risk of not achieving the set objectives [27–30].

3. Materials and Methods

3.1. Context of the Analysis

The new governance of the Common Agricultural Policy (CAP) marks a transition from compliance to performance, aiming to effectively address current and future challenges. In a rapidly changing global economic context and amid an urgent need for climate action, the CAP must make an essential contribution to achieving an ecological transition and creating a sustainable food system with social, ecological, and economic impact. The budget of over 380 billion EUR for the 2021–2027 period reflects the strategic importance of agriculture, food, and rural areas in today's European Union, ensuring the necessary support for achieving the objectives of the European Green Deal and the Sustainable Development Goals [35]. However, to fully capitalize on these resources, the CAP must simplify governance and modernize its implementation mechanisms, shifting to a policy model focused more on results and performance.

Currently, the CAP relies on a series of complex and detailed requirements at the EU level, applicable to all beneficiaries down to the individual farm level. However, given the significant energy, ecological, and climate diversity across the Union, universal or top-down approaches are no longer effective in achieving the desired results. In response, EU legislators have agreed on a new and more flexible governance based on the introduction of national CAP strategic plans [36]. Starting in 2023, the CAP will, for the first time, integrate the most important support tools into a single programming framework, ensuring a more coherent approach to their implementation.

By including both the first pillar (direct payments and sectoral support) and the second pillar (rural development) in a single strategic plan, Member States will be able to allocate resources more efficiently and tailor measures according to national specifics [37]. This new decentralized approach implies that the EU reduces its prescriptive level and focuses more on strategic objectives and performance, while Member States have in-creased responsibility for achieving the established objectives. At the same time, fun-damental mandatory requirements remain, ensuring a common ambition across all Member States and a clear direction towards achieving a more sustainable agricultural sector.

The new Common Agricultural Policy brings a programming approach based on detailed analysis and a common set of objectives and indicators, being performance oriented and adapted to the diversity of Member States. The legal framework for the CAP now includes general and specific objectives at the EU level, integrating the three dimensions of sustainability: economic, social, and environmental. These objectives constitute the basis of each national Strategic Plan [38], thus supporting the sustainability ambitions of the CAP and contributing to European priorities, including the Green Deal [39]. Thus, the paper presents the analysis of the projected targets for the relevant indicators regarding energy, environment, and climate within the framework of the European Green Deal regarding agriculture in the EU, with targets expected to be achieved by 2030 [39].

3.2. Analysis Methodology

Regarding performance monitoring and evaluation, the new PMEF (Performance Monitoring and Evaluation Framework) integrates all CAP instruments into a unified monitoring system, based on reliable, comparable, and timely updated indicators. PMEF uses a comprehensive set of indicators: 38 achievement, 44 result, 30 impact, and 49 context, with quantified targets for each CAP Strategic Plan [37].

Member States are required to report annually to the Commission on the progress in implementing their strategic plans, and the evaluation of these reports will allow the Commission to monitor results and expenditures, supporting necessary adjustments.

Every two years, the Commission will conduct a full performance evaluation, which may include improvement requests or financial sanctions for Member States that do not meet the set targets.

Member States are also responsible for evaluating their own strategic plans, while the Commission will provide a synthesis of evaluations at the EU level. In 2026, an interim evaluation will analyze the contribution of strategic plans to the Green Deal ambitions, including the objectives of the Farm to Fork Strategy and the Biodiversity Strategy.

Last but not least, the new CAP introduces core indicators that allow annual reporting at the EU level in the context of the performance of the EU budget under the multiannual financial framework 2021–2027. This indicator structure ensures transparency and efficiency in the dialogue regarding CAP performance between the Commission and other European institutions, including the European Court of Auditors.

The methodology used in this paper combines the monitoring of the progress of agricultural and environmental policies in the European Union with a comparative analysis between Member States; thus, the evaluation is based on the indicators of the new Performance Monitoring and Evaluation Framework (PMEF) of the Common Agricultural Policy for the period 2021–2027. These indicators are categorized into the following: (i) output indicators examining specific interventions at project level; (ii) outcome indicators, looking at the effectiveness of the measures supported by the CAP (e.g., R.12 for climate change adaptation, R.15 for renewable energy); (iii) impact indicators measuring the long-term effects on the environment and the agricultural sector; and (iv) context indicators, used to contextualize the results in relation to economic, social, and environmental conditions.

Benchmarking between Member States focused on their performance in key areas such as emission reduction, organic farming, and the use of renewable resources and highlighted the link between the objectives of the European Green Pact and CAP measures, underlining the degree of support for the green transition.

The analysis will examine the European legislative and policy framework regarding the Green Deal and the Common Agricultural Policy Reform to identify specific measures dedicated to reducing greenhouse gas emissions, promoting renewable energies, and conserving natural resources. The main sources will include policy documents and official strategies [37]. Data will be collected based on the key indicators proposed by the CAP for the period 2023–2030, with a focus on environmental and energy aspects, grouped into three levels:

1. Emission reduction and adaptation to climate and energy changes in agriculture (R.12, R.13, R.14, R.15, R.16, R.25, R.26) [37]: the result indicators are used to measure the effectiveness of CAP supported interventions in reducing emissions and supporting adaptation to climate change in the agricultural sector (Table 1).

Table 1. Analyzed result indicators and types of interventions within the CAP for adaptation to climate change, environmental protection, and sustainable resource management.

Code	Result Indicator	Definition	Purpose	Targeted Intervention Types
R.12	Adaptation to climate change	Percentage of agricultural area in use (UAA) under supported commitments to improve adaptation to climate change.	Measures the coverage of climate adaptation commitments.	limate, environment, and animal welfare schemes (Article 31) [8] Management commitments related to environment and climate (Article 70) [8] Sectoral interventions (climate change adaptation practices: Article 47 (1) (i) [40], Article 47 (1) (a) (iii)) [40] Sectoral interventions to reduce climate change in the livestock sector (Article 47 (1) (a) (i)) [40]
R.13	Reducing emissions in the livestock sector	Percentage of livestock units (LU) under supported commitments to reduce greenhouse gas and/or ammonia emissions.	Measures progress in reducing emissions in the livestock sector.	
R.14	Carbon storage in soils and biomass	Percentage of UAA under supported commitments to reduce emissions or maintain/store carbon.	Measures the coverage of commitments for carbon storage in agriculture.	Sectoral interventions (soil conservation practices, carbon sequestration: Article 47 (1) (a) (i) [40], Article 47 (1) (i)) [40]
R.15	Renewable energy from agriculture	Supported investments for renewable energy production capacity, including biomass (in MW).	Measures the renewable energy capacity supported in the agricultural sector.	Investments (Article 73) [8] Sectoral interventions with an investment component (renewable energy from agriculture, forestry, and other sources)
R.16	Climate-related investments	Percentage of farms benefiting from CAP investment support for climate change mitigation, adaptation, and the production of renewable energy or biomaterials.		Sectoral interventions with an investment component (investments in tangible and intangible assets to save water, energy, ecological packaging: Article 47 (1) (a)) [40]
R.25	Environmental performance in the livestock sector	Percentage of livestock units (LU) under supported commitments to improve environmental sustainability in the livestock sector.	Measures the progress of ecological commitments in animal husbandry.	Management commitments related to the environment and climate (Article 70, support for endangered species) Sectoral interventions (sustainable practices in the livestock sector: Article 47 (1)) [40]
R.26	Investments related to natural resources	Percentage of farms benefiting from support for CAP investments aimed at the care of natural resources.	Measures the coverage of investments for the protection of natural resources.	Sectoral interventions with an investment component (saving water, energy, ecological packaging: Article 47 (1) (a)) [40]

2. Sustainable management of natural resources and energy efficiency in agriculture to meet the objectives of the European Green Pact (R.19, R.20, R.21, R.22, R.23, R.24) [37]: intended to measure the effectiveness of supported interventions in improving the management of natural resources, energy, and environmental protection in agriculture (Table 2).

Table 2. Analyzed result indicators and types of CAP interventions for sustainable management of energy, soil, air, water, and pesticides.

Code	Result Indicator	Definition	Purpose	Targeted Intervention Types
R.19	Soil improvement and protection	Percentage of UAA under commitments supported for soil management, to improve soil and biota quality.	Measures the coverage of soil conservation commitments.	limate, environment, and animal welfare schemes (Article 31) [8] Management commitments related to environment and climate (Article 70) [8] Sectoral interventions (soil conservation practices: Article 47 (1) (a) (i)) [40]
R.20	Improving air quality	Percentage of UAA under supported commitments to reduce ammonia emissions.	Measures the coverage of commitments to improve air quality.	
R.21	Water quality protection	Percentage of UAA under supported commitments for water quality.	Measures the coverage of water quality protection commitments.	Sectoral interventions (organic farming: Article 47 (1) (d)) [40]
R.22	Sustainable nutrient management	Percentage of UAA under supported commitments for sustainable nutrient management.	Measures the coverage of commitments for sustainable nutrient management.	Sectoral interventions (organic and integrated agriculture: Article 47 (1) (d)) [40]
R.23	Sustainable use of water	Percentage of UAA under commitments supported to improve the water balance.	Measures the coverage of commitments for sustainable water use.	Sectoral interventions (sustainable water use practices: Article 47 (1) (a) (ii)) [40]
R.24	Sustainable and reduced use of pesticides	Percentage of UAA under specific commitments for the sustainable use of pesticides, to reduce their risks and impacts.	Measures the coverage of commitments for the sustainable use of pesticides.	Sectoral interventions (organic and integrated agriculture, pest management practices: Article 47 (1) (a) (viii)) [40]

3. Preservation of biodiversity, landscape, and energy efficiency in the promotion of ecological agriculture (R.29, R.31, R.32, R.34) [37]: the result indicators measure the degree of coverage of commitments to support these objectives (Table 3).

Table 3. Analyzed result indicators and types of CAP interventions to promote organic agriculture, energy and biodiversity conservation, and landscape management.

Code	Result Indicator	Definition	Purpose	Targeted Intervention Types
R.29	Development of ecological agriculture	Percentage of utilized agricultural area (UAA) supported by the CAP for organic farming, split between maintenance and conversion.	Measures the coverage of commitments to promote organic agriculture.	limate, environment, and animal welfare schemes (Article 31) [8] Management commitments related to environment and climate (Article 70) [8] Sectoral interventions (Article 47 (1) (d) and 57 (1) (m)) [40]
R.31	Conservation of habitats and species	Percentage of UAA under commitments for biodiversity conservation/restoration, including agricultural practices of high nature value.	Measures the coverage of biodiversity commitments.	Sectoral interventions, e.g., creation and maintenance of habitats (Article 47 (1) (a) (x)) [40]
R.32	Investments related to biodiversity	Percentage of farms benefiting from CAP investment support in biodiversity.	Measures the coverage of investments to support biodiversity.	Investments (Article 73) [8] Sectoral interventions with an investment component, e.g., investments in tangible and intangible assets for the creation of habitats (Article 47 (1) (a) (x)) [40]
R.34	Conservation of landscape features	Percentage of UAA under commitments for managing landscape features such as hedges and trees.	Measures commitments to manage landscape features.	Sectoral interventions, e.g., preservation/restoration of terraces and walls (Article 58 (1) (a)) [8]

Correlating the objectives of the Green Deal and the Common Agricultural Policy involves a method to analyze to what extent the measures implemented through the CAP support the objectives of the European Green Deal. This method consists of identifying the correspondences between the specific objectives of the Green Pact, such as the achievement of climate neutrality and the national targets adopted by the Member States through the CAP until the year 2030. Thus, by evaluating the common environmental, economic, and sustainability objectives, the analysis allows for the observation of the commitment of each member state to the transition to a more ecological agriculture.

The comparative analysis between the Member States completes this correlation, using comparable indicators to evaluate regional differences and the efficiency of the implemented measures, highlighting the differences between the states according to the local specifics and the capacity to adapt, contributing to a better understanding of the regional needs and challenges in the implementation of the objectives of the Green Pact.

4. Results

4.1. Emission Reduction and Adaptation to Climate and Energy Changes in Agriculture

The European Green Deal includes strategies that call for a significant transition in European agriculture to keep agricultural activities within planetary boundaries and support biodiversity [41]. The "Farm to Fork" and Biodiversity strategies aim to reduce the use of pesticides and fertilizers and restore landscape elements necessary for biodiversity. Although there is a target to reduce food waste, measures to support a transition to healthier and more sustainable diets are insufficient, and the new CAP modifications for the 2023–2027 period [42,43] do not bring major improvements, instead transferring a large part of the implementation responsibilities to the Member States. Without strict reporting requirements on biodiversity impact, the effectiveness of measures remains limited, and in some cases, funding is directed to programs that do not truly contribute to biodiversity, while "enhanced conditionality" is insufficient [44]. For example, only 3% of arable land is allocated to nature, although studies indicate that a minimum of 10% is needed for biodiversity restoration. Moreover, greening measures, which aimed to reduce the impact of agriculture on the environment, have been integrated into conditionality but with weak standards and options that allow intensive exploitation, including supporting intensive animal farming, which negatively impacts biodiversity and climate. Although eco-schemes are allocated a significant budget, they are not directed towards clear environmental protection measures, allowing Member States to develop schemes that do not produce significant effects [45].

Figure 3 illustrates the commitments (targets) of EU Member States to adapting to energy and climate changes and reducing emissions in agriculture and the livestock sector by 2030, including the percentage of agricultural areas and livestock units involved in climate adaptation initiatives, reducing greenhouse gas emissions, and storing carbon in soils and biomass.

Figure 3a presents the commitments of the European Union member countries within the objective R.12 of the Common Agricultural Policy 2023–2027, which aims to adapt agriculture to climate change. Countries such as France (65.27%), Finland (64.61%), and the Netherlands (64.15%) have set high targets for adapting agriculture to climate change, indicating a deeper integration of sustainable energy policies and an increased willingness to invest in agricultural practices that reduce reliance on fossil fuels and promote renewable resources. For example, in France, although 1.2 billion EUR is earmarked to support renewables, the complexity of administrative requirements and low access for small farms in France limits the expansion of projects [46], but simplifying administrative procedures could accelerate the uptake of green technologies, and the Netherlands has high costs and strict regulations that limit the expansion of biogas and emission reduction projects, requiring more flexible policies [47]. These commitments include energy efficiency technologies, increasing carbon storage capacity in soils, and using solar or bioenergy in agricultural operations, all contributing to the Green Deal objectives. However, the replication of these approaches in other Member States may face significant obstacles, such as lack of financial resources, different climatic conditions, or the difficulty of implementing advanced technologies on small farms.

In contrast, countries such as Estonia (0%) having emission reduction schemes and bioenergy use are supported by national policies, but Estonia faces limited agricultural land and a focus on small farms, making project scalability a major challenge [48]; thus, modernization of agricultural infrastructure could boost the uptake of renewable energy.

Romania (0.01%), with solar and biogas projects held back by lack of technical knowledge and poorly developed infrastructure, affecting small- and medium-sized farmers [49], and Malta (0.04%), with limited land and unfavorable climatic conditions, making the integration of renewables a challenge, despite allocated funds [50], have much lower rates for this indicator, reflecting challenges in financing, infrastructure, and technological support, as well as different priorities in national agricultural policies. This variation can generate an uneven transition to sustainable agricultural practices in Europe and may exacerbate disparities in implementing Green Deal objectives, particularly in the areas of energy efficiency and climate resilience. Analyzing these data suggests that adapting agriculture to climate change is not just a matter of agricultural policies but also of energy policies, which directly influence consumption and energy sources in this sector.

Figure 3b shows the share of livestock units (LU) supported for reducing greenhouse gas (GHG) and/or ammonia emissions by 2030, with Finland having the highest share, with 46.52% of livestock units supported for emission reduction. Thus, it invests considerably in integrating bioenergy on farms, but severe climatic conditions reduce the efficiency of green technologies [51], and thus increasing access to solutions adapted to Nordic conditions is necessary to maximize the use of renewable sources. The next country in terms of share is Croatia with 39.62%, with support to small farms being counteracted by the low implementation rate in the use of renewables due to lack of technological resources, where technological modernization remains an acute need [52], followed by Latvia (29.34%), which is implementing pilot projects for biogas and solar energy [53], but the lack of consistent financial support for farmers and the low level of accessibility to modern technologies are holding back large-scale adoption; thus, strengthening financial schemes could stimulate the use of renewables. These percentages indicate a strong commitment to the transition towards greening agriculture and rigorous management of emissions from the livestock sector, with Austria (28.23%) and Greece (15.71%) also demonstrating some level of commitment. On the other hand, Spain shows a very low share of only 0.12%; thus, funds for the modernization of irrigation with solar energy are insufficient in the face of frequent droughts and high costs, which reduce the feasibility of projects, which may signal a low priority given to this aspect in its national agricultural policy [54]. In Belgium (Flanders) (2.81%), although 25% of the rural budget is allocated to eco-schemes that include renewable energy, small farmers face difficulties in accessing funding for advanced technologies, requiring no additional support programs [55], and Slovenia (7.91%) has small-scale projects for biomass and solar panels that face a lack of technological support and high up-front costs, requiring more substantial support [56].

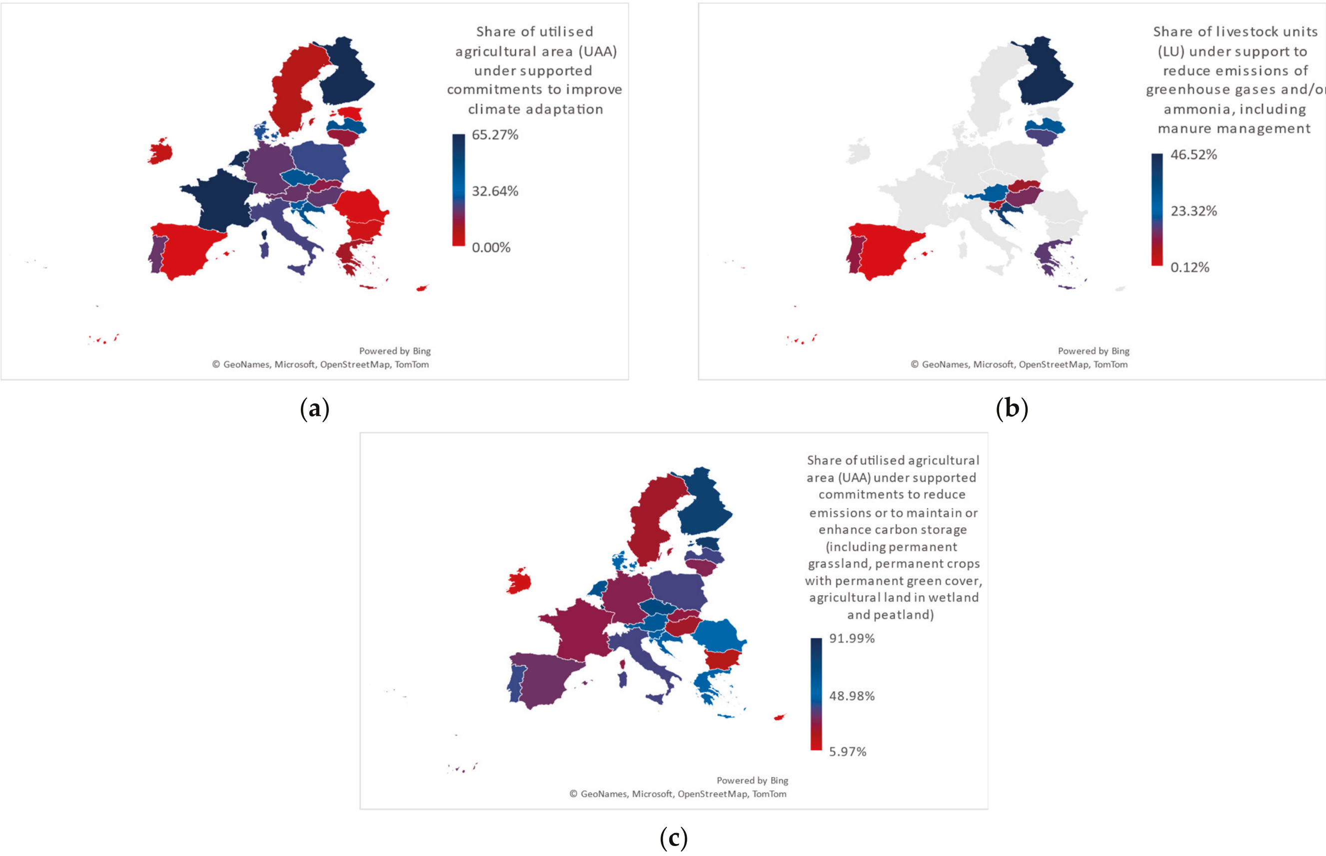


Figure 3. Commitments (targets) for adapting to energy and climate changes and reducing emissions in agriculture and the livestock sector until 2030: (**a**) R.12: Adapting to climate change, (**b**) R.13: Reducing emissions in the livestock sector, (**c**) R.14: Carbon storage in soils and biomass. Source: own interpretation based on CSPs Master file and key data, Publications Office of the European Union [37].

The analysis of this indicator highlights differences in national commitments and underscores the need for a coordinated approach to support a fair and sustainable transition in the European Union. These measures are essential for achieving the Green Deal targets and supporting a sustainable energy policy in agriculture.

Figure 3c illustrates the share of utilized agricultural area (UAA) in each European country benefiting from supported commitments for emission reduction or maintaining and improving carbon storage by 2030. These commitments include sustainable practices on agricultural lands, such as permanent pastures, permanent crops with green cover, and agricultural lands located in wetlands and peatlands. The indicator highlights each country's efforts to contribute to the climate objectives of the European Green Deal by reducing emissions and managing carbon. Luxembourg has the highest share of agricultural land dedicated to emission reduction and carbon storage, with 91.99%, followed by Estonia

(79.22%) and Finland (76.96%). These high values reflect a strong commitment to sustainable agricultural practices and achieving the ecological objectives of the European Union. Other countries with significant shares, such as the Czech Republic (69.89%), Belgium (Wallonia) (68.53%), and the Netherlands (64.18%), demonstrate the implementation of effective agricultural policies in carbon storage and emission reduction during the 2023–2027 period. On the other hand, countries like Malta (5.97%), Cyprus (8.95%), and Ireland (8.88%) have lower shares of agricultural land dedicated to these commitments, suggesting a lower prioritization, while Romania (49.16%) and Greece (47.50%) have medium shares, indicating a moderate interest in promoting emission reduction and carbon storage measures, with potential for expanding these practices by 2030.

Figure 4 presents the overall target value of supported investments in renewable energy production capacity (in MW) in the agricultural sector for each country in the European Union, a target set until 2030. These investments include renewable energy sources such as bioenergy and are essential for achieving the energy sustainability objectives established by the European Green Deal and the Common Agricultural Policy. However, the integration of renewables into farming practices is often hampered by high upfront costs, limited access to advanced technologies, and a lack of adequate infrastructure, especially in rural regions of Eastern Europe.

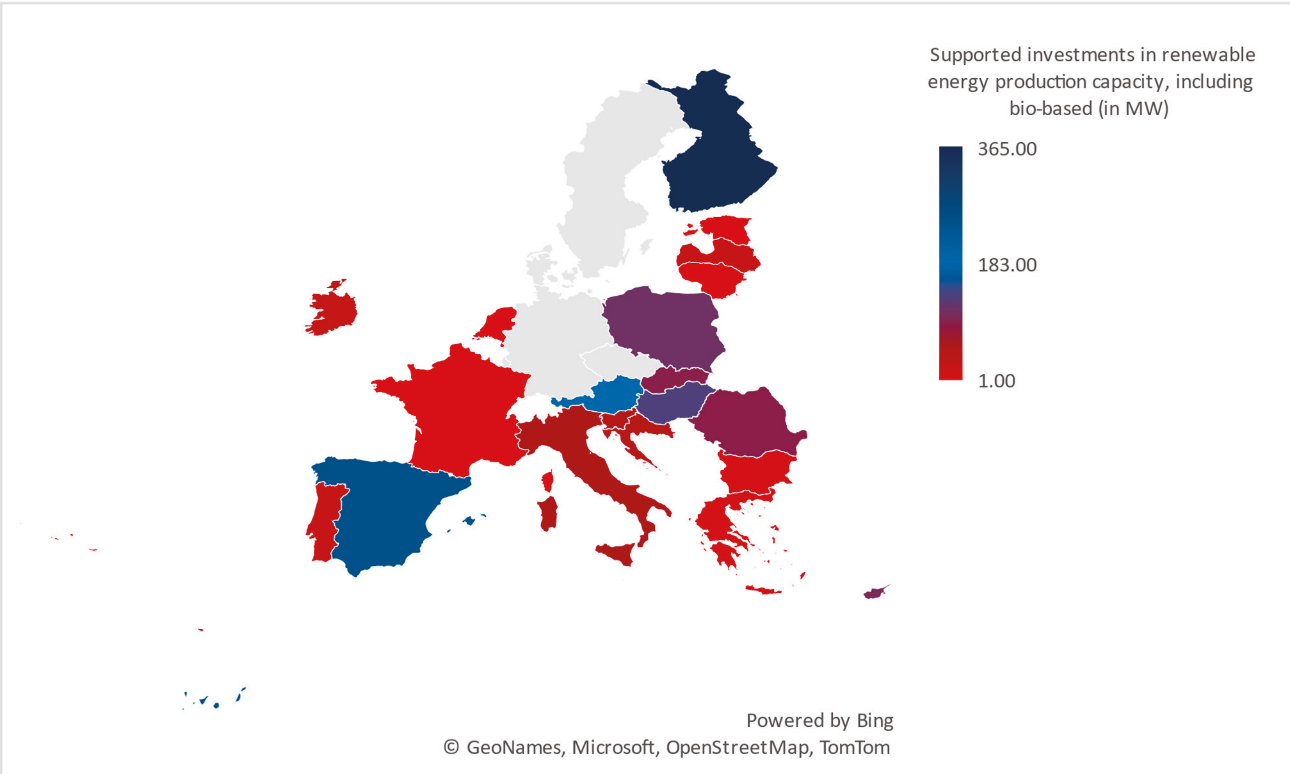
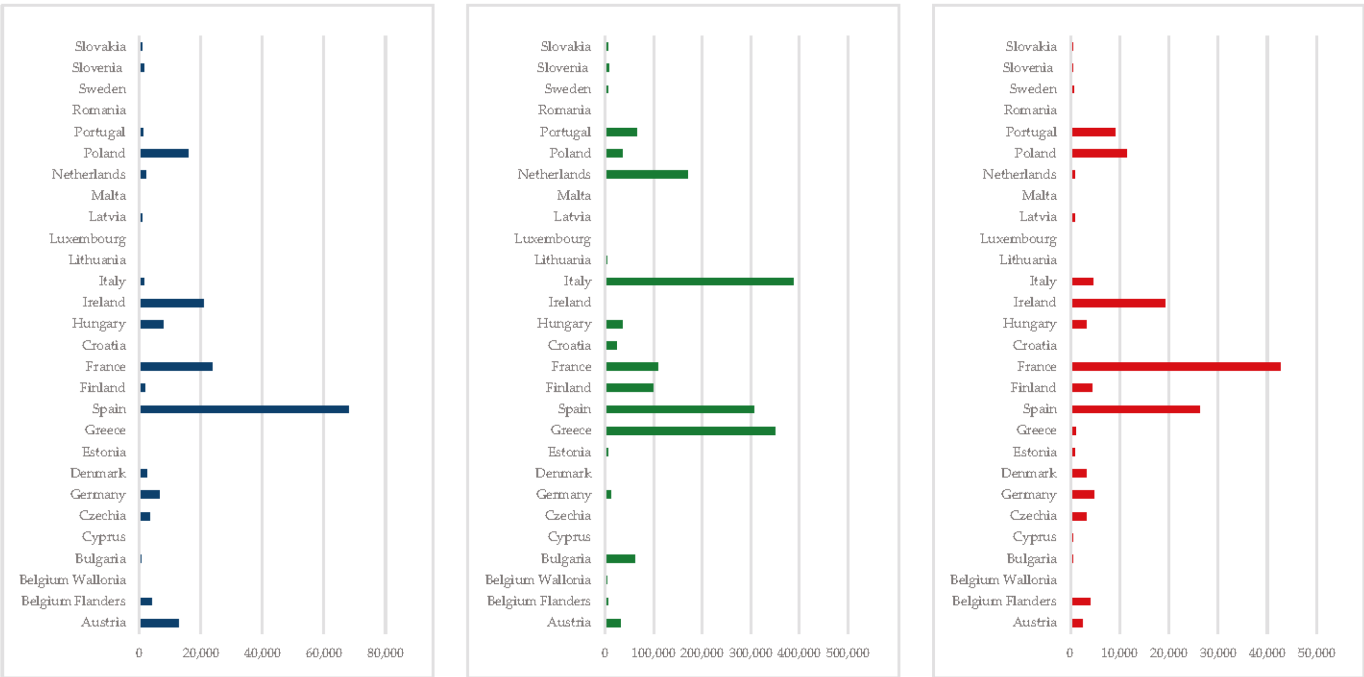


Figure 4. R.15 Renewable energy from agriculture, forestry, and other sources—sustained renewable energy production capacity (in MW). Source: own interpretation based on CSPs Master file and key data, Publications Office of the European Union [37].

Finland has the highest target for supported renewable energy capacity by 2030, with 365 MW, followed by Spain (251 MW) and Austria (182.25 MW). These high values indicate a strong commitment by these countries to invest in renewable energy in the agricultural sector, thus contributing to a transition to a more sustainable and less fossil fuel-dependent agriculture. Other countries with significant investments include Hungary (131.29 MW), Cyprus (101.88 MW), and Romania (89 MW), suggesting a proactive approach to promoting renewable energy at the national level. In contrast, in countries such as Belgium Wallonia (1.26 MW), out of the 132 million EUR allocated to renewable energy projects, modernized infrastructure and the increased costs reduce the access of small farmers to these technologies, and the infrastructure problem remains one of the most pressing [57]. In Lithuania (1.60 MW), the integration of green technologies is slow due to poor infrastructure, despite funding for solar panels and farm modernization [58], and in France (3.23 MW), although 1.2 billion EUR is allocated to support renewable energy sources, the complexity of administrative requirements and low access for small farms in France limit the expansion of projects [46]. A significant number of countries, including the Czech Republic, Germany, Denmark, Luxembourg, and Sweden, have not provided specific targets for this indicator. Investments in renewable energy production capacity play an essential role in achieving the objectives of the European Green Deal, reducing reliance on conventional energy sources and contributing to the reduction of greenhouse gas emissions. These variations suggest a need for increased coordination at the EU level to ensure a uniform energy transition and to support the Green Deal objectives, aiming to develop a more sustainable and energy efficient agricultural sector.

Figure 5 presents the targets related to the number of farms in each country ben-efiting from CAP investment support by 2030, aimed at mitigating and adapting to climate change, as well as producing renewable energy or biomaterials.



(**a**) (**b**) (**c**)

Figure 5. Support for farms and livestock units in the EU Member States for adaptation to climate change, emission reduction, and the production of renewable energy and biomaterials: (**a**) R.16: Number of farms benefiting from CAP investment support contributing to climate change mitigation and adaptation and to renewable energy or biomaterials production; (**b**) R.25: Number of livestock units for which a related payment was made; (**c**) R.26: Number of farms receiving relevant support. Source: own interpretation based on CSPs Master file and key data, Publications Office of the European Union [37].

Spain has the target of the highest number of supported farms by 2030, with 67,937 farms, indicating a considerable commitment of Spanish farmers to adopting sustainability and renewable energy measures, followed by France (23,617 farms) and Ireland (20,700 farms), suggesting an active promotion of these types of investments. Other countries with a sig-nificant number of supported farms include Poland (15,731 farms), Hungary (7612 farms), and Germany (6400 farms), showing a moderate involvement in supporting sustainable investments in agriculture, while countries like Malta (15 farms), Romania (138 farms), and Estonia (153 farms) have a very low number of supported farms, suggesting either a lack of sufficient support programs or a limited adoption of these measures by farmers by 2030.

Support for CAP investments that help farms mitigate the impact of climate change and contribute to the production of renewable energy (R.16) is essential for achieving the European Green Deal objectives. These investments help create a resilient and energy-efficient agricultural sector, promoting environmentally friendly practices. Countries with a large number of supported farms demonstrate a strong commitment to sustainability, being better positioned to meet the EU's climate targets. In contrast, countries with a low number of supported farms may need additional support or better structured policies to increase the adoption rate of sustainable measures in agriculture. This aspect highlights the need for efficient coordination at the EU level to ensure a uniform transition to sustainable agricultural practices in all Member States.

Regarding indicator R.25 (number of livestock units for which a related payment was made), Italy has the highest supported value, with 386,968 units, followed by Greece (350,404 units) and Spain (307,415.2 units), indicating a substantial commitment of these countries to implementing agricultural sustainability measures. Other countries with significant values include Finland (98,750 units), France (108,196 units), and the Netherlands (170,000 units), while countries with lower values include Malta (2133 units), Luxembourg (194 units), and Romania (2382 units).

Indicator R.26, "Number of farms receiving relevant support", reflects the im-portance of supporting the transition to greener agricultural and energy practices. France is in first place with 42,534 farms supported, followed by Spain (26,143 farms) and Ireland (19,167 farms), which highlights a high commitment to promoting sustainability measures. Other countries with a significant number of supported farms include Poland (11,426 farms) and Portugal (9101 farms), suggesting an increased degree of involvement in adopting sustainable practices. On the other hand, countries with a low number of supported farms, such as Malta (50 farms), Luxembourg (56 farms), and Lithuania (33 farms), may require additional attention to stimulate the transition to ecological agricultural practices.

Supporting a large number of farms in the implementation of sustainable practices is essential for achieving the objectives of the European Green Deal. Thus, countries with a large number of supported farms demonstrate a strong alignment with the environmental objectives of the European Union, promoting the reduction in emissions, the conservation of biodiversity, and the protection of natural resources; on the other hand, countries with a small number of supported farms could benefit from additional programs to encourage farmers to adopt ecological practices.

Under the European Green Pact, EU Member States have adopted policies and strategies tailored to national specificities, depending on existing infrastructure, local challenges, and economic priorities [59]. Thus, countries with significant budgetary allocations and advanced strategies, such as Austria, France, and Germany, stand out with generous financial allocations and complex plans to reduce carbon emissions and protect biodiversity. Austria is investing 3.4 billion EUR to preserve mountain pastures and support organic farming [60], while France is devoting 26% of its Common Agricultural Policy budget to reducing emissions and expanding organic areas [46]. Germany, with an ambitious target to increase organic farming to 30% by 2030, supports soil management and natural habitat conservation through well-defined financial schemes [61].

Countries such as Cyprus, Malta, and Greece, faced with the challenges of limited water resources, have adopted climate-adapted strategies. Cyprus and Malta are promoting water efficiency and the expansion of organic farming [50,62–64], while Greece is investing 1.4 billion EUR in reducing pesticide use and crop rotation, thus addressing the specific environmental problems of the Mediterranean region [63].

Bulgaria, Croatia, Latvia, and Lithuania are examples of countries in a transition process towards sustainability, with Bulgaria, for example, aiming to increase the former organic farming area to 200,380 ha [64] and Croatia supporting organic management of 12%

of its agricultural area [52]. In practice, these countries allocate resources to modernizing irrigation, reducing pesticides, and supporting less favored areas, while the Netherlands and Denmark stand out for policies that encourage the use of advanced technologies in agriculture. The Netherlands, with its intensive agriculture, is investing in precision farming and reducing emissions [47], while Denmark is prioritizing the development of biorefineries and crop diversification to reduce emissions by 55–65% by 2030 [65].

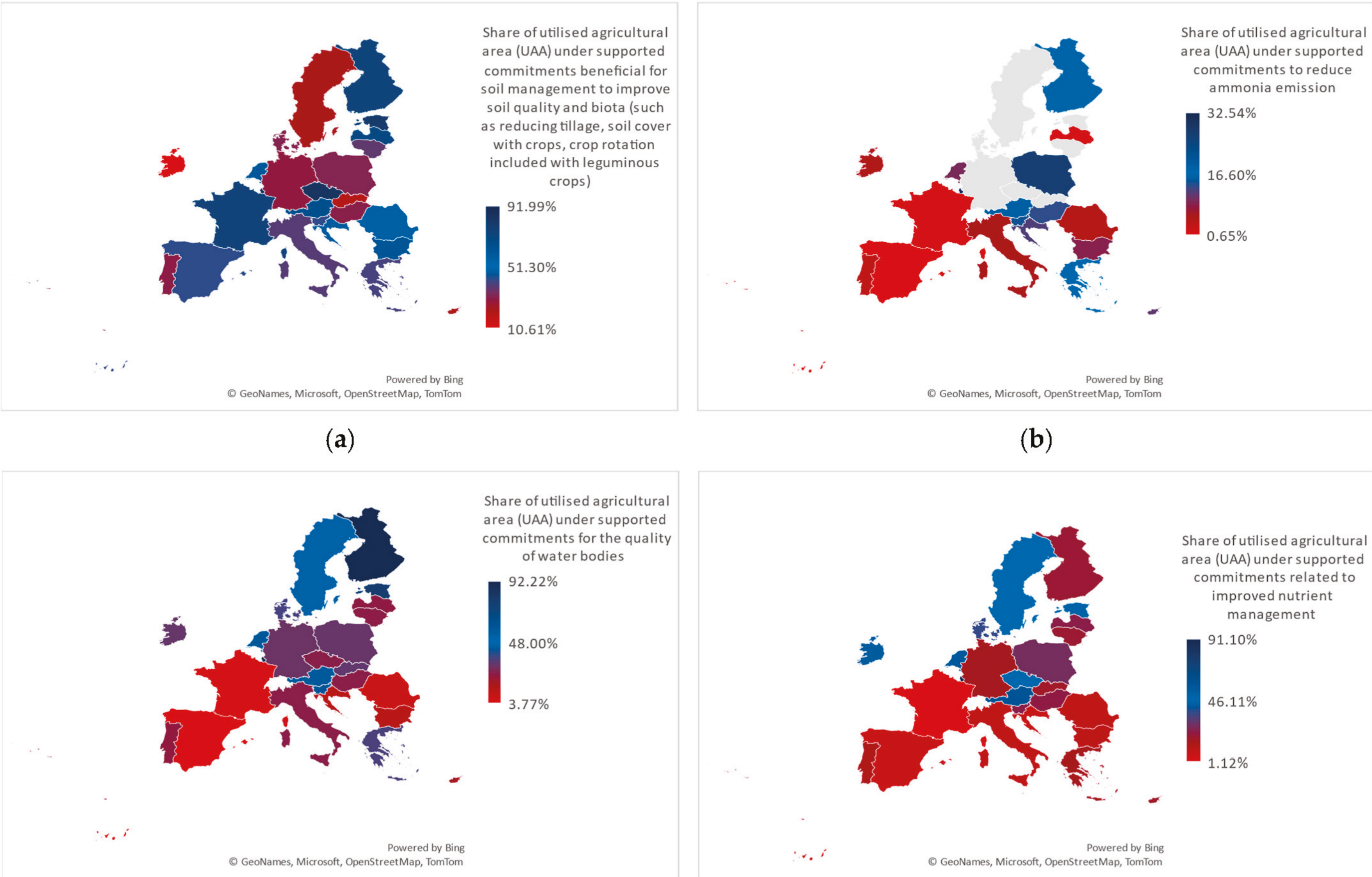
Countries such as Luxembourg, Portugal, and Slovakia are putting particular emphasis on supporting small farmers and rural areas. Luxembourg invests in schemes to preserve biodiversity and support small farmers [66], while Portugal promotes sustainable irrigation and soil protection [67].

4.2. Sustainable Management of Natural Resources and Energy Efficiency in Agriculture to Meet the Objectives of the European Green Deal

Implementing the Green Deal objectives in agriculture largely depends on the CAP's ability to support clear energy and environmental measures, backed by efficient national strategic plans [46], and to achieve the EU's ambition to become the first climate neutral bloc by 2050 and to reduce greenhouse gas emissions by 55% by 2030. It is essential to intensify efforts to improve energy efficiency [59,68]. In this regard, the European Commission has committed to reviewing the current legislation, including the Energy Efficiency Directive (EED) [69], to adapt it to the new 2030 target. The review process was initiated in the summer of 2020 with the launch of the roadmap and the initial impact assessment, providing the public with an opportunity to give feedback. In parallel, a series of stakeholder workshops were organized, held from September to November 2020, to collect suggestions related to the evaluation of the existing Directive and potential improvement solutions. The Commission is currently analyzing these contributions, which will be integrated into the preparations for the future review of the Energy Efficiency Directive [70].

Figure 6 illustrates the commitments (targets) of EU Member States regarding sustainability in agriculture by 2030, focusing on the protection of essential natural resources. It presents four key indicators of agricultural sustainability, according to the Common Agricultural Policy and the European Green Deal objectives [71]: indicator R.19 reflects each country's efforts to improve and protect soils, including through sustainable land management practices; R.20 highlights commitments to reduce ammonia emissions, a major air pollutant; R.21 aims to protect water quality by implementing agricultural practices that reduce water pollution; and R.22 focuses on sustainable nutrient management to reduce soil and water pollution and maintain fertility. These indicators underline the diversity of Member States' approaches to environmental protection and alignment with the EU's sustainability objectives.

Figure 6a presents the percentage of utilized agricultural area (UAA) in each European country that benefits from commitments to sustainable soil management, including measures to improve soil quality and biodiversity by 2030. Such practices are essential not only for sustainable agricultural policies but also for the European Green Deal, having a positive impact on energy consumption in agriculture. Thus, countries like Luxembourg (91.99%), Czech Republic (85.07%), and Estonia (79.62%) have the highest projected targets by 2030, and France (74.07%), Finland (73.93%), and Latvia (69.73%) also show significant commitment. In contrast, Ireland (10.61%), Malta (11.04%), and Cyprus (21.47%) have low values. Sustainable soil management is important not only for soil health and biodiversity but also for energy efficiency, as practices that improve soil structure and fertility can reduce the need for energy inputs such as fertilizers and intensive labor, thus contributing to the EU's sustainability objectives. Therefore, coordination at the EU level can support all Member States in the transition to a more energy efficient and ecologically sound agricultural sector. In Ireland, although biogas and solar panels are supported, large-scale uptake is limited by high costs and lack of technical expertise [72], while in Malta, constraints related to small land area and unfavorable climatic conditions are significant barriers to the integration of renewable sources, despite available funding [72].



(**a**) (**b**) (**c**) (**d**)

Figure 6. The sustainability commitments (targets) in the agriculture of the EU Member States for the protection of natural resources until 2030: (**a**) R.19: Improving and protecting soils, (**b**) R.20: Improving air quality by reducing ammonia emissions, (**c**) R.21: Water quality protection, (**d**) R.22: Sustainable nutrient management. Source: own interpretation based on CSPs Master file and key data, Publications Office of the European Union [37].

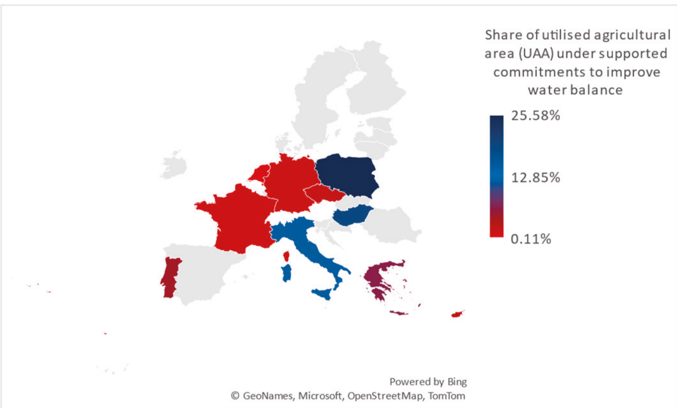
Figure 6b illustrates the share of utilized agricultural area (UAA) benefiting from commitments to reduce ammonia emissions, a key element of the European Union's environmental policies due to ammonia's impact on air quality and atmospheric pollution. Luxembourg leads with 32.54% of agricultural land dedicated to these measures, followed by Poland (26.81%) and Belgium (Wallonia) (22.41%), reflecting significant commitment to reducing emissions. Finland (17.59%), Greece (16.87%), and Slovenia (14.30%) have moderate values, demonstrating involvement, while Spain (0.65%), France (1.12%), and Ireland (4.88%) have smaller shares, which may suggest the prioritization of other objectives or difficulties in implementation by 2030. Reducing ammonia emissions also has a positive impact on energy efficiency in agriculture, as practices such as efficient manure management and the use of controlled-release fertilizers help reduce energy inputs by minimizing nutrient losses. These measures support the European Green Deal objectives, promoting more sustainable agriculture and reducing energy costs associated with intensive fertilization.

Figure 6c shows the percentage of utilized agricultural area (UAA) in each European country engaged in measures to improve water quality, essential for reducing pollution and sustainably using water resources, thus contributing to the European Green Deal objectives. Finland (92.22%), Luxembourg (91.99%), and Estonia (77.70%) have the highest shares of agricultural land dedicated to water protection, suggesting a high commitment to conserving water resources. Other countries with significant shares, such as the Netherlands (57.81%), Austria (56.65%), and Sweden (51.75%), demonstrate substantial involvement in maintaining water quality through sustainable agricultural practices. In contrast, Spain (3.77%), France (4.98%), and Romania (8.09%) have low shares. Water protection measures have a positive impact on energy efficiency by reducing the need for intensive inputs such as fertilizers and limiting the energy consumption associated with treating contaminated water.

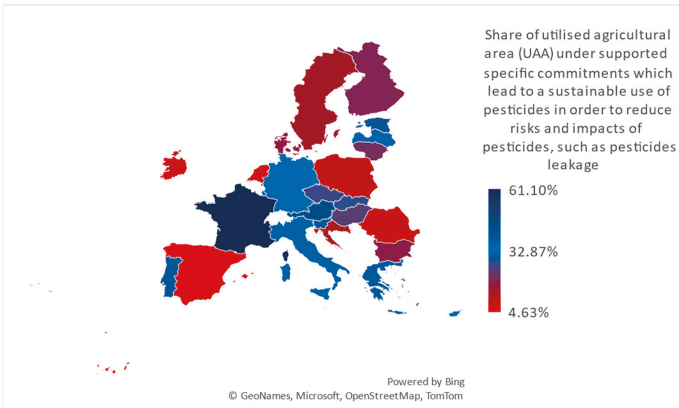
Figure 6d presents the share of utilized agricultural area (UAA) in each country benefiting from commitments to improved nutrient management, an essential element for reducing pollution, improving soil fertility, and minimizing environmental impact, according to the European Green Deal objectives. Luxembourg has the highest share (91.10%) of agricultural land dedicated to sustainable nutrient management, suggesting a significant commitment to these practices. Other countries with high values include Austria (58.09%), the Netherlands (55.06%), and the Czech Republic (45.99%), highlighting the adoption of practices that reduce the use of chemical fertilizers and runoff into surface waters. Ireland (42.44%) and Sweden (46.63%) also have important shares, suggesting active support for maintaining soil fertility and reducing pollution. In contrast, France (1.12%), Spain (5.61%), and Croatia (5.91%) have lower shares, indicating either limited adoption of these measures or the prioritization of other environmental objectives by 2030.

Improved nutrient management directly contributes to energy efficiency in agriculture by reducing dependence on synthetic fertilizers, which involve high energy consumption, and through sustainable nutrient use practices, thus not only supporting soil and water health but also reducing energy costs associated with agricultural production.

Figure 7 highlights the commitments (targets) of the Member States of the European Union for the sustainable use of resources in agriculture until 2030, focused on two critical aspects of sustainable management: R.23—sustainable use of water, aiming at improving the water balance and reducing excessive water consumption, and R.24—the sustainable use of pesticides, aimed at reducing the risks and the negative impact on the environment.



(**a**)



(**b**)

Figure 7. The commitments (targets) of EU Member States for the sustainable use of resources in agriculture until 2030: (**a**) R.23: Sustainable use of water to improve the water balance, (**b**) R.24: Sustainable use of pesticides to reduce risks and the impact on the environment. Source: own interpretation based on CSPs Master file and key data, Publications Office of the European Union [37].

These commitments are essential for achieving the environmental objectives of the European Green Deal, contributing to the protection of natural resources and the promotion of ecological agricultural practices. Responsible use of water in agriculture prevents water scarcity and conserves resources in the long term, while sustainable pesticide management reduces soil and water contamination and protects biodiversity.

Figure 7 highlights the variability of national approaches to adopting these sustainable practices and underlines the importance of a coordinated strategy at EU level to uniformly support the transition to a greener, more energetic, and resilient agriculture by 2030.

Figure 7a presents the share of utilized agricultural area (UAA) in each country benefiting from commitments to improve water balance. These commitments are essential for the sustainable management of water resources, reducing excessive consumption, and preventing pollution, contributing to the European Green Deal objectives and energy efficiency. Poland (25.58%), Hungary (18.94%), and Italy (11.81%) show a strong commitment to these practices, limiting water consumption and the energy needed for intensive irrigation. Countries with lower shares, such as the Netherlands (0.11%) and Germany (1.21%), could benefit from additional support to adopt similar measures, ensuring a sustainable and equitable use of water resources at the European level by 2030.

Figure 7b shows the percentage of utilized agricultural area (UAA) in each country engaged in the sustainable use of pesticides to reduce their risks and impact on the environment. France (61.10%), Austria (44.78%), and Slovenia (40.24%) have the highest shares, reflecting concern for reducing the impact of pesticides and protecting the environment. Italy (36.21%), Luxembourg (36.36%), and Latvia (34.82%) also demonstrate a significant commitment to these sustainable practices by 2030. The sustainable use of pesticides supports not only soil and water protection but also energy efficiency, as reducing repeated applications of chemicals decreases energy consumption. Countries with lower shares, such as Spain (4.63%) and the Netherlands (6.50%), could benefit from additional support to adopt similar practices.

4.3. Conservation of Biodiversity, Landscape, and Energy Efficiency in the Promotion of Ecological Agriculture

The new Common Agricultural Policy offers opportunities for European agriculture to actively contribute to achieving the ambitious objectives of the European Green Deal [73], but success depends on several factors, including implementation at the national and regional levels, funding availability, and effective monitoring. The European Commission launched the proposal to reshape the post-2020 CAP with the aim of aligning EU agriculture with the objectives set out in the Paris Agreement and the United Nations Sustainable Development Goals [74]. The proposal also reflects the EU's commitment to reducing greenhouse gas emissions, aiming for a 40% reduction by 2030 compared to 1990 levels. This modernization is essential to increase the added value of the CAP and to respond to concerns related to the sustainability of agricultural production.

In 2019, the European Green Deal introduced a new framework for the sustainable transformation of the economy, setting the EU to achieve climate neutrality by 2050, with a 55% reduction in emissions by 2030. The Green Deal includes the "Farm to Fork" Strategy and the Biodiversity Strategy, which aim to integrate economic, environmental, and social aspects across the entire food chain and ensure the sustainability of agriculture. The new CAP framework includes a flexible delivery model, giving Member States the possibility to develop national strategic plans adapted to their needs [75]. This model encourages ecological agricultural practices through mandatory standards and eco-schemes designed to support the transition of farmers to more environmentally friendly practices. However, many of these initial proposals have been diluted, and the eco-schemes risk being perceived more as income support than as tools for ecological transition. The CAP's effectiveness in supporting the Green Deal will largely depend on the ambition of each member state's strategic plans, the resources allocated, and their monitoring capacity. The European Commission will review and approve these strategic plans, although it relies more on dialogue than on coercive measures, raising concerns about the effectiveness of this model and the fact that Member States might view CAP funds as "national property", without considering ecological performance standards.

Figure 8 illustrates the percentage of utilized agricultural area (UAA) in each country, supported by the Common Agricultural Policy for the development of organic farming, differentiated between the maintenance of already organic lands and the conversion of conventional lands to organic practices. CAP support for organic farming plays a central role in creating a sustainable agricultural system, reducing the use of pesticides and synthetic fertilizers, protecting biodiversity, and promoting environmentally friendly practices. This support contributes to achieving the environmental objectives of the European Green Deal, facilitating the transition to agricultural practices with a lower impact on ecosystems and natural and energy resources.

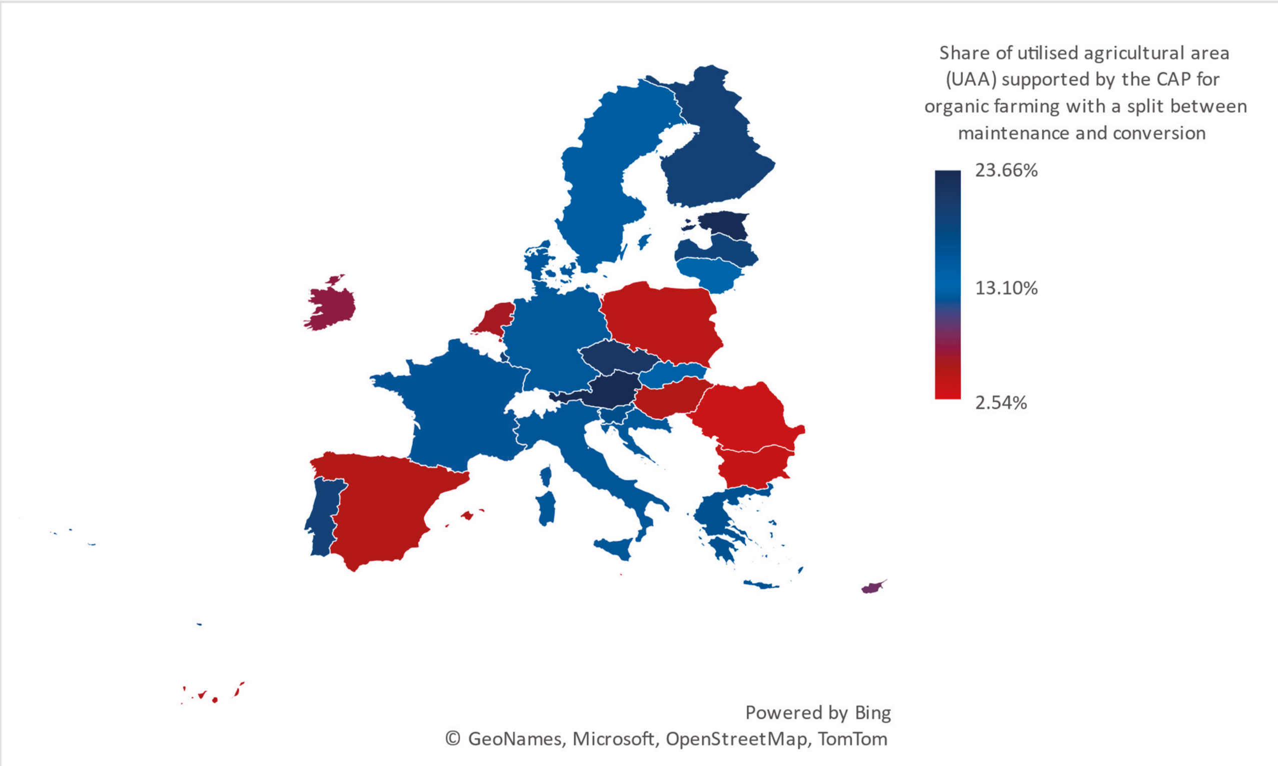


Figure 8. R.29: Development of organic agriculture—percentage of UAA supported by the CAP for organic agriculture, differentiated between maintenance and conversion. Source: own interpretation based on CSPs Master file and key data, Publications Office of the European Union [37].

Indicator R.29 presents the share of utilized agricultural area (UAA) in each country, supported by the Common Agricultural Policy for organic farming, divided between the maintenance of already organic lands and the conversion of conventional lands to organic practices. This support contributes to a more sustainable agricultural system, reducing reliance on pesticides and synthetic fertilizers, protecting biodiversity, and promoting ecological and energy efficient practices.

Organic farming has a positive impact on energy consumption by reducing chem-ical inputs and resources needed in intensive agricultural processes. Austria (23.66%) and Estonia (23.27%) have the highest shares dedicated to organic farming, reflecting strong commitment, while the Czech Republic (21.28%), Luxembourg (19.84%), and Finland (19.44%) also have high shares, demonstrating active support. Austria has allocated approximately 3 billion EUR for biodiversity conservation measures, a significant investment in protecting mountain pastures and agricultural land [60]. More than 76,000 hectares of pastures and about 30% of agricultural land are included in eco-schemes to protect biodiversity. In practice, these measures have had a positive impact on the conservation of natural habitats and reduced pressures on vulnerable ecosystems; however, challenges remain in the effective management of mountainous land where accessibility conditions and agricultural infrastructure are limited.

Estonia has allocated 456 million EUR for environmental and biodiversity measures; 23% of agricultural land is managed organically, and over 70,000 hectares of grassland are supported for conservation [48]. Through these measures, Estonia has supported the protection of biodiversity and the improvement of soil quality, but their effectiveness depends on continued financial support and working with local farmers.

Countries such as Malta (2.54%), Poland (4.53%), and Romania (3.53%) have low shares, indicating either limited uptake of environmentally friendly practices or the need for additional transition stimulus by 2030. Malta faces significant challenges in biodiversity conservation due to the country's small size and limited natural resources. However, 10 million EUR has been allocated annually for biodiversity conservation projects, focusing on the protection of endemic species and the conservation of water resources [50]. Measures adopted include the protection of natural areas and the promotion of organic farming, especially for small farms, but their implementation is limited by the small agricultural area and the climatic conditions, which are drier and less favorable for agricultural diversification. Some progress has been made in protecting endemic species and managing water resources, but further strategies are needed to address the challenges of limited land and drought.

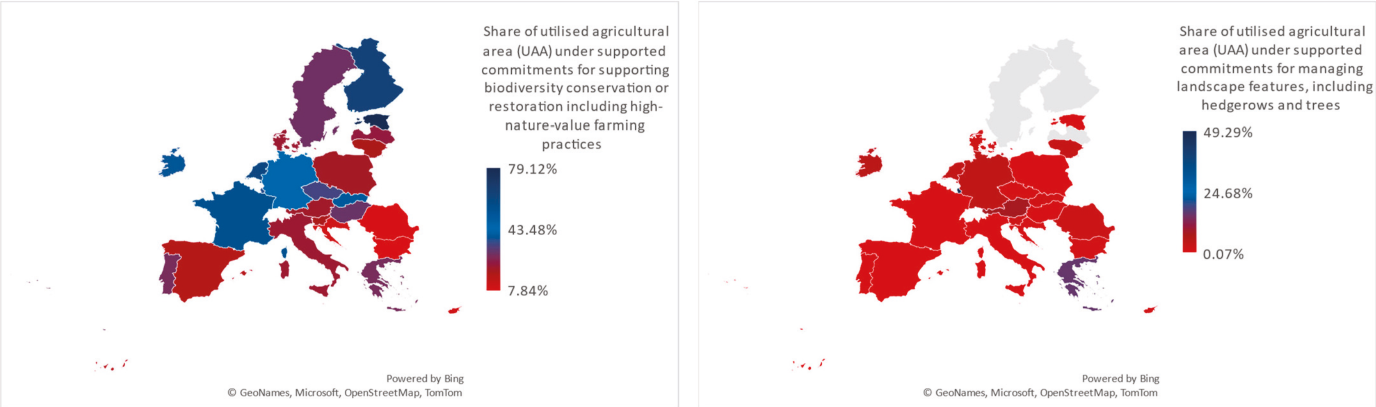
Poland has earmarked 860 million EUR for biodiversity conservation measures, including schemes to reduce pesticides and support the expansion of organic farming [76]. Almost 15% of Polish farms are involved in ecological farming practices, and various organic schemes are aimed at protecting natural habitats and vulnerable species. Poland has also implemented measures to protect aquatic ecosystems and forests, and the effectiveness of the measures has been visible in reducing pesticide use and promoting more sustainable farming practices. However, difficulties stem from the underdeveloped agricultural infrastructure in many rural regions and the resistance of small farmers to change traditional production methods. In addition, Poland faces significant land fragmentation, which makes it difficult to implement measures on a large scale.

Romania has included around 2 million hectares in biodiversity conservation schemes, with a strong focus on less favored areas, which account for a significant percentage of the country's agricultural land [49]. The measures adopted include eco-schemes for crop rotation, soil protection, and conservation of protected areas, as well as support for farmers adopting sustainable farming methods. These schemes are essential for the conservation of biodiversity in mountainous regions and ecologically fragile land areas, and the effectiveness of these measures can be seen in protecting natural habitats and reducing soil erosion. However, Romania faces major challenges related to weak agricultural infrastructure, lack of technical knowledge among small farmers, and the need for additional incentives to integrate these sustainable practices in all regions of the country. In addition, the large scale implementation of conservation measures in disadvantaged regions may be hampered by economic conditions and farmers' lack of access to EU funds dedicated to the implementation of these projects.

Organic farming plays a key role in achieving the objectives of the European Green Deal by protecting natural resources and reducing the energy footprint. Thus, extended support for organic farming can contribute to a fair transition and a more resilient and sustainable European agricultural sector by 2030. These commitments highlight the differences between Member States in adopting organic farming, suggesting the need for a coordinated EU strategy to encourage equitable expansion of land dedicated to organic farming. Such an approach would support Europe's green transition and contribute to a more sustainable and environmentally friendly agricultural system by 2030.

Figure 9 presents the commitments of EU Member States for the conservation of biodiversity and landscape in agriculture, highlighting two essential aspects: R.31—Conservation of habitats and species, which promotes agricultural practices that protect local ecosystems and species, and R.34—Conservation of landscape features, including natural elements such as hedges and trees, contributing to biodiversity maintenance and the improvement of agricultural habitat quality. These commitments supported by the Common Agricultural

Policy are essential for achieving the objectives of the European Green Deal, promoting environmentally friendly agriculture and supporting the stability of ecosystems and natural resources in European agricultural landscapes.



(**a**) (**b**)

Figure 9. Commitments (targets) for biodiversity and landscape conservation in agriculture until 2030: (**a**) R.31: Conservation of habitats and species, (**b**) R.34: Conservation of landscape characteristics. Source: own interpretation based on CSPs Master file and key data, Publications Office of the European Union [37].

Figure 9a indicates the proportion of utilized agricultural area (UAA) in each country engaged in the conservation and restoration of biodiversity by 2030, through high ecological value agricultural practices supported by the Common Agricultural Policy. These commitments contribute essentially to maintaining ecological diversity, protecting natural habitats, and supporting a healthy environment while reducing dependence on intensive energy inputs such as chemical fertilizers and pesticides. However, in less developed regions, the implementation of these measures remains limited, due to insufficient resources and economic priorities that often take precedence over environmental ones. The impact of these measures on ecosystems needs to be monitored, given the risk of unexpected ecological imbalances.

Estonia leads with 79.12% of agricultural land dedicated to biodiversity, followed by Finland (64.12%) and the Netherlands (60.56%), values that underline these countries' commitment to sustainable agricultural practices. France (55.67%), Slovakia (50.94%), and Germany (45.19%) also demonstrate significant involvement, contributing to reducing the agricultural impact on ecosystems. Countries with lower shares, such as Romania (7.93%), Bulgaria (7.84%), and Malta (10.59%), could benefit from additional support to expand ecological areas and align with the European Green Deal standards.

France has earmarked 26% of the CAP budget for biodiversity protection [46], so eco schemes include Natura 2000 areas, supporting the protection of natural habitats on 2.4 million hectares. The effectiveness of the measures is visible in diversifying habitats and reducing soil erosion; however, in intensive agricultural regions, their integration can be more difficult due to costs and farmers' resistance. While Germany has dedicated 1.7 billion EUR to biodiversity conservation, and grassland protection and soil management schemes cover 1.9 million hectares, the measures have had a significant impact on biodiversity protection and reducing the use of fertilizers [61].

Supporting biodiversity in agriculture not only protects ecosystems but also increases energy efficiency by reducing the use of intensive external resources. Thus, an equitable distribution of these measures would contribute to a more sustainable and energy-efficient European agricultural system. The EU strategy could stimulate Member States to adopt uniform conservation measures, benefiting a stable ecological balance and a more resilient agricultural sector, efforts that support Europe's transition to a green agricultural system, aligned with the European Union's environmental objectives.

Figure 9b shows the share of utilized agricultural area (UAA) in each country dedicated to landscape feature management commitments, such as hedges and trees. These natural elements play an essential role in biodiversity conservation, improving the quality of agricultural habitats, and soil protection, in line with the European Green Deal objectives and supported by the Common Agricultural Policy. Luxembourg, with a share of 49.29% of UAA dedicated to landscape management, shows major involvement in biodiversity conservation and agricultural ecosystem protection. Other countries, such as Greece (15.84%) and Ireland (4.69%), also have notable values, suggesting an interest in maintaining the natural features of the agricultural landscape. In contrast, Belgium (Flanders), Poland, and Spain have shares below 0.5%, which may indicate either low prioritization of these measures or the need for additional support to promote landscape management.

Greece has earmarked 425 million EUR for biodiversity eco-schemes, which include crop rotation and the protection of mountain regions [63]. These measures have had a positive impact in protecting biodiversity, but their large-scale integration in less developed regions remains a challenge due to high costs and limited infrastructure, while Ireland has allocated 1.4 billion EUR to support biodiversity and 32% of agricultural land benefits from conservation schemes [72]. Over 50,000 farmers are involved in these schemes, and their effectiveness can be seen in improving soil quality and protecting natural habitats.

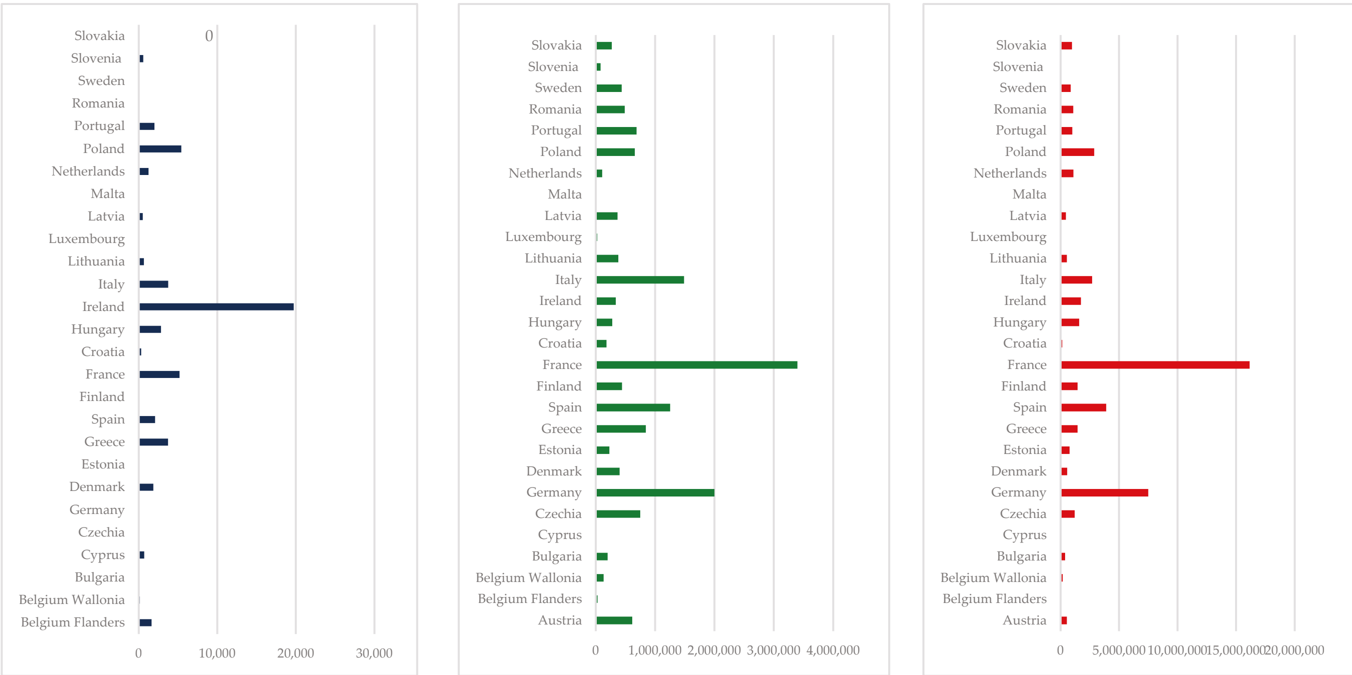
Managing agricultural landscape features indirectly contributes to energy efficiency, as hedgerows and trees reduce soil erosion and protect local ecosystems, minimizing the need for energy inputs associated with soil restoration and intensive fertilizer application. Additionally, conserving the agricultural landscape contributes to ecosystem stability, reducing agricultural impact on the climate and supporting a more sustainable agriculture. Expanding the management of agricultural landscapes can contribute to an ecological, environmentally friendly, and energy-efficient agriculture, aligned with the European Green Deal objectives.

Figure 10 illustrates the support provided by the Common Agricultural Policy for biodiversity conservation and the promotion of organic farming in the European Union by 2030. This includes three key aspects: (a) the number of farms benefiting from biodiversity investments, (b) the area of land dedicated to organic farming (in paid hectares), and (c) the area of land supported for habitat and species conservation. This support is essential for achieving the environmental objectives of the European Green Deal by encouraging farmers to adopt sustainable and ecological practices. The figure highlights the different commitments (targets) of EU countries in implementing these measures, emphasizing the importance of a coordinated strategy to support a greener, more resilient, and environmentally friendly agricultural sector across the European Union by 2030.

Figure 10a presents the number of farms in each country benefiting from CAP support for biodiversity investments by 2030. This support helps farmers adopt environmentally friendly practices, contributing to biodiversity conservation and achieving the European Green Deal objectives. Supporting biodiversity not only protects ecosystems but also reduces the need for energy inputs in agriculture, as farms that integrate natural elements benefit from greater resistance to diseases and pests, diminishing the use of pesticides and fertilizers. Ireland records the highest number of supported farms (19,733), reflecting a strong commitment to ecological farming practices. Poland (5420), France (5190), and Italy (3754) also demonstrate substantial involvement, while Malta (25 farms), Romania (62), and Sweden (83) have a low number of beneficiary farms, suggesting either a different prioritization of resources or a need for additional support.

Figure 10b shows the number of hectares supported for the development of organic farming. France stands out with the largest area (approximately 3,398,864 hectares), followed by Germany, Spain, and Italy. These values reflect major investments in organic farming, which contribute to reducing the use of pesticides and synthetic fertilizers, supporting biodiversity and environmental protection. In contrast, countries like Malta and

Cyprus have small areas dedicated to organic farming, suggesting a potential need for additional support by 2030.



(**a**) (**b**) (**c**)

Figure 10. CAP support for the conservation of biodiversity and the development of organic agriculture until 2030: (**a**) Investments in biodiversity—the number of beneficiary farms, (**b**) Development of organic agriculture—the number of hectares paid, (**c**) Conservation of habitats and species—the number of hectares paid. Source: own interpretation based on CSPs Master file and key data, Publications Office of the European Union [37].

Figure 10c presents the number of hectares supported for habitat and species conservation. France leads with 16,157,172 hectares, followed by Germany and Spain with considerable areas. This support is vital for maintaining biodiversity, protecting natural habitats, and reducing the agricultural impact on the environment. Countries with small areas, such as Malta and Cyprus, could benefit from additional resources to expand these conservation measures.

The figures underline the EU's commitment to biodiversity conservation, landscape protection, and energy efficiency in agriculture. By supporting organic farming and habitat conservation, the CAP promotes a sustainable agricultural sector, reducing dependence on intensive energy inputs and supporting biodiversity, and the differences between Member States suggest the need for coordinated support to expand these practices, ensuring equitable application of environmental measures throughout the European Union.

5. Discussion

The new Common Agricultural Policy brings a more pronounced ecological orientation, part of the European Union's sustained efforts to manage climate, energy, and biodiversity crises [77]. The European Green Deal includes all economic sectors in the transition to sustainability, but agriculture plays an essential role. With a contribution of approximately 10% to greenhouse gas emissions and being a significant factor in biodiversity loss, this sector must respond to sustainability needs through new practices and policies [70,78]. European agriculture, although it has massively contributed to the continent's food security, now faces the challenge of adapting to a changing environment and, implicitly, the need to implement more sustainable practices [79]. The new CAP proposes a performance-based model, evaluating and rewarding farmers not only for production but also for their contributions to climate, energy, and biodiversity [80]. This transition to a performance-based system is thus necessary and urgent, considering its impact on the environment, energy, and natural resources essential for agriculture. Farmers need a CAP that genuinely supports them in facing climate, energy, and biodiversity challenges, rewarding them for their efforts in environmental and energy conservation and emission reduction. These measures will bring long-term benefits to both agriculture and society, contributing to food security and protecting Europe's natural resources.

For the CAP to effectively contribute to the European Green Deal objectives, a much more ambitious approach is needed regarding the implementation and evaluation of environmental and energy impacts. Despite greening intentions, as highlighted by the European Court of Auditors (ECA) [81], many of the measures introduced so far have not produced the desired effects on biodiversity and reducing energy and climate impact. A significant issue is that farmers have continued to apply the same practices without being encouraged to adopt more sustainable methods, as the sanctions for non-compliance with energy and environmental requirements have not been sufficiently dissuasive. A major point of interest in the new CAP is the flexibility granted to Member States, which have the freedom to define their own objectives and measures through national strategic plans [82]. This degree of autonomy, while allowing adaptation to each state's specifics, also brings the risk that environmental and energy ambitions may fall short of the expecta-tions set at the European level.

Agriculture and climate change are closely interconnected, and the data show that the agricultural sector in the EU is responsible for approximately 15% of greenhouse gas emissions [83]. Thus, measures within the Common Agricultural Policy must actively contribute to achieving the EU's environmental, energy, and climate objectives, from reducing GHG emissions to protecting biodiversity and energy efficiency. A central aspect of the European Green Deal is the evaluation of Member States' CAP strategic plans to ensure that they align with the pact's objectives [84]. In the Special Report 5/2018 [85], the ECA emphasized the importance of renewable energy in reducing GHG emissions, encouraging its integration into sustainable rural development through support from the European Agricultural Fund for Rural Development. Although renewable energy has the potential to support rural development, the report revealed that synergies between renewable energy policies and rural development remain insufficiently exploited [86].

Within the CAP, EU Member States have set national targets for reducing emissions in the agricultural sector [87]; however, the analysis results highlight considerable variations in the level of commitment and the capacity to implement these measures, reflecting an unequal situation between Member States. In Western and Northern European states, such as France, Finland, and the Netherlands, commitments to reducing agricultural emissions are higher. Indicator R.12 shows that France has allocated 65.27% of its UAA for climate adaptation measures. This substantial value is partly due to investments in energy efficiency technologies and agricultural practices that contribute to carbon capture and storage in soils. Finland and the Netherlands also present high values of 64.61% and 64.15%, respectively, reflecting a solid integration of climate adaptation policies into national agricultural strategies. These states are characterized by policies that support the transition to sustainable agricultural practices and the allocation of significant financial resources to improve agricultural capacity to reduce emissions. In contrast, Eastern European countries, such as Romania and Estonia, face major challenges in implementing measures to adapt agriculture to climate change. For example, Estonia has allocated only 0.01% of its UAA for climate adaptation measures, and Romania records a similar value, indicating a considerably lower allocation of resources compared to other Member States. This discrepancy can be explained by the lack of support infrastructure, adequate funding, and national agricultural policies that actively support climate adaptation objectives.

Another essential aspect of reducing emissions in the agricultural sector is investments in renewable energy capacities. Indicator R.15 within the CAP measures the renewable energy production capacity supported in agriculture, showing significant differences between Member States in terms of commitments and results achieved.

Finland and Spain stand out for notable investments in renewable energy within the agricultural sector, with the renewable energy capacity supported being in Finland365 MW and in Spain 251 MW, reflecting strong commitments to developing sustainable energy in agriculture. In Finland, for example, investments in bioenergy and solar energy on farms have been promoted, thus contributing to reducing dependency on fossil fuels and the GHG emissions associated with using conventional energy resources. In Spain, investments in renewable energy are integrated into the national strategy for reducing emissions and supporting the transition to sustainable agriculture, and the 251 MW production capacity supported by the CAP includes sources such as solar energy and biomass, which are essential for achieving the environmental targets set at the European level. Thus, Spanish investments in agricultural energy infrastructure directly contribute to the Green Deal objectives, ensuring the transition to a low-carbon agricultural sector. However, in other Member States, such as Belgium (Flanders) and Lithuania, renewable energy production capacities in agriculture remain at extremely low levels. Belgium (Flanders) has a supported capacity of only 1.26 MW, and Lithuania's capacity is 1.60 MW, these values being negligible compared to the investments made by Finland and Spain. In these countries, the implementation of renewable energy infrastructure is limited by economic factors and the lack of adequate infrastructure, making it difficult to achieve national environmental objectives.

EU Member States are implementing diverse strategies, tailored to their specific contexts, to meet these ambitious targets, taking into account economic, social, and geographical challenges. For example, Austria is allocating 3.4 billion EUR to reduce carbon emissions, focusing on preserving mountain landscapes and biodiversity. Thus, by supporting farmers in disadvantaged areas, including eco-schemes and incentives for organic farming, Austria is addressing the challenges of soil protection and reducing greenhouse gas emissions, and mountain pasture conservation plays a key role by providing natural solutions for carbon storage and habitat protection [60].

Belgian strategies emphasize the need for integrated regional approaches adapted to geographical and socio-economic diversity. Thus, in Wallonia [57], 56% of the rural development budget is dedicated to environmental protection, with measures to conserve biodiversity in protected areas and promote organic farming, and in Flanders [55], 25% of direct payments are reserved for eco-schemes, with a focus on reducing chemical fertilizers and preserving biodiversity.

With only 2.25% of the agricultural area managed organically [64], Bulgaria aims to expand this to 200,380 hectares. The strategy includes the modernization of irrigation systems, pesticide reduction, and crop rotation with the aim of protecting water and soil resources, while investment in agricultural infrastructure and the promotion of sustainable practices will enable Bulgaria to meet its environmental targets, while Croatia plans to devote 12% of its agricultural area to organic farming methods [52]. Supporting extensive grassland and permanent crops is a priority, thus addressing biodiversity loss and soil degradation, and support programs for farmers are key in this process, providing financial and technical incentives for the transition to sustainable practices.

In an arid climate, water resources in Cyprus are critical, so the national treaties include the promotion of water efficiency and conversion of agricultural land to organic methods, which are essential to protect fragile ecosystems and ensure climate resilient agriculture, while Denmark aims to reduce emissions by 55–65% by 2030, focusing on biorefinery development and crop diversification, which help reduce dependence on fossil fuels and promote circular and sustainable farming patterns.

With 23% of agricultural land managed organically, Estonia supports agricultural cooperatives to increase farmers' competitiveness, and sustainable grassland management is another priority, helping to preserve biodiversity and store carbon in soils [48], while France devotes 26% of its CAP budget to reducing carbon emissions and protecting biodiversity, with schemes to protect wetlands and expand organic farming central to its strategies [46]. These measures reflect France's commitment to improving soil and water quality, contributing to the ecological transition.

Greece, with a budget of 1.4 billion EUR allocated to organic farming, focuses on reducing pesticides and implementing crop rotation. These measures address soil degradation and biodiversity loss, facilitating the transition to sustainable farming practices [63]. Romania faces significant challenges, with 57% of its agricultural land in disadvantaged areas [49]; thus, strategies include schemes for rural infrastructure development and biodiversity conservation that aim to reduce economic and social gaps between rural and urban areas while promoting environmental sustainability.

In Spain, 86% of agricultural land already complies with environmental conditions [54], so modernizing irrigation and supporting farmers to reduce greenhouse gas emissions are key priorities, measures that will help make Spanish agriculture resilient to climate change, while Sweden supports crop rotation and reduced pesticide use on 19% of organically managed agricultural land [88], thus contributing to the protection of biodiversity and the promotion of nature friendly farming practices.

These discrepancies in investments in renewable energy capacities indicate the need for better targeted policies to facilitate fund absorption and the development of necessary infrastructure in less performing states. A relevant proposal would be the consolidation of a European fund dedicated to supporting renewable energy in the agricultural sector, to be distributed especially to states with low investment capacity, thus ensuring a more balanced transition across the Union.

With regard to sustainable management of essential natural resources, this assessment focuses on soil conservation measures, reducing ammonia emissions, and protecting water quality, all essential for achieving the European Green Deal objectives. Although many countries have made significant commitments, there are notable variations in the implementation of these measures, suggesting the need for a more equitable and coordinated support strategy at the EU level. Countries like Luxembourg and Estonia stand out for strong commitments in this regard, reporting a share of 91.99% and 79.22%, respectively, of their UAA dedicated to soil conservation measures. Luxembourg has consolidated its commitments by adopting ecological practices, including crop rotation, soil cover crops, and reduced tillage intensity, approaches that contribute to maintaining a stable ecological balance and reducing the use of chemical inputs. Estonia, with a similar approach, has placed a strong emphasis on soil conservation practices, which help achieve biodiversity objectives and increase the soil's capacity to capture carbon. In other states, such as Ireland and Malta, the recorded values are significantly lower, at 10.61% and 11.04%, respectively, suggesting either a low prioritization of soil conservation practices or structural and economic difficulties in their implementation. A possible explanation for these low values may be associated with the lack of adequate local support or infrastructural limitations that hinder the adoption of these ecological practices, and this significant difference between states highlights the need for a more coordinated approach at the European level to ensure soil conservation in all EU regions.

Ammonia emissions represent a major challenge for air quality and a significant pollution factor for the environment. Indicator R.20 highlights large discrepancies between Member States in terms of air pollution reduction measures. Luxembourg and Poland stand out positively in this regard, with shares of 32.54% and 26.81% of UAA dedicated to ammonia emission reduction measures, respectively. Luxembourg has implemented proactive policies for ammonia emissions control, including the use of technologies for manure management and reducing the use of quick release fertilizers. In Poland, the measures implemented for emissions control in the agricultural sector are closely linked to national air pollution reduction objectives, thus promoting agricultural sustainability in the region. On the other hand, Spain and France have much lower values for this indicator, 0.65% and 1.12%, respectively, which may suggest either a lower priority given to ammonia emission reduction or challenges encountered in implementing the necessary measures to achieve these objectives.

The differences in agricultural policies between these countries suggest that there is a need for more uniform integration of ammonia reduction practices at the European level through the adoption of common regulations, as well as more consistent and targeted financial support for the implementation of technologies and agricultural practices that contribute to ammonia reduction. In order to achieve the European Green Deal objectives, the CAP aims to encourage the adoption of organic farming and to preserve the natural features of the agricultural landscape. However, the analysis shows significant variations between Member States, suggesting the need for a more coordinated approach to supporting biodiversity protection measures and promoting ecological and energy-efficient agricultural practices. EU Member States have recorded significant differences in the implementation of organic farming. Austria and Estonia, for example, are among the states with the highest shares of agricultural areas dedicated to organic farming. In Austria, approximately 23.66% of UAA is dedicated to this type of agriculture, and in Estonia, the percentage is 23.27%. These values reflect a strong commitment to the transition to sustainable agricultural practices. Austria, in particular, is known for its consistent support for organic farms, and Estonia has significantly invested in policies to support organic farming and soil conservation, contributing to the consolidation of a sustainable agricultural system.

In contrast, countries like Malta and Poland have recorded much lower values of approximately 2.54% and 4.53% of UAA for organic farming. Thus, financial support for organic farming should be better adapted to the needs of each member state, and support measures should be better targeted based on local conditions and the specifics of national agriculture.

To ensure biodiversity protection, the CAP includes measures for the conservation of natural habitats and the management of agricultural landscape features. Indicators R.31 and R.34 measure the percentage of agricultural areas involved in commitments for biodiversity conservation and the natural elements of the agricultural landscape. Thus, countries like Estonia and Finland have demonstrated a remarkable commitment to biodiversity conservation, recording high values for indicators R.31 and R.34. In Estonia, approximately 79.12% of UAA is dedicated to the conservation of habitats and local species, reflecting an active policy of protecting natural ecosystems in agriculture. Finland, with a percentage of 64.12%, has focused its efforts on managing the natural features of the agricultural landscape, thus supporting biodiversity stability and reducing the negative impact of agriculture on the environment. These states have implemented consistent support measures for farmers involved in habitat conservation and have integrated policies that promote agricultural landscapes with high ecological value. In contrast, Romania and Bulgaria have recorded much lower values, of 7.93% and 7.84% of UAA, respectively, suggesting limited attention to biodiversity and habitat protection.

The significant differences between these countries suggest the need for a more coordinated approach at the European level to expand biodiversity conservation measures. The European Union should increase support for states facing economic and structural difficulties, thus facilitating the adoption of biodiversity protection measures and natural habitat management. Additionally, training programs for farmers in biodiversity conservation techniques and ecological management could contribute to the wider adoption of these practices in Member States facing challenges.

6. Conclusions

The study demonstrated that the Common Agricultural Policy significantly contributes to the implementation of the environmental objectives set by the European Green Deal, but differences in implementation and prioritization between Member States highlight the need for adjustments for a more equitable and effective application. Countries such as France, Finland, and the Netherlands have shown a strong commitment to transitioning to greener agricultural practices, significantly investing in technologies and methods for reducing emissions and using renewable energy in agriculture. The progress of these states indicates a high potential for the CAP to support the transition to a less energy-dependent agricultural sector and to contribute to achieving the European Green Deal objectives. Additionally, some countries, such as Luxembourg and Estonia, have made remarkable progress in soil conservation and ammonia emission reduction by implementing effective measures for the sustainable management of natural resources. These practices contribute to maintaining biodiversity and improving air and soil quality, thus supporting long-term sustainable agriculture.

The example of these countries can serve as a model for other Member States facing difficulties in the sustainable management of resources. Thus, Austria and Estonia, among others, have allocated significant percentages of agricultural areas to organic farming and have promoted measures for the conservation of natural habitats and landscapes. These initiatives not only contribute to environmental protection but also support a sustainable food system by reducing the use of pesticides and synthetic fertilizers. Thus, the CAP becomes a valuable instrument for implementing ecological and environmentally friendly agriculture.

A major limitation of the current implementation of the CAP is represented by the significant discrepancies between Member States. Countries in Eastern and Southern Europe, such as Romania, Bulgaria, and Malta, have encountered difficulties in adapting to ecological measures and will record limited progress in achieving the Green Deal objectives. These discrepancies highlight an acute need for additional support and more efficient coordination to ensure a fair transition at the European level. Although states like Finland and Spain have made notable progress in investments in renewable energy, other states, such as Belgium (Flanders) and Lithuania, remain at a very low level of use of renewable energy sources in agriculture. The lack of adequate infrastructure and sustained financial support limits these states' capacity to reduce emissions and align with the EU's ecological objectives. States with low adoption rates of organic farming, such as Poland and Malta, and those recording low values for biodiversity conservation indicators, such as Romania and Bulgaria, face major challenges in implementing these practices. Without financial incentives and accessible training programs, these states risk falling behind in their efforts to transition to ecological agriculture.

The paper achieves its goal of highlighting both the progress and the difficulties encountered in implementing sustainable energy and environmental policies within the CAP by 2030. The Common Agricultural Policy plays an essential role in supporting the transition to sustainable agricultural practices and can significantly contribute to achieving the European Green Deal objectives. However, the differences between Member States in terms of implementing ecological and energy measures suggest that a review of support strategies is necessary, with an emphasis on standardizing support and adapting funding measures to the needs of each country. To maximize the efficiency of these policies and reduce regional disparities, it is recommended to increase financial and technical support for less performing states, create stricter monitoring mechanisms, and stimulate cooperation between Member States. These adjustments will facilitate a fair transition, ensuring the achievement of the ambitious environmental objectives of the European Green Deal and contributing to the development of a sustainable agricultural sector across the European Union.

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Article

Efficiency of Renewable Energy Potential Utilization in European Union: Towards Responsible Net-Zero Policy

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Abstract: 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 used to estimate the efficiency of the utilization of natural resources. The research is of a computational-empirical nature on the basis of publicly available data. The basic variables included in the model are: mean wind speed, Global Horizontal Irradiance, population, land area, wind energy capacity, solar PV capacity, wind energy generation, and solar power generation. The relationship between the environmental potential and the installed power capacity is evaluated in the first stage. In the second stage, the actual production from the installed capacity is analyzed. The efficiency trends over time are also investigated. This approach offers a comprehensive assessment by considering both the technical performance and environmental constraints. Considering all studied countries together, a slight increase in the relative efficiency of renewable energy potential utilization is observed—from 23.2% in 2018 to 28.7% in 2022. Germany and the Netherlands achieved 100% relative efficiency in 2022. The results reveal that the development of alternative energy sources and the efficiency of the installed power capacity utilization are not always in line with the local environmental conditions. The average efficiency of the analyzed countries from this perspective was 26.8% in 2018, with an improvement to 37.4% in 2022. The relative efficiency of the installed capacity utilization was high in both periods (76.3% and 74.9%, respectively). The impact of exogenous variables on performance (GDP and R&D expenditures) is discussed. Broader implications of the results for a responsible renewable energy policy in the EU demonstrate the need to combine overarching targets with a flexible governance system. That flexibility should allow for individual energy transition pathways, cooperative mechanisms, market integration, and targeted funding in order to account for the diversity of renewable resource utilization potentials among countries.

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

1. Introduction

In recent years, global wind and solar capacity have been growing faster than other major means of electric energy production. Analyzing 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 [1]. These sources are also believed to be the most environmentally neutral. Moreover, the integration of wind energy and solar photovoltaic systems as high-variable renewable energy sources significantly contributes to the reduction of CO_2 emissions [2].

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, and safety [3]. 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 [4]. According to the paper "Wind-energy Potential in Europe 2020–2030" [5], the potential of energy source development can be analyzed from the theoretical, technical, economic, and market perspectives. Geographical potential may be differentiated from theoretical, technical, and economic potential [6]. It has been emphasized that energy generation from a given source depends on the geographical location and is also influenced by macroeconomic factors, industry, and the structure of energy consumption [7]. The theoretical potential of solar energy systems is greatly diminished when considering the technical, economic, social, and environmental factors and constraints that affect their implementation [8].

In the case of solar and wind energy, geography strongly impacts the assessment of the 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. The literature emphasizes that the development of solar technologies on a national scale largely depends on the distribution and intensity of solar radiation [9]. 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 [10].

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. 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.

This work adopts a two-stage radial network data envelopment analysis (NDEA) to estimate the efficiency of utilization of natural resources at the country level. NDEA addresses the limitations of the conventional DEA that treats measurement efficiency as a 'black box' [11]. It is an extension of traditional DEA that considers the structure of the processes inside DMU and the intermediate products and sub-processes [12]. The two-stage NDEA approach offers several advantages over alternative models such as other multi-stage DEA models. It is a relatively simple model that captures intermediate processes and does not focus on the overall relationships between inputs and outputs. It recognizes that inefficiencies can occur at different stages in renewable energy systems and provides greater insight into process performance. A comprehensive description of the methodology and model is presented in Section 3: Research Methods and Data.

In this paper, the following definitions were assumed. According to the ISO 9000 standard [13], efficiency is the relationship between the achieved result and the resources used. From the perspective of the DEA method, efficiency refers to the ratio of the minimum input (reference input) required to achieve a specified outcome to the actual input, as well as the ratio of the actual output to the maximum possible output (reference output) from a given level of input. The work also uses the definition of environmental potential, which refers to the natural, physical, and spatial resources that determine the suitability of a region to produce renewable energy from wind and solar sources. It represents the theoretical upper limit of renewable energy production that can be achieved based on natural conditions, geographical factors, and available space for infrastructure development.

According to [8], there was no correlation between EU investment and the suitability of solar energy during the period from 2007 to 2013. The analysis covers the years 2018–2022. This period represents significant regulatory and policy advancements, technological progress, and geopolitical developments. In 2018, the RED II Directive (2018/2001/EU) established a target of 32% renewable energy in the EU's gross final energy consumption by 2030. The European Green Deal, launched in 2019, set the EU's goal of achieving climate neutrality by 2050 and increasing investment in renewable energy sources. The COVID-19 pandemic (2020–2022) has disrupted energy consumption patterns but has triggered recovery programs such as NextGenerationEU, allocating significant resources to the clean energy transition. During the energy crisis of 2021–2022, the REPowerEU initiative was created. This initiative focused on diversifying energy sources, achieving energy independence, and increasing investments in renewable energy.

The key research questions defining the purpose of this article are:

Q1: To what extent do EU countries differ in terms of efficiency in utilizing their available solar and wind energy potential?

Q2: Which countries are leaders in the efficient use of available solar and wind energy potential?

Q3: What changes have occurred in the efficiency of utilizing available solar and wind energy potential between 2018 and 2022?

To answer these questions, this study builds on a multidimensional approach that combines methodological innovation, empirical evaluation, and a systematic synthesis of existing knowledge. By integrating these elements, the research provides a comprehensive assessment of renewable energy efficiency across EU countries. Accordingly, the contribution of this article is threefold: (i) Methodological contribution: This study proposes a novel framework based on the NDEA method for assessing the efficiency of natural resource utilization in the context of renewable energy technology development. This approach addresses key limitations of traditional DEA methodologies by explicitly incorporating geographic and natural resource dimensions; (ii) Empirical contribution: The study evaluates the compatibility between the development of renewable energy technologies and the environmental potential of EU countries. This analysis identifies benchmarks for improvement and provides actionable implications for energy policy at both national and regional levels; and (iii) Systematization of knowledge: The research is grounded in an extensive review of recent studies, which systematically highlights advances in DEA efficiency assessment methodologies applied to renewable energy sources. This synthesis provides a robust foundation for further academic exploration and practical applications.

The originality and innovation of this study lie in the application of NDEA to compare countries based on geographical data while considering the dual development path and the dynamic substitution between solar and wind electricity production. Reviews of articles on DEA applications in sustainability [14–17] have revealed a prevalent practice of juxtaposing regions or countries based on factors such as capital, labor force, and energy consumption, on the one hand, and GDP and CO_2 emissions, on the other hand. These comparative analyses typically employ basic DEA models. This is justified because GDP per capita reflects the country's economic development [18]. 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. In this study, firstly, the relationship between environmental potential and installed power capacity has been evaluated, and then production from installed power has been analyzed. The model reflects the sequential nature of renewable energy production. In the first stage, it assesses how efficiently countries convert their natural renewable energy potential into installed capacity. A country with high solar potential but low installed solar capacity may indicate inefficiencies in policy, investment, or infrastructure. The second stage examines how efficiently the installed capacity is used to generate actual energy production. Even with significant capacity, operational inefficiencies, grid limitations, or technology, underperformance can reduce energy production. By separating these two stages, the DEA framework reflects different aspects of efficiency, identifying bottlenecks in the conversion of natural potential to capacity and from capacity to production. 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 article follows a well-structured format, adhering to best practices, such as in [19]. 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 NDEA 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. The research process is illustrated in Figure 1.

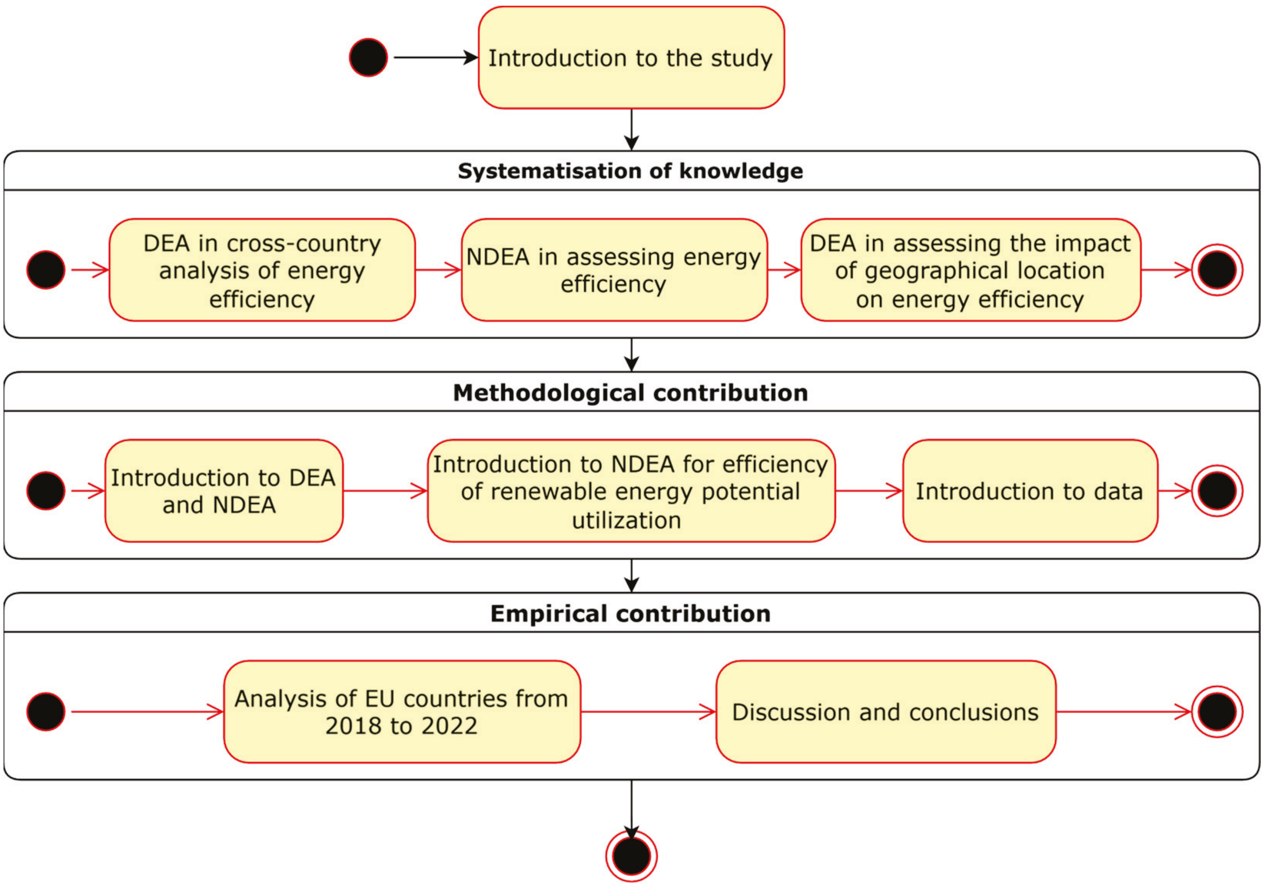


Figure 1. UML diagram of the study flow.

2. Literature Review

2.1. Scope, Categories, and Methodological Framework

The awareness of the necessity and the benefits of the development of energy generation from renewables for long-term sustainability and circularity has been evoking huge interest from scientists and practitioners in recent decades [20,21]. The clean energy aspect has become a core element of every innovation aspiring to be seen as responsible and sustainable [22,23]. In energy efficiency analyses, DEA is commonly used as the primary performance assessment method. Researchers emphasize its applicability and suitability in the energy sector, particularly for renewable energy, environmental management, and general sustainability assessments. The purposes and scopes of these studies enable their classification into several categories. Regarding application areas, research can be grouped into nine domains: environmental efficiency, economic and eco-efficiency, energy efficiency issues, renewable and sustainable energy, water efficiency, energy performance, energy saving, integrated energy efficiency, and others [24]. Based on the objects of analysis, the following categories emerge: (i) country- or region-level performance analysis; (ii) sector-, industry-, or enterprise-level analysis; (iii) the efficiency of individual power farms; and (iv) others, such as renewable energy development plans [25] or supply chain evaluations [26]. A common distinction is between the eco-efficiency of countries and the technical efficiency of power plants [27].

Aligned with the purpose of this paper, which focuses on assessing the efficiency of European countries in utilizing renewable energy potential using NDEA, relevant studies have been categorized into three groups based on objects (DMU), DEA models, and the variables considered: (i) conventional DEA for comparing energy and renewable energy sources across countries; (ii) NDEA for broader geographical comparisons (e.g., countries, districts, provinces, regions); and (iii) DEA (both conventional and NDEA) for evaluating the impact of geographical location. These groupings are discussed in detail in the following sections: (Section 2.2) DEA in cross-country analysis of energy efficiency, (Section 2.3) NDEA in assessing energy efficiency, and (Section 2.4) 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 Xplore 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.

2.2. DEA in Cross-Country Analysis of Energy Efficiency

Table 1 provides a summary of selected recent studies on renewable energy efficiency analysis in different countries using the DEA method. The table highlights the objects of analysis, the DEA models applied, and the variables considered. The summary excludes studies that broadly address country comparisons, where energy efficiency constitutes just one aspect of a general sustainability assessment (e.g., [28]), circular economy (e.g., [29]), or, conversely, focus narrowly on specific topics such as electric vehicles (e.g., [30]).

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

Work	DMU	DEA Model	Analysis Criteria
[31]	25 European countries from 2005 and 2020	Two-stage: DEA and regression	Inputs: renewable energy consumption, capital, labor Outputs: GDP Influencing factors: GDP, energy price, renewable energy consumption, information and communications technology, industrial value added
[32]	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
[33]	26 countries from 2000 to 2020	Three-stage: DEA-SFA-DEA	Inputs: capital, labor, PV installed capacity, PV patents Output: PV generation Environment variables: proportion of the urban population, GDP per capita, CO_2
[34]	14 Asian countries in 2019	DEA with undesirable output	Inputs: labor, energy consumption, the share of renewable energy, and total renewable energy capacity Outputs: CO_2 and GDP
[7]	36 countries from 2009 to 2018	Super efficiency DEA, MI, and random forest regression model to analyze 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, urbanization rate, production level, industrialization level and structure, electricity and energy structure, carbon emissions, and technology level
[35]	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
[36]	126 countries from 2000 to 2016	BCC DEA	Inputs: renewable and non-renewable energy sources generation capacity Outputs: power generation, CO_2 emissions avoided
[37]	26 OECD countries	Bootstrap IO CCR DEA	Inputs: six different energy R&D expenditure indicators in 2015 Outputs: CO_2 emission per capita
[4]	Selected OECD countries in 2012, 2014, and 2016	OO BCC DEA 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

Table 1. *Cont.*

Work	DMU	DEA Model	Analysis Criteria
[38]	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
[39]	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
[40]	17 European countries from 2013 to 2017	SBM DEA with undesirable outputs model and MI	Inputs: energy consumption, labor productivity, the share of renewable energy in energy consumption, gross capital formation productivity Outputs: GDP per capita, CO_2 per capita
[41]	28 EU countries 2010 and 2014.	DEA Directional Distance Function model	Inputs: labor, capital, GHG, acidifying gases, ozone precursors Outputs: GVA
[42]	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: labor, capital, energy Outputs: GDP, CO_2
[43]	17 countries highly and newly industrialized from 2013 to 2018	DEA with undesirables preceded by Grey Prediction Model	Inputs: total renewable energy capacity, labor force, total energy consumption Outputs: CO_2, GDP
[44]	132 countries from 2007 to 2014	MinSum DEA	Inputs: GDP per unit of energy use, renewable energy consumption Outputs: GDP, CO_2 emissions per GDP
[45]	25 EU member states and Norway from 2000 to 2015	CCR DEA	Inputs: PV fee, wind fee, LCOE PV, LCOE wind Outputs: PV share, wind share, REs share
[46]	156 Latin American countries from 1991 to 2013	SBM VRS DEA with window analysis	Inputs: labor, capital, energy consumption Outputs: GDP, CO_2
[47]	20 of the largest producers of renewable energy from 2009 to 2013	BCC DEA and truncated regression	Input: primary energy consumption, capital, labor Output: GDP Regression: renewable energy consumption, GVA per capita, population density
[48]	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; CO_2—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; GVA—gross value added; IO—input-oriented; LCOE—levelized cost of electricity; MI—Malmquist Index; OO—output-oriented; PV—photovoltaics; RE, REs—renewable(s); SFA—stochastic frontier analysis; 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, studies on the assessment of provinces or regions are worth mentioning. They are represented by China [49–51], as well as India, e.g., [52], Turkey, e.g., [53], and Vietnam, e.g., [54].

Literature analysis, including broader review papers on sustainable development and eco-efficiency, i.e., [14–16,24,55,56], 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, labor force, total energy consumption, and GDP and CO_2 emissions. Some studies analyze 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; and (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.

2.3. NDEA in Assessing Energy Efficiency

Table 2 presents a selection of recent studies on energy efficiency and renewable energy sources analyzed using NDEA. These studies encompass evaluations at various levels, including countries, regions, states, and provinces. The broader scope of the review reflects the relatively limited number of studies employing NDEA models.

Table 2. Works on evaluation of energy from renewables by NDEA.

Work	DMU	DEA Model	Analysis Criteria
[57]	30 Chinese regions during 2000–2012	multiplicative two-stage relational NDEA	capital, labor, energy, GDP, CO_2, SO_2
[58]	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
[52]	18 Indian states from 2008 to 2016	two phases consisting 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
[59]	Iran’s electricity distribution network	two-stage NDEA	labor, capital, energy consumption, GDP, CO_2, the total population
[60]	30 Chinese regions in 1996–2015	two-stage serial NDEA and PLS-SEM	labor, asset, energy consumption, land used, water, GDP, wastewater, exhaust, SO_2, investment in pollution control, solid waste utilization, wastewater treatment, greening rate
[61]	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
[62]	8 EU and 53 non-EU countries from 2010 to 2014	two-stage meta-frontier dynamic serial NDEA	labor, renewable and non-renewable energy consumption, assets, GDP, health expenditure, survival rate, tuberculosis rate, CO_2, PM2.5, mortality rates

Table 2. *Cont.*

Work	DMU	DEA Model	Analysis Criteria
[63]	15 old and 13 new EU states from 2010 to 2014	two-stage meta-frontier dynamic serial NDEA	labor, renewable and non-renewable energy consumption, assets, GDP, health expenditure, survival rate, tuberculosis rate, CO_2, PM2.5, mortality rates
[64]	28 EU countries 2006–2013	dynamic DEA	labor, capital, energy consumption, GHE, SOx, GDP, GCF
[65]	35 OECD countries	dynamic SBM DEA	labor, energy consumption, new energy consumption, GDP, CO_2, PM2.5, fixed assets
[66]	major economies	SBM two stages NDEA	energy resources, economic outputs, energy consumption, CO_2
[67]	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 modeling; SBM—slacks-based measures; SOx—sulfur oxides.

NDEA 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 labor, 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., labor, capital, energy into GDP, and main pollutant CO_2), 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 unrecognized and underestimated.

2.4. 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.

Work	DMU	DEA Model	Analysis Criteria
[68]	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

Table 3. *Cont.*

Work	DMU	DEA Model	Analysis Criteria
[69]	3 PV power plants in multiple periods	multi-period DEA	solar insolation, daily sun-hours, temperature, installation cost, installed capacity
[70]	China's provinces	DEA cross-efficiency	cumulative installed capacity, annual equipment utilization hours, electricity consumption of power generation companies, electricity generation
[71]	14 offshore sites of the Moroccan seas for 2016–2020	DEAM (supper-efficiency DEA model)	water depth, distance to coast, accessibility, maximum wave height, maximum wind speed, wind power density
[72]	12 locations in Vietnam	DEA (CCR-I, CCR-O, BCC-I, BCC-O, SBM-I-O, SMB-O-C) and AHP	DEA: frequency of natural disasters, land cost, wind blow, population, quantity of proper geological and topographical area AHP: location characteristic, technical, economic, social, environmental
[73]	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
[74]	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
[75]	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
[76]	solar PV power plants in Taiwan	epsilon-based DEA	surface area, number of modules, ambient temperature, plant capacity, PV module temperature, irradiation, generated energy
[77]	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
[27]	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
[78]	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 studies referenced in Table 3 highlight the effective application of the DEA method for evaluating location suitability at the country or regional level. Common criteria in the reviewed works include geographical data (e.g., wind speed, likelihood of natural disasters, solar irradiance, accessibility, water depth), social factors (e.g., electricity demand, population), and technical parameters (e.g., construction costs, generated energy, avoided CO_2 emissions, proximity to transmission lines, and energy losses).

This review does not encompass all possible categorizations of research applying the DEA method to assess progress toward zero-emission economies. Notably, there are growing calls for enhancing assessment robustness through hybrid models that combine DEA with AI algorithms. Such approaches leverage the strengths of both methods, offering improved interpretability and transparency alongside advanced capabilities for pattern detection, self-learning, and managing large datasets.

3. Research Methods and Data

Data envelopment analysis was developed by A. Charnes, W.W. Cooper, and E. Rhodes [79], who extended M.J. Farrell's [80] 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}, $i = 1, \ldots, m$) into multiple outputs (y_{rj}, $r = 1, \ldots, s$) (Figure 2a), solving linear programming tasks for each DMU ($j = 1, \ldots, n$), where λ_j represents the weights and indicates the benchmarks and φ is the radial efficiency score of jth DMU:

$$\begin{gathered} max\varphi, \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ij_O}, i = 1, \ldots, m, \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq \varphi y_{rj_O}, r = 1, \ldots, s, \\ \lambda_j \geq 0, j = 1, \ldots, n. \end{gathered} \tag{1}$$

The efficiency score φ ranges from 0 to 100%. In DEA, 100% efficiency indicates that the evaluated unit is the most effective within its reference group in converting available resources into outcomes, as defined by the chosen inputs and outputs. Such a unit serves as a benchmark for less efficient entities. This allows for further analysis of the policies, technologies, or strategies that contribute to its efficiency. However, achieving 100% efficiency does not imply absolute perfection; improvements may still arise through innovation, technological advancements, or redefining sustainability goals. It is also important to note that DEA results are highly dependent on the model specification, the reference set, and the selection of inputs and outputs. A different configuration of these elements could lead to a different assessment of the same unit's efficiency.

NDEA is an extension of the traditional DEA approach, permitting the consideration of the internal process structure and the examination of intermediate products and subprocesses [12]. The enhancement of NDEA is attributed to R. Färe and S. Grosskopf [81,82], who introduced the term and developed the concept in the context of analyzing complex systems [11]. 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 [83] or in the measurement of the efficiency of a two-stage agricultural production system with intermediate products [84].

NDEA 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 [85]. NDEA contributes to a deeper understanding of the multifaceted nature of resource management efficiency and its implications for achieving sustainable development goals [28].

NDEA 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, assuming that the influence of some inputs on the outputs might be indirect. The exogenous inputs are utilized in the first phase to get the intermediate products (inputs) for the second phase to produce the final outputs [11]. Multi-stage (multi-level, serial) DEA is a generalization 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 [11]. Supply chain DEA is a specific case of NDEA, 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 [86]. Suppliers, manufacturers, distributors, and retailers can also be analyzed in terms of their performance and impact on other units in the chain. Dynamic NDEA is used to analyze the efficiency over time [87]. 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 2 (serial, parallel, parallel-serial, hierarchical, with feedback, dynamic DEA, 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 NDEA models with undesirable factors [88] and stochastic NDEA that could handle uncertainty in the data [89]. To deal with uncertain data, fuzzy [90] and rough [91] NDEA models have been developed. The other extensions are multi-period NDEA models with feedback [92].

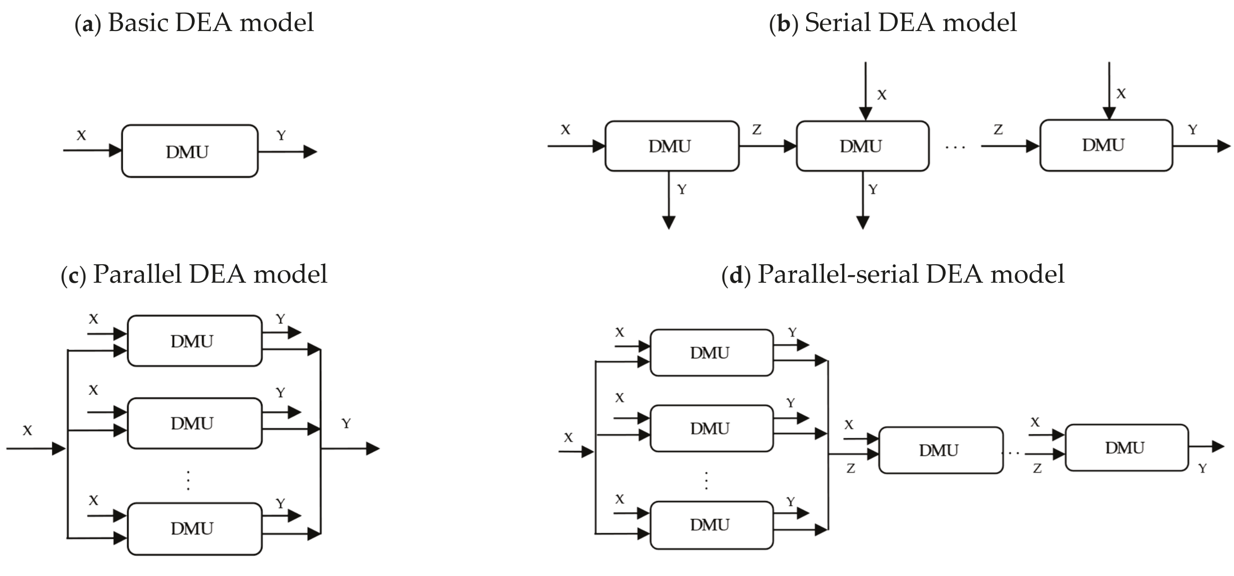


Figure 2. *Cont.*

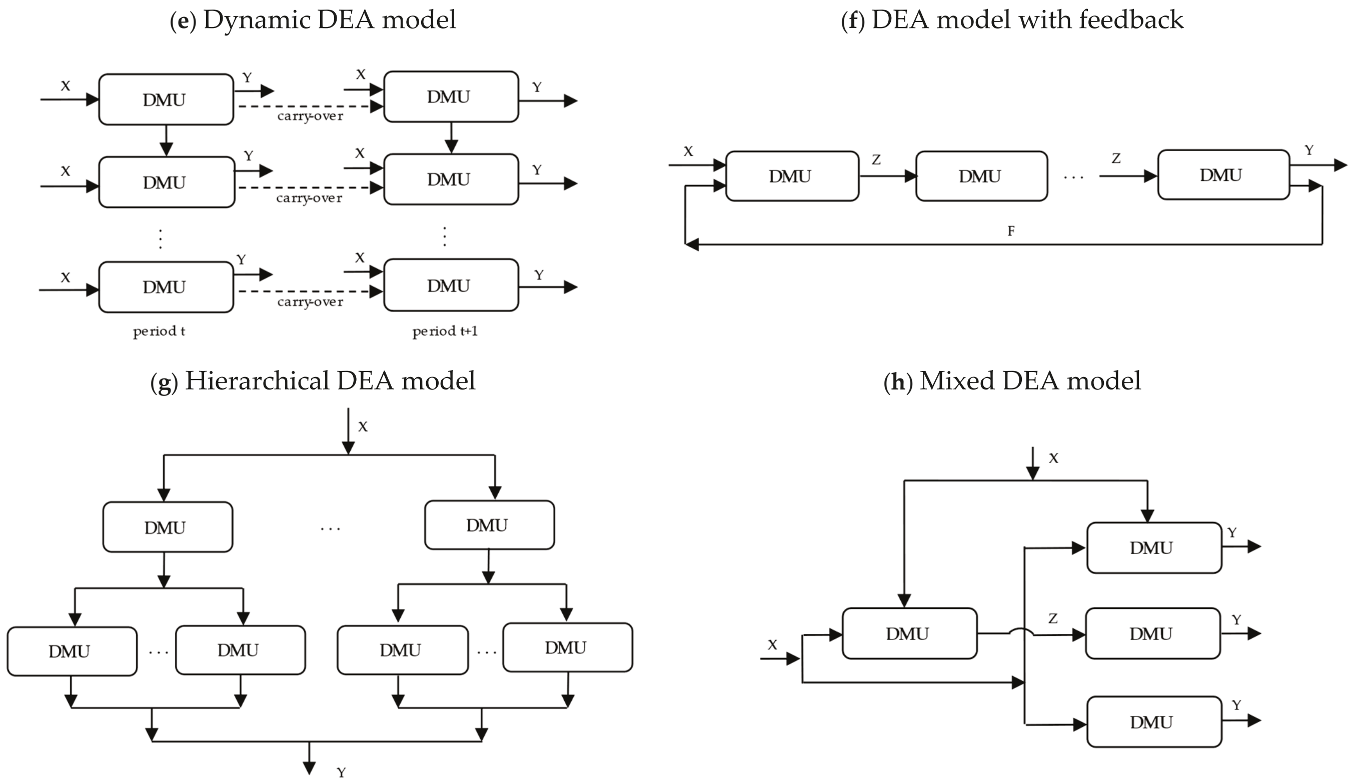


Figure 2. NDEA models (**a**) basic DEA model; (**b**) serial DEA model; (**c**) parallel DEA model; (**d**) parallel-serial DEA model; (**e**) dynamic DEA model; (**f**) DEA model with feedback; (**g**) hierarchical DEA model; (**h**) mixed DEA model. Source: Own elaboration based on [11,12,93,94].

In the article, the two-stage DEA model has been applied, and 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. The model engaged is an output-oriented adaptation of [95] with the solution by [96] to ratio data as follows:

$$\begin{gathered} max\textstyle\sum_{r=1}^{s} \varphi_r/s, \\ \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ij_O}, i = 1, \ldots, m, \\ \textstyle\sum_{j=1}^{n} \lambda_j z_{kj} = \sigma_k z_{kj_O}, k = 1, \ldots, d, \\ \textstyle\sum_{j=1}^{n} \lambda_j z_{kj} \geq \textstyle\sum_{j=1}^{n} \mu_j z_{kj}, k = 1, \ldots, d, \\ \textstyle\sum_{j=1}^{n} \mu_j z_{kj} = \omega_k z_{kj_O}, k = 1, \ldots, d, \\ \textstyle\sum_{j=1}^{n} \mu_j y_{rj} \geq \varphi_r y_{rj_O}, r = 1, \ldots, s, \\ \lambda_j \geq 0, j = 1, \ldots, n,\ \mu_j \geq 0, j = 1, \ldots, n, \\ \omega_k \geq 0, k = 1, \ldots, d, \\ \sigma_k \geq 0, k = 1, \ldots, d, \\ \varphi_r \geq \tau, r = 1, \ldots, s, \\ \textstyle\sum_{j=1}^{n} \mu_j = \tau,\ \textstyle\sum_{j=1}^{n} \lambda_j = \tau. \end{gathered} \tag{2}$$

The x_{ij} is the ith input, z_{kj} is the kth intermediate, and y_{rj} is the rth output of DMUj for $j = 1, \ldots, n$. To account for variable returns to scale, τ is set to 1. The study used a model assuming constant returns to scale.

A key advantage of the DEA method is its computational simplicity, enabling its implementation in any software that supports linear optimization models. In this study, we utilized Microsoft Excel formulas and macros, combined with Python release ver. 3.12.4 libraries, to conduct the calculations efficiently and ensure result accuracy.

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 as: $\sum_{r=1}^{s} \varphi_r / s$. The efficiency for the first and second stage and the overall efficiency are defined as follows:

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

To measure changes over time, in periods 1 and 2, the Malmquist index was calculated. The Malmquist index decomposes changes in efficiency into frontier-shift (covered efficiency in period 2 with respect to period 1 frontier $\psi_{t_2 j_O}^{*t_1}$, efficiency in period 2 with respect to period 2 frontier $\psi_{t_2 j_O}^{*t_2}$, efficiency in period 1 with respect to period 1 frontier $\psi_{t_1 j_O}^{*t_1}$, and efficiency in period 1 with respect to period 2 frontier $\psi_{t_1 j_O}^{*t_2}$) and catch-up effect (efficiency in period 2 with respect to period 2 frontier $\psi_{t_2 j_O}^{*t_2}$ and efficiency in period 1 with respect to period 1 frontier $\psi_{t_1 j_O}^{*t_1}$). 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:

$$M_{j_O}^* = \left(\psi_{t_2 j_O}^{*t_2} / \psi_{t_1 j_O}^{*t_1}\right) \left(\sqrt{\left(\psi_{t_2 j_O}^{*t_1} / \psi_{t_2 j_O}^{*t_2}\right)\left(\psi_{t_1 j_O}^{*t_1} / \psi_{t_1 j_O}^{*t_2}\right)} \right). \tag{4}$$

The selection of data for analysis was made based on a literature review and a substantive analysis of the cause-effect analysis. The data used allow for a comprehensive assessment of efficiency and analysis of resource relation to infrastructure and production, taking into account differences in the scale of human and spatial resources between countries. Figure 3 presents the structure of the adapted network system. The energy generated by wind turbines depends on wind speed, while modern turbines should adjust to wind direction to maximize efficiency. The overall efficiency of a wind turbine is determined by its technology, including blade design, control systems, and power conversion mechanisms [97]. To determine the potential wind power, the mean wind speed in the 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: $P = \frac{1}{2}\rho A v^3$. The photovoltaic power potential (x_2) was expressed in Wh/m^2 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.

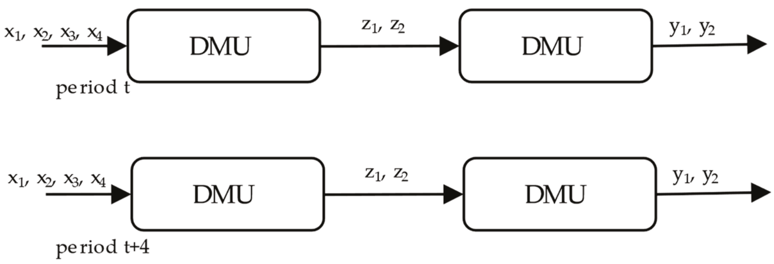


Figure 3. Model structure. Source: Own elaboration.

Table 4. Data set.

Variable	Description, Source	Unit, Year	Source
x_1	Mean wind speed	m/s (data for 10% windiest area)	[98]
x_2	GHI	kWh/m^2/day	[99]
x_3	Population	million people, 2018–2022	[100]
x_4	Land area	square thousand km, 2021	[101]
z_1	Wind energy capacity	MW, 2018, 2022	[102]
z_2	Solar PV capacity	MW, 2018–2022	[102]
y_1	Wind energy generation	GWh per year, 2018–2022	[103]
y_2	Solar power generation	TWh per year, 2018–2022	[104]
v_1	Wind capacity per capita	W	
v_2	PV capacity per capita	W	
v_3	Wind energy generation per capita	kW	
v_4	Solar power generation per capita	kW	

The study covers 27 EU 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 analyzed set in 2022 is 507.5% and 138.3% for wind power. Table 5 shows the correlations of variables in 2022, and Table 6 presents basic statistics.

Table 5. Correlations of variables.

	Population	**Land Area**	**Mean Wind Speed**	**GHI**	**Wind Capacity**	**Solar PV Capacity**	**Wind Capacity per Capita**	**Solar PV Capacity per Capita**	**Wind Energy Generation**	**Solar Power Generation**	**Wind Energy Generation per Capita**
Population	1.000										
Land area	0.769	1.000									
Mean Wind Speed	0.101	0.103	1.000								
GHI	0.058	−0.002	−0.555	1.000							
Wind capacity	0.842	0.641	0.267	−0.051	1.000						
Solar PV capacity	0.873	0.503	0.183	−0.027	0.930	1.000					
Wind capacity per capita	0.128	0.365	0.675	−0.376	0.406	0.205	1.000				
Solar PV capacity per capita	0.309	−0.037	0.182	0.014	0.399	0.575	0.132	1.000			
Wind energy generation	0.825	0.652	0.297	−0.058	0.996	0.914	0.455	0.409	1.000		
Solar power generation	0.906	0.597	0.141	0.084	0.932	0.968	0.195	0.511	0.922	1.000	
Wind energy generation per capita	0.060	0.295	0.687	−0.374	0.327	0.130	0.990	0.113	0.381	0.120	1.000
Solar power generation per capita	0.345	0.039	0.022	0.324	0.411	0.540	0.032	0.903	0.421	0.563	0.013

Table 6. Basic statistic for 2022.

	Min	Max	Mean	Std. Dev.
x_1	5.66	10.11	7.79	0.91
x_2	2.53	5.21	3.44	0.76
x_3	526.87	83,771.56	16,580.09	22,265.03
x_4	0.32	547.56	148.02	158.63
z_1	0.00	66,315.00	7556.96	13,688.60
z_2	56.00	66,554.00	7413.63	13,961.76
y_1	0.00	124,816.00	15,593.41	26,271.58
y_2	0.04	60.79	7.81	13.92
v_1	0.00	1392.65	392.94	372.79
v_2	26.71	1269.86	343.48	254.52
v_3	26.71	3239.64	869.30	894.69
v_4	21.31	960.13	361.62	240.09

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 favorable 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.

Based on the analysis of the minimum, maximum, and standard deviation values, it can be concluded that countries share similar environmental conditions. However, their utilization varies. Wind energy potential and the amount of wind energy produced per capita are the most diverse. These variations are depicted in Figure 4, highlighting the differences between countries.

(**a**) Geographical characteristics

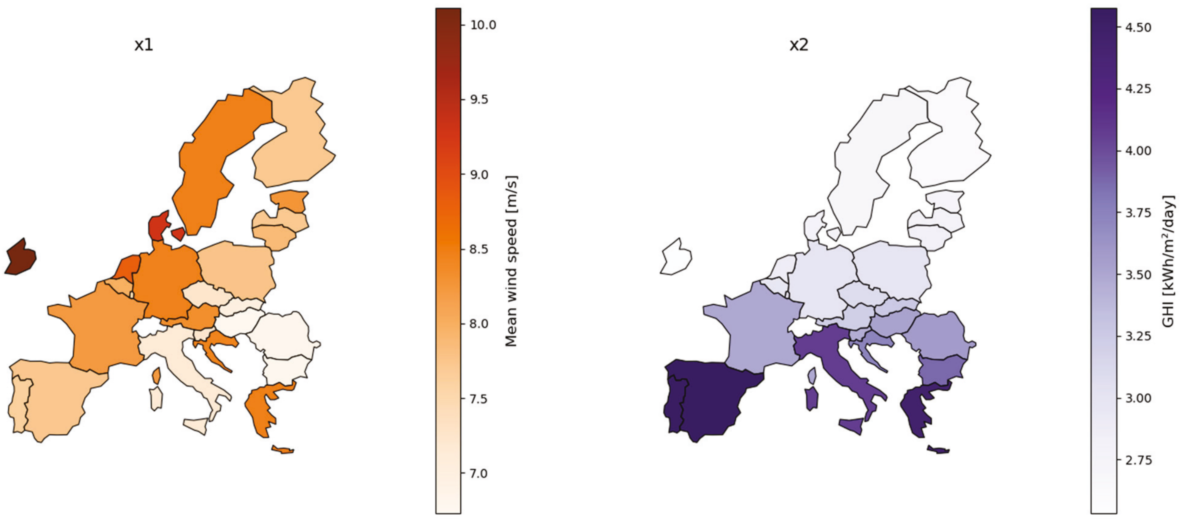


Figure 4. *Cont.*

(**b**) Wind power per capita (**c**) Solar power per capita

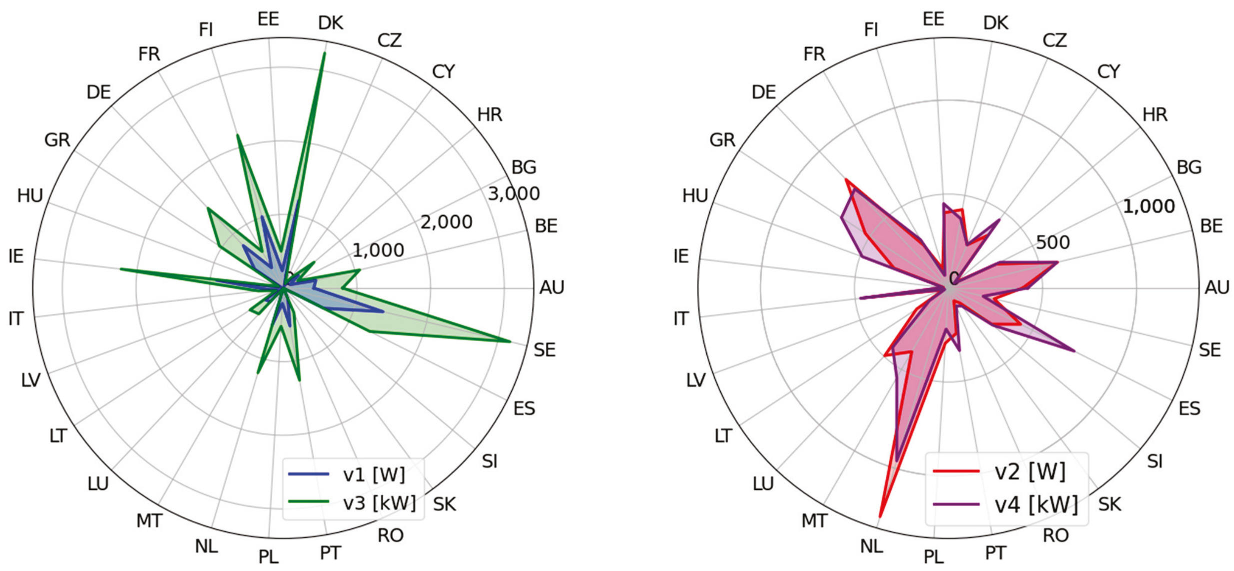


Figure 4. Countries characteristics: (**a**) geographical characteristics; (**b**) wind power per capita; (**c**) solar power per capita.

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

4. Results

The results of the efficiency analysis, obtained through both traditional one-stage DEA and two-stage NDEA methods, are summarized in Table 7. The table provides efficiency scores for 2018 and 2022, along with the Malmquist index, which measures changes in efficiency over time. Figure 5 visualizes the results.

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	40.5%	50.0%	37.9%	78.4%	29.7%	47.3%	74.5%	35.2%	1.19	0.53	0.63
BE	Belgium	100.0%	71.0%	83.7%	88.1%	73.7%	60.7%	95.2%	57.8%	0.78	0.66	0.52
BG	Bulgaria	35.7%	31.8%	17.5%	83.3%	14.6%	15.8%	84.9%	13.4%	0.92	0.81	0.74
HR	Croatia	13.7%	16.9%	5.7%	73.5%	4.2%	7.5%	54.5%	4.1%	0.97	0.46	0.45
CY	Cyprus	29.8%	47.2%	20.3%	60.6%	12.3%	17.7%	56.8%	10.0%	0.81	0.96	0.78
CZ	Czechia	42.0%	26.0%	6.6%	86.5%	5.7%	6.1%	79.7%	4.8%	0.84	0.94	0.80
DK	Denmark	100.0%	100.0%	54.4%	73.6%	40.0%	75.5%	62.0%	46.8%	1.17	0.50	0.59
EE	Estonia	20.1%	46.9%	8.4%	66.6%	5.6%	32.5%	84.5%	27.4%	4.89	0.12	0.58
FI	Finland	47.0%	67.3%	9.1%	47.3%	4.3%	21.9%	41.5%	9.1%	2.11	0.23	0.49
FR	France	32.6%	40.1%	29.7%	100.0%	31.2%	36.4%	100.0%	36.4%	1.17	0.66	0.77
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	66.3%	75.1%	42.1%	96.3%	40.5%	57.8%	89.3%	51.6%	1.27	0.54	0.69
HU	Hungary	12.1%	50.9%	6.6%	78.2%	5.1%	6.3%	81.1%	5.1%	0.99	0.78	0.77
IE	Ireland	74.2%	68.5%	2.6%	43.5%	1.1%	5.8%	67.0%	3.9%	3.49	0.14	0.48
IT	Italy	70.5%	64.0%	34.5%	96.7%	33.3%	33.8%	96.4%	32.6%	0.98	0.84	0.82
LV	Latvia	2.6%	3.9%	0.4%	0.4%	0.0%	4.5%	46.4%	2.1%	1491.46	0.00	0.45
LT	Lithuania	17.4%	21.2%	9.6%	78.1%	7.5%	27.6%	42.6%	11.7%	1.57	0.30	0.48
LU	Luxembourg	37.4%	45.2%	35.9%	77.9%	28.0%	40.5%	70.7%	28.7%	1.02	0.62	0.63
NL	Netherlands	98.1%	100.0%	93.7%	80.3%	75.3%	100.0%	100.0%	100.0%	1.33	0.59	0.79
PL	Poland	24.0%	31.8%	4.8%	50.1%	2.4%	31.7%	80.0%	25.3%	10.47	0.06	0.66
PT	Portugal	68.7%	57.6%	21.1%	100.0%	21.1%	41.0%	90.2%	37.0%	1.75	0.35	0.61
RO	Romania	21.5%	18.5%	16.8%	96.5%	16.2%	13.2%	90.0%	11.9%	0.73	0.87	0.64
SK	Slovakia	20.0%	12.5%	0.1%	85.2%	0.1%	0.1%	38.8%	0.0%	0.52	1.50	0.78
SI	Slovenia	22.8%	32.0%	0.3%	71.3%	0.2%	0.2%	71.5%	0.2%	0.74	1.07	0.79
ES	Spain	79.3%	98.2%	40.3%	100.0%	40.3%	64.4%	100.0%	64.4%	1.60	0.56	0.90
SE	Sweden	88.8%	100.0%	14.9%	72.1%	10.7%	54.9%	49.5%	27.2%	2.53	0.22	0.55
	Average	48.7%	52.9%	26.8%	76.3%	23.2%	37.4%	74.9%	28.7%	1.19	0.53	0.63

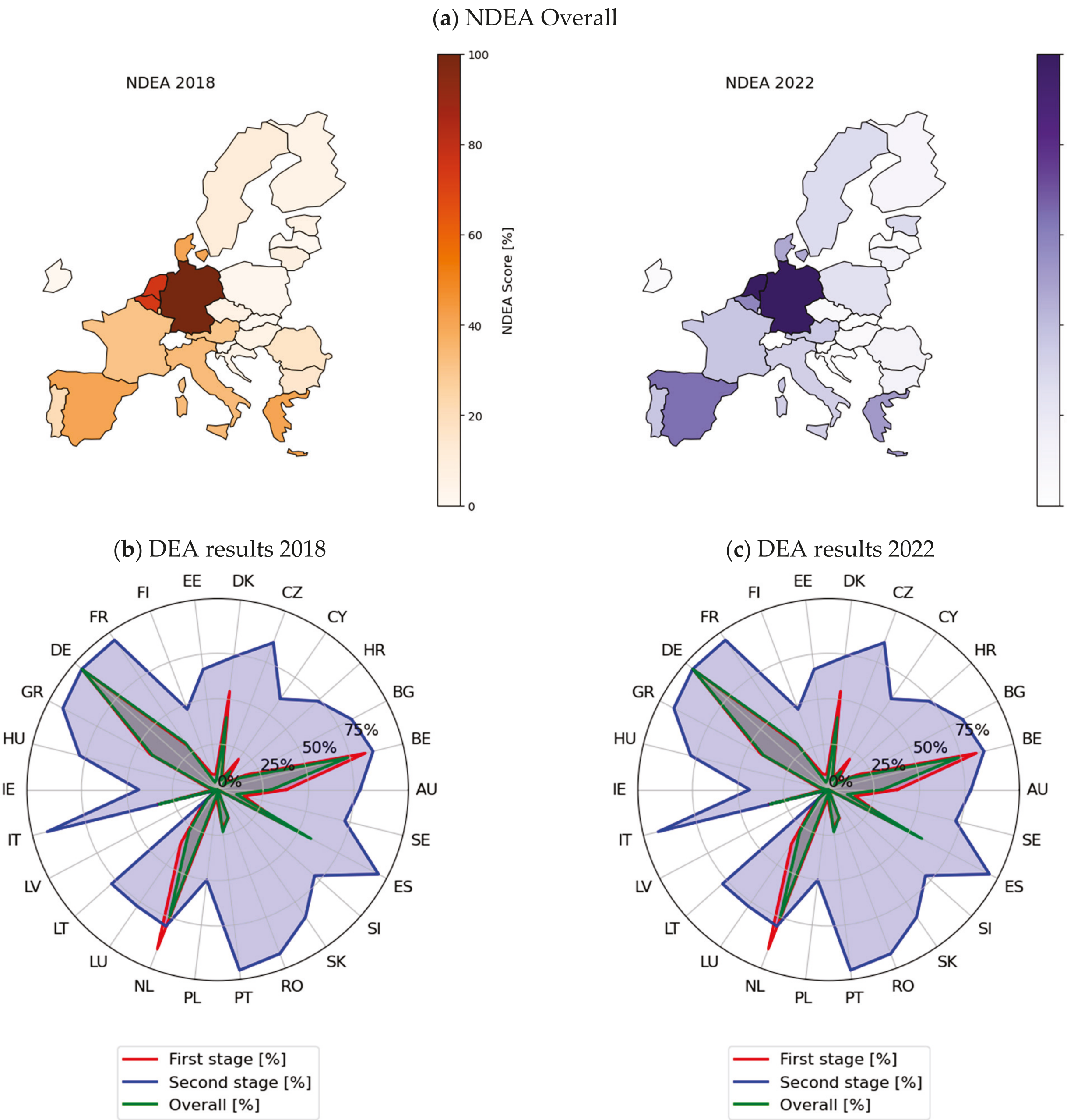


Figure 5. NDEA results: (**a**) NDEA overall; (**b**) first stage, second stage, and overall, 2018; (**c**) first stage, second stage, and overall, 2022.

Malta, the smallest country in the EU, both in terms of land area and population, was excluded from the analysis. In 2022, renewable energy accounted for approximately 10% of Malta's electricity supply, almost all of it generated from photovoltaic panels. This indicates that wind energy plays a negligible role in the country's energy mix.

The NDEA 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, in 2022, the first stage of the DEA method, which evaluates the potential of the environment, has a lower efficiency (34.7%) than the second stage's efficiency (74.9%). This means that the natural suitability is not exploited, but the use of the already installed capacity is high. The leaders of the second stage in 2022 were France, Germany, the Netherlands, and Spain. In consideration of the NDEA in 2018, Germany was identified as the leading country. In 2022, the Netherlands joined Germany among the nations that have reached 100%.

Considering the changes over time, in most cases, there was an increase in efficiency change—catch-up. The most remarkable increase was recorded by countries that did not use solar energy in 2018: Latvia, Poland, and Estonia. However, taking into account the achievements of other countries and the frontier shift, the Malmquist index is low. The largest frontier shifts were in Slovakia and Slovenia. Examples of countries with a balance between catch-up and frontier shift are Italy, Bulgaria, Cyprus, and Czechia. The reference country is Germany, which has a catch-up, frontier shift, and Malmquist index equal to 1. Figure 6 illustrates the Malmquist index for the first and second stages, as well as overall. The high indexes concern the second stage.

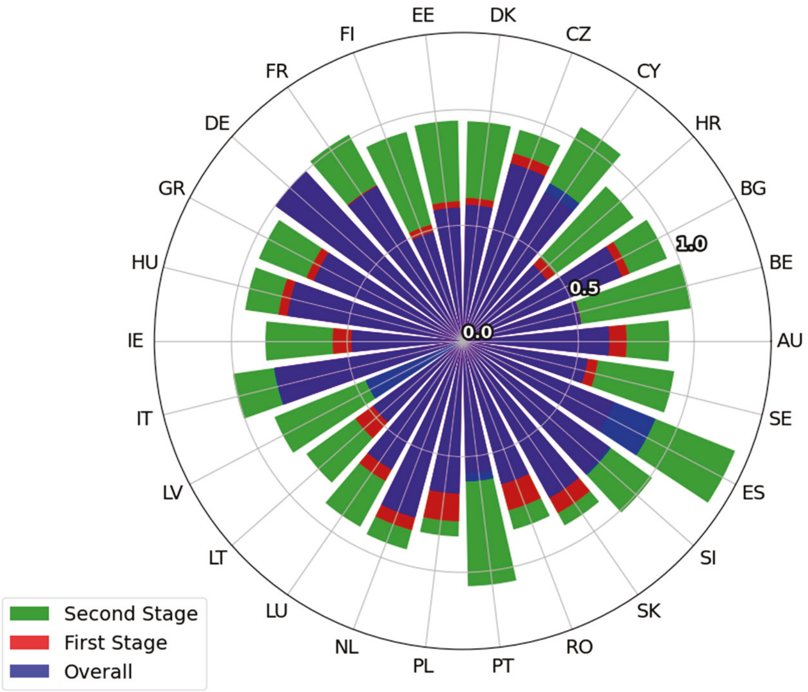


Figure 6. Malmquist indexes for the first stages, second stages, and overall.

Table 8 further illustrates the correlation between efficiency scores derived from the standard DEA and NDEA models for 2018 and 2022. The results confirm a high degree of alignment between the DEA and first-stage NDEA calculations, while the NDEA offers additional insights into the intermediate processes. Due to the mathematical formula of the product, the overall NDEA is primarily a result of lower first-stage efficiency.

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)	0.748		0.901
DEA 2022 (X $\rightarrow$ Y)		0.753	
Overall NDEA 2018 (X $\rightarrow$ Z $\rightarrow$ Y)		0.934	
	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)	0.795		0.924
DEA 2022 (X $\rightarrow$ Z)		0.830	
First-stage NDEA 2018 (X $\rightarrow$ Z $\rightarrow$ Y)		0.898	
	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)	0.256		0.503
DEA 2022 (Z $\rightarrow$ Y)		0.0884	
Second-stage NDEA 2018 (X $\rightarrow$ Z $\rightarrow$ Y)		0.608	
	First-stage NDEA 2022 (X $\rightarrow$ Z $\rightarrow$ Y)	Second-stage NDEA 2022 (X $\rightarrow$ Z $\rightarrow$ Y)	
DEA 2022 (X $\rightarrow$ Y)	0.818	0.368	
	First-stage NDEA 2018 (X $\rightarrow$ Z $\rightarrow$ Y)	Second-stage NDEA 2018 (X $\rightarrow$ Z $\rightarrow$ Y)	
DEA 2018 (X $\rightarrow$ Y)	0.763	0.358	

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 NDEA 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.

Figure 7 visually represents the distribution of efficiency scores across countries, highlighting distinct clusters of performance. In 2022, the distribution appears to be more even compared to 2018. When analyzing the overall efficiency of Data Envelopment Analysis (DEA), there is a noticeable decrease in the number of inefficient countries, accompanied by a decline in the number of fully efficient countries. This trend is similarly observed in the evaluation of efficiency at the first stage. Histograms also indicate an equalization of the results of the second stage. This means that the EU countries are unifying their achievements in installed capacity utilization.

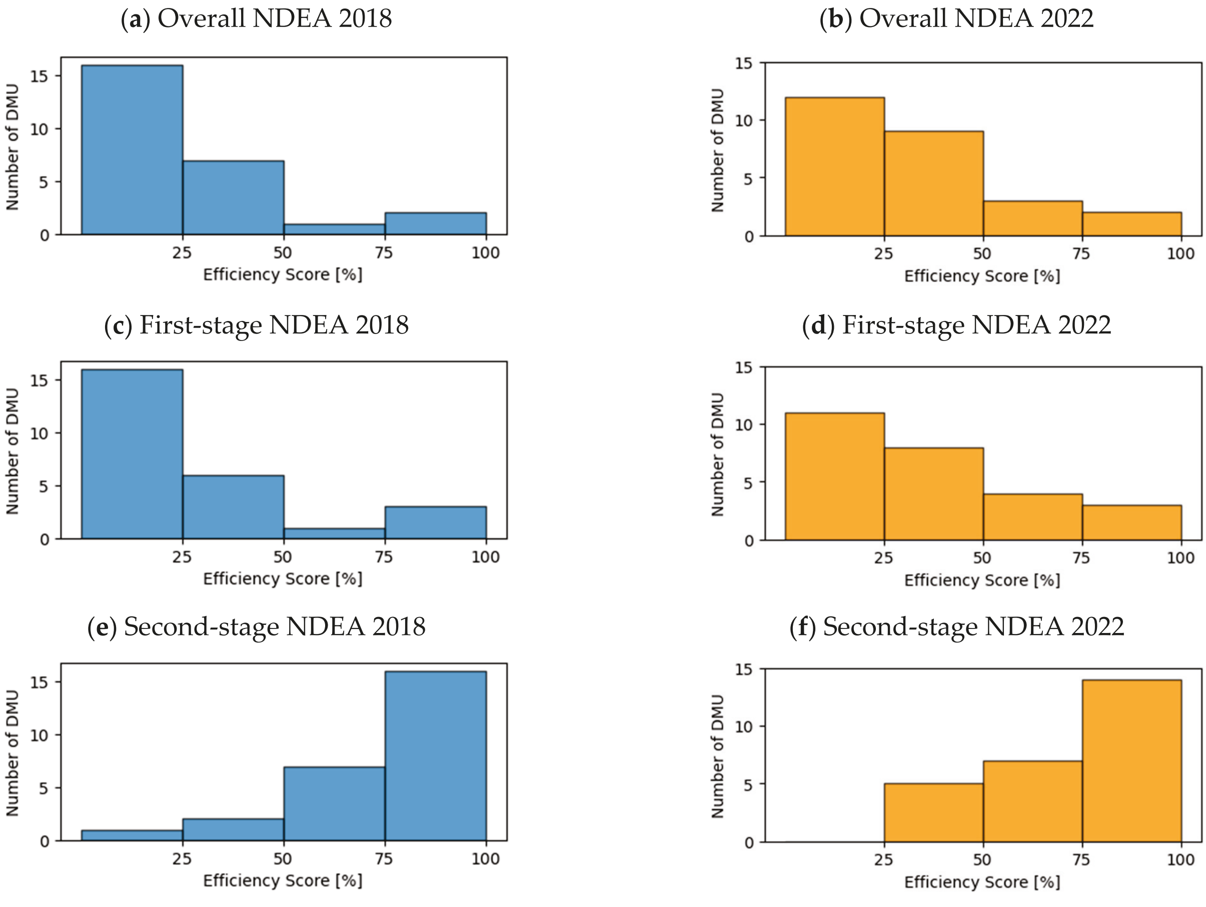
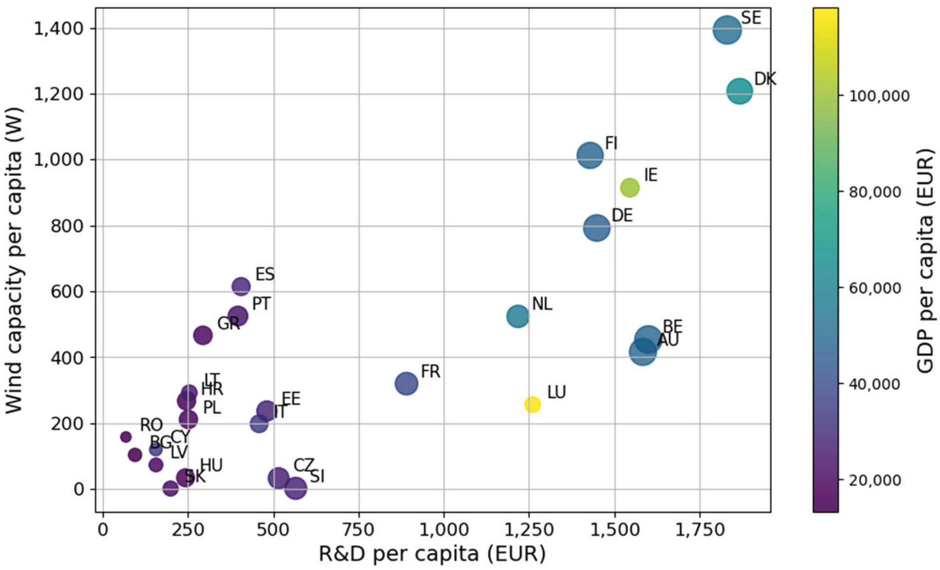


Figure 7. Histograms of efficiency scores by NDEA: (**a**) overall 2018; (**b**) overall 2022; (**c**) first-stage NDEA 2018; (**d**) first-stage NDEA 2022; (**e**) second-stage NDEA 2018; (**f**) second-stage NDEA 2022.

In summary, although the current results confirm some trends observed in previous studies, using a two-stage NDEA model and including additional variables such as per capita measures and spatial constraints allows for a more comprehensive and detailed understanding of renewable energy efficiency. NDEA, unlike single-stage DEA models, provides a more detailed view by assessing both the efficiency of the utilization of natural resources and the actual production from installed capacity. It offers targeted insights not captured by previous single-stage or ensemble models. The results confirm that countries with higher environmental potential (e.g., wind speed and GHI) do not always achieve proportional energy production, highlighting persistent inefficiencies in infrastructure deployment and use.

It should be recognized that factors such as GDP, economic productivity, inflation, energy prices, human capital, technological capacity, urbanization, grid characteristics, regulatory frameworks, and broader policy environments play a key role in shaping the dynamics of the energy transition. These factors interact in complex ways and can affect renewable energy deployment through multiple pathways. To exemplify this, the relationships between GDP per capita, R&D expenditures per capita, and renewable energy capacity per capita are illustrated in Figure 8.

(**a**) Wind capacity per capita, R&D expenditures, and GDP per capita



(**b**) Solar capacity per capita, R&D expenditures, and GDP per capita

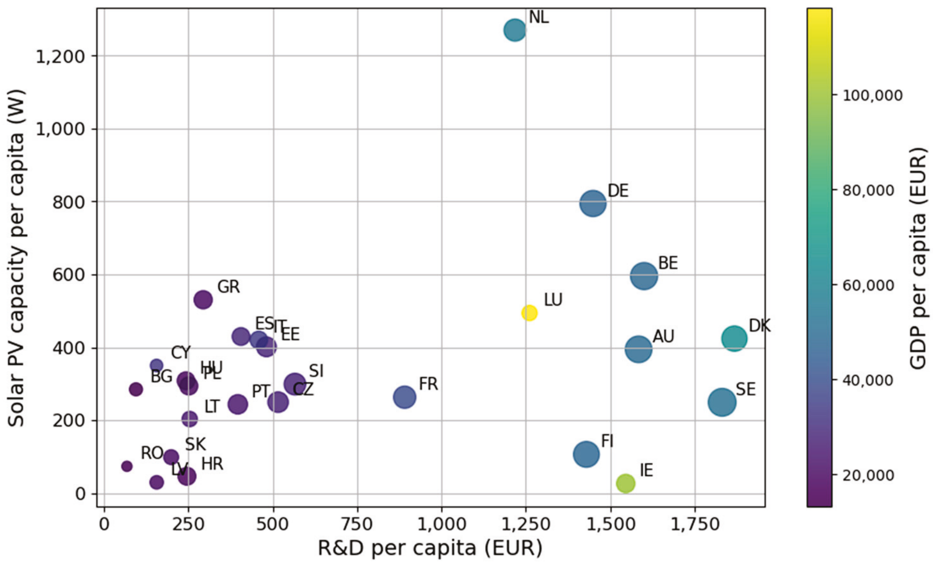


Figure 8. Relationship between (**a**) wind capacity per capita and (**b**) solar capacity per capita, R&D expenditures, and GDP per capita.

The visible relationship indicates that the standard of living measured by GDP per capita and, to an even greater extent, the associated higher expenditure on R&D per capita determine the development of the potential of renewable energy sources. To measure the impact on the final NDEA results, a backward stepwise regression model was implemented, with the initial set of variables: R&D expenditures per capita (which may indicate the level of innovation and technological development), R&D expenditures as percent GDP (which may indicate the level of support for innovation in economic priorities), GDP per capita (indicating the level of economic development, quality of life, and well-being of society). The only significant variable in the model is R&D expenditures per capita, which has a positive impact on the dependent variable and the coefficient of 0.2365 (p-value = 0.007). However, the model explains only 0.268 of the variability, measured by R^2, so other factors may have an impact on the efficiency result.

5. Discussion and Conclusions

The article proposes an assessment of the relationship between the location of countries and the development of solar and wind technologies, as well as the level of their use by the NDEA. As a result, energy production was evaluated in relation to the installed capacity and the geographic location, which is expressed in wind density and irradiation.

The research presented in this article provides answers to the key research questions formulated earlier. The findings reveal substantial differences among EU countries in the relative efficiency of utilizing their available solar and wind energy potential, with efficiency levels ranging from a value of just a little over 0% (Slovakia and Slovenia) to 100% (Germany and the Netherlands), and average efficiency of 34.7% of the first-stage and 28.7% of overall (Q1). The most efficient countries that serve as performance benchmarks are Germany and the Netherlands (Q2). The use of already installed capacity is high, with an average of 74.9%; the leaders are France, Germany, the Netherlands, and Spain. The impact of exogenous variables on performance, GDP, and R&D expenditures was discussed. Additionally, a modest increase in the average relative efficiency of EU countries was observed, rising from 23.8% to 28.4% between 2018 and 2022. Germany, with a Malmquist index value of 1, can be considered the reference country in this analysis (Q3).

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. NDEA has advantages over conventional DEA as it assesses both potential development and actual implementation. This study proposes the NDEA model that utilizes 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, which compensate for the lack of solar energy in winter months with wind energy. It is important to note that this study does not refer to hydropower due to its controversial nature and limitations.

The presented study has important policy implications, especially when energy policy instruments are designed and implemented at a supra-national level. In the case of the European continent, the European Union has a major influence over the energy policies of its member states. The European Parliament and the Council of the European Union enact binding legislation that member states must incorporate into national laws, for example, Renewable Energy Directive, Energy Efficiency Directive, and the EU Emissions Trading System (ETS). Although member states retain formal control over their energy mix and how they exploit their natural resources, overarching energy and climate goals set in the European Green Deal and "Fit for 55" package do not leave the EU members much autonomy in this area. This puts an even greater responsibility on the EU institutions to enact regulations and incentives that help each member state follow the best-tailored transition pathway to a net-zero economy. Such pathways may be technology-specific or location-specific.

The study affirms 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, thereby combining overarching targets with a flexible governance system. Such a flexible system accommodates the heterogeneous nature of its member states' renewable energy resource endowments as well as the utilization efficiency of the installed capacity. 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 a one-size-fits-all approach. The EU renewable energy policy system should allow for the adjustments mentioned above in the following areas:

1. National Energy and Climate Plans (NECPs)—member states should tailor their NECPs to their unique resource potentials. Within each country's renewable energy policy, adaptive use of feed-in tariffs (guaranteed purchase, fixed rates, long-term contracts) may serve as effective instruments fostering the development of photovoltaic and wind power capacity in accordance with local natural and technical possibilities [105,106].
2. Joint Projects and Joint Support Schemes—multiple countries can collaborate on large projects to tap into renewable resources where they are most abundant and cost-effective.
3. Cross-border grid integration and development—interconnectors, advanced transmission systems, digital monitoring, and energy storage capacity to increase resilience to fluctuating power generation potential, avoid bottlenecks, and allow surplus power to flow to demand centers.
4. Cross-border Power Purchase Agreements (PPAs)—one member state can invest in or buy renewable electricity generated in another state. This further improves the overall renewable energy generation efficiency of the European Union.
5. Tailored funding for innovation and technical assistance (Horizon Europe, European Regional Development Fund, the Just Transition Fund)—funds should be directed towards regions with strong but underutilized renewable resources. Such targeted support helps unlock local potential and diversifies the EU's renewable energy mix [48]. Furthermore, strategically situated R&D centers and specialized supply chains help form sustainable energy innovation hubs that drive improvements in technology and create opportunities for knowledge and skill transfer to other EU regions [107].

Regular monitoring and evaluation of countries' performance with methods such as NDEA allow for policy design and adjustments that respond to the fast-changing environmental, economic, and technological circumstances. This is a critical aspect of a responsible and sustainable energy policy that, similarly to Responsible Research and Innovation, should pass the test of fairness (ethical acceptability), directionality (social desirability, human well-being orientation, sustainability), reflexivity (evidence-based solutions, risk mitigation measures), responsiveness (adaptive governance, stakeholder inclusion), and anticipation (foresight) [108].

The developed approach can be extended to other countries due to methodological flexibility and reliance on widely available indicators. The only limitation is the accessibility and accuracy of data. Nevertheless, the variables used in this approach are widely measurable and applicable in many countries. However, the recommendations concerning the countries require adjustment and adaptation to different contexts, including the level of economic development. NDEA assumes that all DMUs operate under similar conditions. The European countries are a relatively homogeneous group, analyzed together in many studies as having many common regulations and adopting coherent priorities [109].

Although NDEA is a powerful and robust tool for the analysis of multi-stage systems, its application to the complex process of renewable energy systems—including environmental potential, infrastructure development, and energy production—faces several notable limitations. The most significant challenge lies in the risk of oversimplifying the complexity of real-world energy systems. As with any methodological framework, the NDEA model involves unavoidable simplifications. It assumes a linear and deterministic relationship between stages, which may not fully capture the intricate interdependencies between physical, economic, and technological factors. Another limitation concerns data quality and variable selection, which is inherently subject to a degree of subjectivity. Considering too many variables diminishes the discriminative power of the NDEA model. As the number of inputs and outputs rises, the capacity to distinguish between efficient and inefficient units declines, resulting in excessive efficiency scores. Moreover, NDEA is sensitive to outliers and noise. In our study, the choice of variables was guided by three key considerations: the specific research objectives, insights from existing literature, and the availability and quality of data. While alternative variables could theoretically have been included if they were logically justified, available, and consistent with the NDEA model framework, the selected variables reflect a balance between methodological rigor and practical constraints. Discrepancies in the availability and accuracy of data across countries also pose challenges, potentially affecting the reliability of results. When considering the limitations, it should also be noted that the optimization and flexibility of weighing—one of the most significant advantages of the NDEA method under certain conditions—may sometimes result in unrealistic efficiency assessments if DMU benefits from extreme weight allocations. These limitations should be carefully considered when interpreting the findings and applying them to policy or decision-making.

The proposed two-stage NDEA methodology represents one of several methods available for the analysis of renewable energy systems. The popular alternative methods that have been proposed in the literature are Free Disposal Hull (FDH) and Stochastic Frontier Analysis (SFA). FDH, sometimes referred to as a variant of DEA, does not assume a convex production frontier. This provides flexibility in adapting to irregular production structures. However, like DEA, it is sensitive to extreme observations. SFA, whose results are often validated with DEA, is a parametric approach that separates inefficiency from statistical noise by introducing an error term. It allows for hypothesis testing and confidence intervals, increasing robustness. However, it requires certain assumptions about the functional form (e.g., Cobb-Douglas or Translog production function). Research indicates that specific solutions that augment the complexity of analytical models might be hybrid approaches that integrate the DEA method with technologies such as AI algorithms. Such approaches use the strengths of the methods, offering better interpretability and transparency, as well as advanced capabilities for pattern detection, self-learning, and managing large data sets.

The study intentionally focuses on the geographic and environmental potential of EU countries, allowing the use of standardized data and ensuring objective, comparable results. Future research could build upon our results by integrating political and economic dimensions to provide a more comprehensive perspective on the interplay between geographic potential and other critical determinants of renewable energy efficiency. The authors acknowledge the importance of sociopolitical considerations in the context of renewable energy use. However, addressing this topic comprehensively requires extensive interdisciplinary research conducted by international teams.

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 NDEA 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. Inspiration for prospective directions for research can also be found in works not using the DEA method, e.g., shifting from the country level to the spatial grid-scale and including residual demand in the power system into DEA models [2], as intra-country variations in renewable energy suitability are significant [8]. An interesting direction of future development is to combine DEA with machine learning methods to exploit big data sets for advanced forecasting.

In conclusion, the NDEA approach is useful in informing policies that strategically support both countries with high renewable energy generation potential and those that excel in efficient and innovative energy operations. By coupling resource-based development with technology-driven excellence, the EU can achieve a more flexible, adaptable, secure, and cost-effective energy system for all member states.

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Nomenclature

Abbreviation	Description
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
APEC	Asia-Pacific Economic Co-Operation
BCC (VRS)	Variable Returns to Scale DEA Models
CCR	Constant Returns to Scale
CEF	Cost Efficiency Indicator
CO_2	Carbon Dioxide Emissions
DEA	Data Envelopment Analysis
DEAM	Data Envelopment Analysis Modified
DHW	Domestic Hot Water
DMU	Decision-Making Unit
DNSBM-DDF	Dynamic Slacks-Based Measure with Network Structure with Directional Distance Function
EPI	Environmental Performance Index
EU	European Union
FAHP	Fuzzy Analytic Hierarchy Process
FTOPSIS	Fuzzy Technique for Order of Preference by Similarity to Ideal Solution
FWASPAS	Fuzzy Weighted Aggregated Sum-Product Assessment
GDP	Gross Domestic Products
GHG	Greenhouse Gas Emissions
GVA	Gross Value Added
HDI	Human Development Index
IO	Input-Oriented
LCOE	Levelized Cost of Electricity
MI	Malmquist Index
MPI	Malmquist Productivity Index

NDEA	Network Data Envelopment Analysis
OLS	Ordinary Least Squares
OO	Output-Oriented
PLS-SEM	Partial Least Squares Structural Equation Modelling
PV	Photovoltaics
RE, REs	Renewable(s)
SBM	Slack Based Model
SFA	Stochastic Frontier Analysis
SOx	Sulfur Oxides
VRS (BCC)	Variable Returns to Scale DEA Models

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Leveraging System Dynamics to Predict the Commercialization Success of Emerging Energy Technologies: Lessons from Wind Energy

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Abstract: The United States urgently needs to tackle the climate crisis while enhancing energy security and resiliency. The complexity of the U.S. energy system, with its interconnected elements, makes predicting future states challenging, especially with the introduction of novel energy systems like wind, solar, clean hydrogen, and advanced nuclear technologies. Modern systems engineering methods and tools can provide deeper insights into these dynamics and future behaviors. This research aims to develop a comprehensive model that captures the main elements and behaviors of new energy technologies within the existing energy system. We hypothesized that the market uptake of novel energy systems is influenced by multiple diverse factors, such as technological learning, availability of resources, and economic incentives; examined the history of electricity generation using land-based wind technologies; and developed a system dynamics model to investigate the relationships between capacity growth and influencing factors, both internal and external. The developed model yielded outcomes that confirmed the hypothesized dynamics of wind energy system diffusion through a quantitative comparison of installed capacity and highlighted the significant influence of resource availability, federal incentives (production tax credits), and technological learning on capacity growth and cost reduction. This research aims to support informed decision-making for investments in novel energy systems and aid in developing effective policies for technology deployment.

Keywords: investment and policy decision-making; system dynamics; energy transition; novel energy technology commercialization; investment uncertainty

1. Introduction

The United States is facing an urgent need to address the climate crisis alongside an unprecedented challenge to strengthen the nation's energy security and resiliency. The U.S. energy system is very complex due to multiple interconnected elements that dynamically affect each other, which complicates predictions of future states of energy systems. It is especially hard to predict energy system behaviors when novel energy technologies are introduced (e.g., renewable electricity generation, clean hydrogen, or advanced nuclear). Modern systems engineering methods and tools can support a deeper understanding of system dynamics and future behaviors.

Wind energy has been growing in popularity in the United States since the 1980s, and solar since the late 2000s. As of today, wind energy has reached high technical maturity and has been widely commercialized thanks to costs low enough to compete with incumbent primary electricity generation sources based on fossil fuels. Wind technology is still developing in terms of increased efficiencies and lowering costs [1–3], which increases its attractiveness. Wind energy is getting closer to reaching the level of maturity where it is self-sustained for further commercialization, especially when supported by federal and state policies [4]. Solar energy technology is slightly behind wind energy, but it is rapidly catching up, with an exponential increase in installed capacity since 2010. Costs are rapidly declining, technology is quickly maturing, and solar energy is very near becoming a self-sustainable commercialized energy solution.

Other novel energy technologies, however, are in the early commercialization stage. These include clean hydrogen generation, synthetic fuels, and advanced nuclear technologies. The commercial success of new energy technologies within existing energy systems is highly uncertain due to numerous factors. Yet, we can draw some parallels from recently commercialized technologies, like wind and solar, to better understand the dynamics and future states of new energy systems.

The purpose of this research is to understand the factors affecting the deployment of a new energy technology in order to inform policy or support decision-making. Some technologies are very novel and still developing, like clean hydrogen, with large uncertainties about future market uptake scenarios. The diffusion of developing technologies is very dynamic and highly uncertain due to many factors that could influence the integration of these technologies into the overall energy system. To understand the general trajectory of commercializing novel energy systems, we can examine the experiences of already mature technologies that have penetrated the energy market, specifically onshore wind and solar photovoltaic, and apply insights about the factors influencing their diffusion to still-maturing technologies to better understand their potential for successful commercialization.

The proposed model addresses the stakeholder need for a deeper understanding of factors that potentially affect technology diffusion to allow better-informed decision-making. While multiple methodologies and tools are available to analyze energy transition, none of them specifically focus on understanding holistic energy *system dynamics* to make better decisions and predictions. The model developed in this research is unique compared to other system dynamics or technology transition models, as it provides stakeholders with a clear and intuitive understanding of novel energy system behaviors within established energy systems.

Wind energy is used as a case study to draw lessons from the commercialization of that technology. This research aims to utilize modern systems engineering methods and tools to better understand the dynamics and future behaviors of energy systems. By analyzing the growth and development of wind energy, which has reached high technical maturity and widespread commercialization, we can gain insights into the factors contributing to its success. This research developed a model that captures the key elements and behaviors of a novel energy technology within the established energy system, using historical data from wind-based electricity generation. The model aims to provide a framework that can be applied to other emerging energy technologies, such as electrolysis-based hydrogen, synthetic fuels, and advanced nuclear technologies, to predict their potential for commercial success and integration into the existing energy system.

This paper is organized as follows. Section 2 provides a brief overview of the overall energy system in the United States and the factors affecting the behaviors of energy systems. Section 3 outlines the approaches currently used to model energy systems and introduces appropriate systems engineering principles and tools to assist with the understanding and modeling of complex systems, including energy systems. Section 4 introduces the dynamics of novel technology diffusion and commercialization via a qualitative system dynamics model. Section 5 describes the development of a quantitative system dynamics model for wind technology commercialization. Lastly, Section 6 summarizes the findings of this research and suggests opportunities for future research.

2. Background on Energy Systems

This section provides a brief overview of a large-scale national energy system, as well as the basic factors affecting the integration of a novel energy technology into the overall energy system.

2.1. Description of an Energy System

National, regional, and local energy systems form a complex enterprise comprising many elements and their interconnections. Figure 1 shows a schematic of the overall U.S. energy system. The elements of these systems belong to the following general categories:

- **Sources of Electricity:** In the United States, as of 2023, most electricity is generated from fossil fuels, specifically natural gas and coal [5]. Fossil fuel-based energy sources are associated with heavy carbon dioxide (CO_2) emissions, leading to a large push for the transition to zero- or low-emission sources for electricity generation, such as renewable and nuclear energy. Renewable energy sources include solar- and wind-based power generation, as well as hydropower and smaller sources such as geothermal and wave energy.
- **Energy Sources Other than Electricity:** Large industrial processes rely on energy sources other than electricity (e.g., steam). The energy sources for the industrial processes in the United States are also mainly fossil fuels (i.e., natural gas, coal, and oil). Many industrial processes also require feedstock other than energy to produce their products (e.g., hydrogen and oxygen). For example, the steel manufacturing industry uses large amounts of hydrogen and oxygen, both generated mostly from fossil fuel-based feedstock using processes with heavy CO_2 emissions. These areas are illustrated under "Process Energy Sources" and "Sources of Hydrogen" in Figure 1.
- **Energy Consumption:** Energy consumers rely on electricity and nonelectrical energy sources. Many industrial processes and the transportation sector primarily use fossil fuels. These hard-to-electrify industries drive the need to develop breakthrough clean energy solutions beyond electricity.
- **Energy Economy:** The energy transition is significantly influenced by the energy economy, which encompasses the production, distribution, and consumption of energy. The interplay between energy markets, federal policies, and projected energy demands shapes the trajectory of this transition.

Energy prices of incumbent technologies, such as natural gas-based electricity generation, play a pivotal role. When natural gas prices are low, they can hinder the adoption of renewable energy sources, as natural gas becomes a more economically attractive option [6]. Conversely, high natural gas prices can accelerate the shift toward renewables by making them more competitive in terms of cost [7]. Additionally, fluctuations in global oil prices can impact the broader energy market. High oil prices can drive investments in alternative energy sources, while low oil prices can reduce the economic incentive to invest in clean energy technologies, slowing the transition [8,9].

U.S. federal policies are also crucial in shaping the energy transition. Climate change policies aimed at reducing greenhouse gas emissions, such as the implementation of carbon pricing or emissions trading systems, can incentivize the adoption of clean energy [10–12]. Investments in research and development for renewable energy technologies and energy efficiency measures are critical components of climate change policy [13].

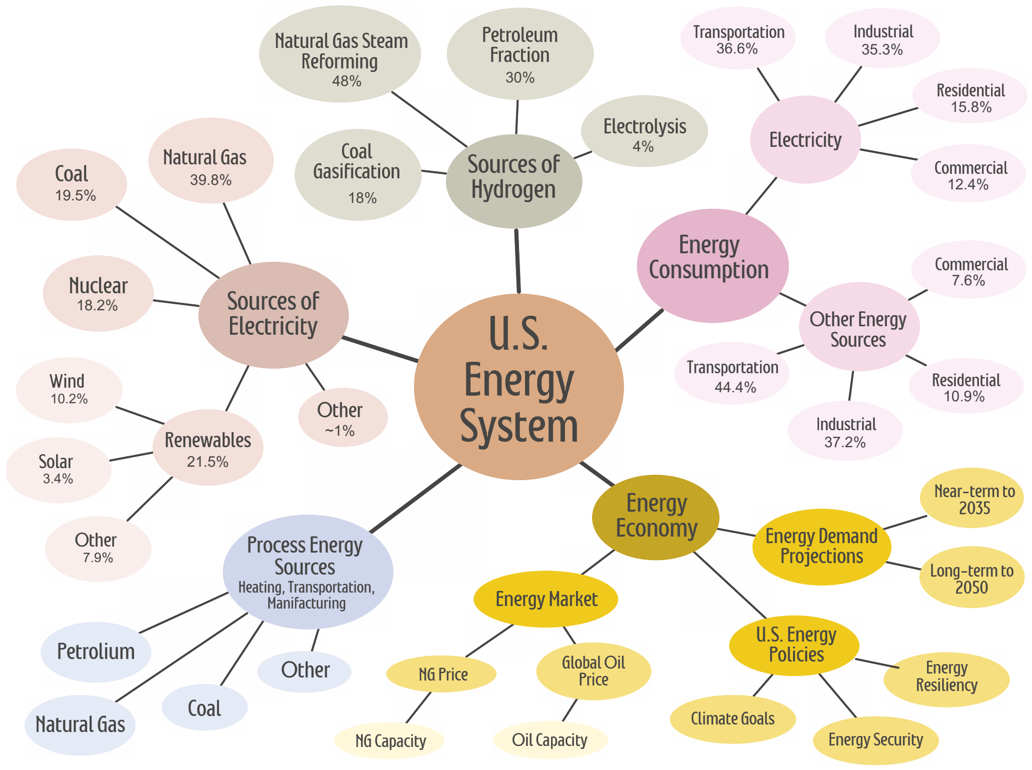

Figure 1. U.S. energy system schematic.

In terms of energy security, reducing dependence on imported fossil fuels by diversifying energy sources enhances national security and stabilizes energy prices. Additionally, diversifying energy sources can make the energy sector more resilient to disruptions, such as natural disasters or geopolitical conflicts [13,14].

Projected energy demands, both short-term and long-term, also impact the energy transition. In the short term, energy demand is influenced by economic conditions, weather patterns, and technological advancements. Long-term energy demand projections consider factors such as population growth, urbanization, and economic development [6]. Sustainable growth requires a significant increase in clean energy capacity to meet rising demand while reducing carbon emissions [15].

Given the complexity of the energy system, the current paradigm demands comprehensive energy planning to maximize the energy system's performance. The optimal planning, design, and operation of such energy systems, which efficiently integrate different energy sources and fluctuating demands, inherently represent a multi-disciplinary complex problem. While this research does not address the planning and optimization of the overall energy system, numerous studies exist, e.g., [16–20]. In addition, multiple novel methodologies and tools are now available that focus on the planning and optimization of the overall energy system. We review some of the most prominent tools in Section 3.2.

It is important to note that the energy system description presented above potentially overlooks some elements or dynamics. However, the presented information provides a clear understanding that the U.S. energy system is influenced by the interplay of energy market dynamics, federal policies, and projected energy demands. The evolving landscape of energy prices, driven by both incumbent and alternative technologies, along with supportive governmental policies and an increasing focus on sustainability, is a key factor that determines the pace and success of the transition to clean energy.

2.2. Dynamics of Novel Energy System Diffusion

The energy system transition is influenced by a complex interplay of factors, including technological advancements, government policies, economic considerations, social acceptance, geopolitical dynamics, environmental concerns, and resource availability [21–26]. Changes in technologies, market forces, regulations, public opinion, and international relations all play a role in driving the shift toward new energy sources and systems.

This multifaceted process involves not only the development and adoption of novel energy technologies but also the transformation of existing infrastructure, market structures, and regulatory frameworks. As nations and industries strive to balance economic growth with environmental sustainability, the energy transition is becoming a central focus of global efforts to combat climate change and ensure energy security for future generations. The key factors affecting the energy system transition are as follows:

- **Policy and Regulation:** Government policies, subsidies, tax incentives, and regulations play a crucial role in encouraging or hindering the energy transition, as supportive policies can significantly accelerate the adoption of novel energy technologies.
- **Technological Advancements:** Technological innovations improve efficiency and reduce costs, making them more competitive with incumbent fossil-fuel-based energy solutions. Cost reductions due to technological advancements have been observed in wind and solar electricity generation and storage technologies [1,2,27].
- **Economic Factors:** The cost of new energy technologies versus incumbent ones, the availability of financing, and the overall economic climate influence investment decisions for the energy sector.
- **Environmental Concerns:** Growing awareness of climate change drives the demand for cleaner energy solutions. International agreements like the Paris Agreement also pressure countries to reduce greenhouse gas emissions, given that the electricity sector is the primary contributor of CO_2 emissions.
- **Energy Security:** Diversifying energy sources can enhance national energy security by reducing reliance on imported fuels and mitigating the risks associated with geopolitical tensions.
- **Market Dynamics:** The energy market’s structure, including energy prices, market competition, and the extent to which markets are open to new entrants, affects the pace and nature of the energy transition.
- **Availability of Resources:** The availability of the resources required for a novel energy technology is a key factor influencing the success of that technology’s commercialization. Resource constraints, either real or perceived, add significant uncertainties to the overall success of the technology’s commercialization, which may preclude willingness to invest in those technologies (e.g., access to fuel and land resources needed for renewable installations).
- **Public Perception and Social Acceptance:** Public awareness and support for novel energy projects can influence their deployment. Social acceptance is crucial for the successful implementation of large-scale projects and the eventual nationwide diffusion of the technology.
- **Infrastructure and Grid Capability:** The existing energy infrastructure’s ability to integrate renewable energy sources, including grid capacity and storage solutions, affects the energy transition process.
- **Research and Development:** Investment in research and development (R&D) for new energy technologies and improvements in existing ones can significantly impact the speed and efficiency of the energy transition.
- **International Cooperation:** Cross-border collaboration on technology transfer, funding, and policy alignment can facilitate an efficient and widespread energy transition.

These factors interact in complex ways, and addressing them holistically is essential for any model that aims to describe or predict energy transition.

3. Literature Review

There are multiple approaches supported by modeling and simulation tools focused on modeling energy system transition. The most commonly used approaches are summarized in this section.

3.1. Existing Approaches to Modeling Energy Systems and Energy Transition

System dynamics (SD) models use feedback loops and stock-flow diagrams to simulate the dynamic behavior of energy systems over time [21,28–34]. These models capture the interactions between different components, such as technology, policy, economics, and social factors, making them particularly useful for understanding long-term trends, feedback effects, and complex interdependencies. **Agent-based models** simulate the actions and interactions of individual agents, such as households, firms, and policymakers, to understand how their behaviors contribute to the overall system dynamics [35–38]. These models are effective for studying market dynamics, adoption behaviors, and the social diffusion of technologies, capturing heterogeneity and individual decision-making processes. **Optimization models** aim to find the optimal configuration of the energy system based on criteria like cost minimization, emissions reduction, or energy efficiency [39–44]. The optimization could be performed using other models, e.g., agent-based models, as the core part to find optimal solutions. Optimization models are well suited for planning and designing energy systems, making investment decisions, and identifying least-cost pathways. **Integrated assessment models** combine insights from multiple disciplines, including economics, environmental science, and technology, to assess the interactions between human and natural systems [45–48]. Integrated assessment models are often used to evaluate the long-term impacts of climate policies, offering a comprehensive and multidisciplinary perspective. **Lifecycle assessment (LCA) models** evaluate the environmental impact associated with all stages of a product's life, from raw material extraction through production, use, and disposal [49–52]. LCAs provide detailed environmental impact assessments, making them useful for comparing different energy technologies in terms of their environmental impact and identifying areas for improvement. **Hybrid models** combine elements from different modeling approaches to leverage their respective strengths. For instance, a hybrid model might integrate system dynamics for long-term trends with agent-based models for individual behavior analysis. This approach offers a more comprehensive and nuanced analysis by addressing complex, multifaceted research questions.

The approaches and models described above are well suited for their applications. However, the models are complex, requiring experts to both develop them and interpret the results. On the other hand, decision-makers desire something that describes the problem in sufficient detail yet simply provides a clearer understanding of underlying issues and potential solutions. In order to make better-informed decisions, the stakeholders must also understand the behaviors of the system, both expected and emergent, to develop solutions that have built-in mitigation strategies for unwanted dynamics. As such, an SD modeling approach was chosen for this research as it is best suited for the purpose of providing an understanding of the dynamics of novel energy systems diffusion within the established energy systems.

3.2. Systems Engineering Principles and Tools to Enhance Decision-Making for Energy Systems

As discussed in Section 2.1, the energy system is a very complex system with multiple interconnected elements. Systems engineering is a discipline developed to deal with this type of problem that addresses the challenges of complex, multidiscipline systems. Therefore, SE is used in this research to guide the formulation of the problem by modeling the factors affecting the deployment of a new energy technology.

Systems thinking is the foundation of SE—it is the discipline that relies on the holistic approach capable of "connecting and contextualizing systems, system elements, and their environment to understand difficult-to-explain patterns of organized complexity" [53]. This capability to understand complex systems is imperative in decision-making for complex systems, which is the reason systems thinking is seen as the foundational methodology to build the decision-support model being researched here.

Model-Based Systems Engineering

The study presented in [54] describes MBSE as "an emerging paradigm for improving the efficiency and effectiveness of systems engineering through the pervasive use of integrated descriptive representations of the system to capture knowledge about the system for the benefit of all stakeholders". The INCOSE handbook [53] discusses the benefits of MBSE compared to the traditional, document-based practice, including improved communications between stakeholders, a better capability to manage system complexity, improved product quality, and enhanced knowledge capture and transfer. Therefore, SE processes can be further improved by implementing a model-based systems engineering (MBSE) approach.

A system dynamics (SD) model is an MBSE tool that leverages feedback loops and stock–flow relationships to examine the intricate interactions within an energy system. The key components of an SD model include the following [55]:

- Feedback loops, or causal-loop diagrams (CLD)s, which illustrate the interconnected relationships between different components, such as how a decrease in costs can drive an increase in technology installations and the increase in installations, further driving down costs.
- Stocks, which represent accumulated quantities, such as installed capacity.
- Flows, which indicate the rates of change within the system, such as the rate of incremental capacity additions.

Software tools like Vensim [56], Stella [57], and Powersim [58] are commonly used for this purpose. SD models are employed to support the understanding of the diffusion of a novel energy system due to their ability to take into account multiple interdisciplinary factors, such as technology adoption, policy changes, economic impacts, and social behavior over time, enabling the simulation and evaluation of different transition pathways and policy scenarios. In addition, the specific benefit of SD models is their unique capability to demonstrate the feedback effects between model elements, which helps in understanding long-term system behaviors resulting from such dynamics.

4. Qualitative Modeling of Energy System Commercialization Dynamics

Technology diffusion is the process of adopting and spreading a new technology across markets and societies involving various stakeholders such as developers, manufacturers, users, policymakers, and regulators. This process unfolds in several phases [11].

In the introduction phase, the technology is brought to market and adopted by early enthusiasts. During this phase, feedback from these early users leads to refinements in design and functionality. As improvements are made, the technology enters the growth phase and becomes more attractive to a broader audience. Adoption rates increase, production scales up, costs decrease, and significant investments in marketing and infrastructure become common. As the technology reaches peak adoption during the maturity phase, the market becomes saturated, and the rate of new adopters slows down. The focus then shifts to incremental innovations, cost optimization, and the enhancement of the user experience.

Eventually, newer technologies may emerge, leading to a decline in the adoption of the existing technology and prompting companies to pivot to the next wave of innovation.

Positive feedback loops are critical in technology diffusion. As more users adopt the technology, more data and feedback are generated, which is invaluable for further innovation and refinement, making the technology even more desirable and driving more adoption, thereby perpetuating the cycle of improvement and diffusion, as shown in Figure 2 (adapted from [59]).

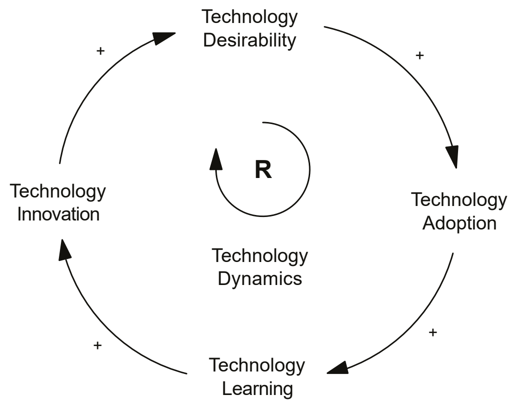

Figure 2. Basic dynamics of technology innovation and diffusion, adapted from [59].

However, diffusion is not without its challenges. Large-scale sociotechnical systems, such as energy generation, involve numerous interdependent components and subsystems that have intricate and dynamic relationships with each other and with external elements. Understanding and leveraging these dynamics is crucial for successfully introducing and scaling new technologies, especially within complex sociotechnical systems like energy generation. The system dynamics (SD) model developed in this research aims to address these interactive dynamics.

4.1. Modeling Methods: Causal-Loop Diagram

The key dynamics of new technology diffusion affected by innovation are presented in Figure 2 [59]. The trajectory of technology commercialization can be modeled using two basic types of models: capacity growth and technology diffusion. The capacity growth model focuses primarily on economic factors as the main influences on the adoption of a product or technology. The technology diffusion model replicates social contagion as the main factor influencing adoption. The basic Bass model [60] of diffusion is well known and widely used in marketing, and many SD studies are based on this model [55,61–63]. These two types of models are often combined to include consideration of both the economic and social factors influencing technology adoption [29,59]. This approach is well suited to analyzing energy systems' commercialization, and several studies have developed integrated SD models, as described in this section.

A few widely used models [64–66] are much broader, with their scope focused on the overall electricity market, either regional or at a national scale, with a large set of endogenous and exogenous variables. These models target scenario assessments focusing on a specific outcome (e.g., minimizing costs, minimizing carbon emissions, or assessing the effect of policies on electricity markets).

Our research focuses on the dynamics of novel energy technology adoption and uses a capacity growth model as the basis, with the addition of multiple variables affecting energy system adoption. The model formulation is discussed below.

4.2. Model of Dynamics of Novel Energy Systems

The dynamics of energy system adoption are presented via a CLD, as shown in Figure 3. Model loops are shown in **bold text** and variables are shown in *italicized text*.

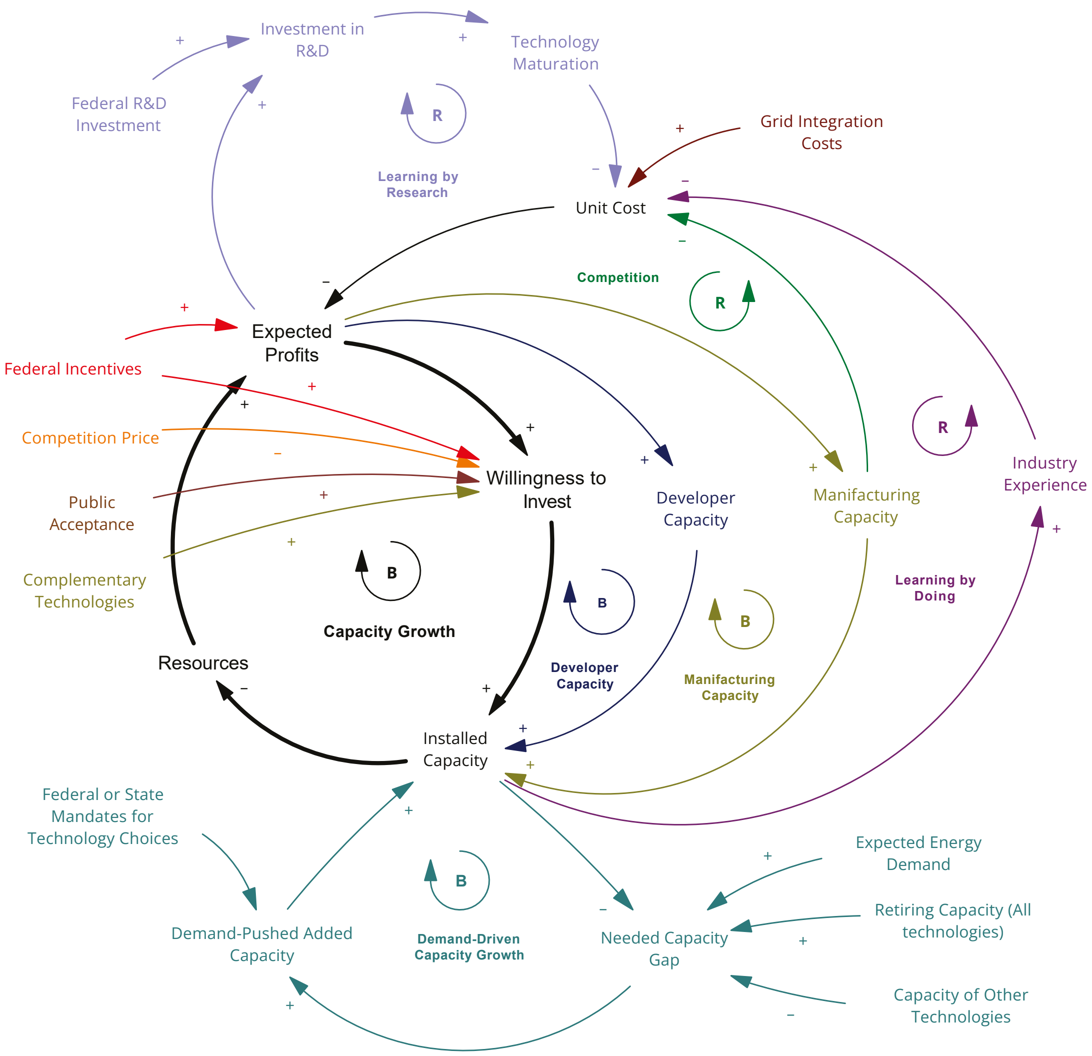

Figure 3. Causal-loop diagram showing the dynamics of deployment of novel energy systems.

The **capacity growth** loop represents the key behavior in energy technology market uptake. *Expected profits* positively affect the *willingness to invest*, which, in turn, positively affects the *installed capacity*. However, for resource-dependent energy systems, the availability of limited resources could constrain growth. Wind and solar energy are dependent on the availability of land for installing large-scale projects. Other energy technologies may be dependent on fuel resources, such as natural gas for combined-cycle power plants or uranium for nuclear power plants. For resource-dependent systems, the increasing *installed capacity* depletes available *resources*. This is negative feedback, or a constraining factor, in the capacity growth loop.

As discussed earlier, positive feedback is depicted with a "+" sign and negative feedback with a "−" sign. Similar to the multiplication rule, where multiplying two negatives results in a positive, an even number of negative relationships in a causal loop results in a positive loop, also known as a reinforcing loop (marked as R), while an odd number of negative relationships makes the loop negative, also known as a balancing loop (marked as B). Given that the capacity growth loop has three positive relationships and one negative, it is a balancing loop that is identified with a "B" and a circular arrow showing the direction of the loop's dynamics.

The "learning-by-doing" concept is the most common approach to projecting technology cost reduction trends [67,68]. It illustrates the relationship between cumulative production output and unit cost reduction. This principle suggests that, as companies increase their production, they gain experience and insights, leading to more efficient manufacturing processes. Consequently, production costs decrease as a direct function of cumulative output. This phenomenon is quantitatively described by the learning rate [69–71], which measures the percentage reduction in cost for each doubling of cumulative production output. As firms continue to produce more, they discover ways to streamline processes and operations, reduce waste, and improve overall efficiency, thereby lowering the unit cost even further. A similar concept is called "learning by research", in which the technology improves due to investments in R&D, which results in improved technology efficiency, improved reliability, and the utilization of more appropriate materials, ultimately decreasing costs. Many analyses use a two-factor learning curve that considers both learning-by-doing and learning-by-research contributions to the declining costs of technologies [72,73]. Many studies have also used system dynamics to explore learning curves within the dynamics of technology development [74–77]. This research considers technological learning to be an essential part of energy technology adoption.

The **learning-by-doing** loop is an extension of the capacity growth loop, where the *expected profits* are directly affected by the *unit cost*. The *unit cost* can be expressed as the cost of a technology unit (e.g., cost of a wind turbine or a solar panel) or it can represent the unit cost of energy expressed as levelized cost of energy (LCOE) measured in dollars per unit of electricity, USD/MWh. The growing *installed capacity* increases *industry experience* (positive feedback), which decreases *unit cost* (negative feedback). The lower *unit cost* makes the *expected profits* larger (negative feedback) with the *willingness to invest* completing the learning-by-doing loop, which is a reinforcing loop.

The **learning-by-research** loop is connected to the rest of the dynamics through the *unit cost* and *expected profit* variables—the increasing *expected profits* allow for larger *investment in R&D* (positive feedback), which, in turn, increases *technology maturation* (positive feedback), resulting in decreasing *unit cost* (negative feedback). The negative feedback between the *unit cost* and *expected profits* completes the learning-by-research-loop, which is a reinforcing loop.

Technology adoption depends heavily on industry readiness to install projects (represented by the **developer capacity** loop) and to supply necessary parts (represented by the **manufacturing capacity** loop). The **developer capacity** loop is a balancing loop in which increasing *expected profits* increases *developer capacity*, which, in turn, increases *installed capacity*, both positive feedbacks. The loop completes through the *resources* and *expected profits* variables. The **manufacturing capacity** loop is very similar to the **developer capacity** loop and is a balancing loop.

The **competition** loop represents the industry dynamic where the spike in demand results in supply chain shortages, which allows manufacturers to increase markup on the components. The dynamic is reversed when *manufacturing capacity* increases to satisfy the demand and increased competition between suppliers results in lower markups and, therefore, decreased *unit cost*, which is negative feedback. The competition loop completes through the *expected profits* variable and is a reinforcing loop.

The **demand-driven capacity growth** loop represents the energy market push or resistance to producing more electricity. The needed electricity generation capacity is affected by several exogenous variables, namely *expected energy demand* (dependent on national economic growth) and available electricity generation capacity, represented by the *other technologies' capacity* and *retiring capacity* exogenous variables. The difference between expected demand and currently available capacity is represented by the *needed capacity gap* variable, which will decrease when the *installed capacity* is increasing (negative feedback). A larger *needed capacity gap* would increase the demand for additional electricity generation capacity, including the demand for the specific technology being modeled. This is represented by the *demand-pushed added capacity*, and its increase will increase the *installed capacity* (positive feedback), closing the balancing demand-driven capacity growth loop.

Other Variables—The variables in the causal loops are endogenous or internal to the system. These variables have a direct effect on system behavior, while the system also affects these variables. There are also multiple exogenous variables that affect the system, but these influencing factors come from "outside" the system and are discussed below.

The *needed capacity gap* is affected by the *expected energy demand* (usually a function of national economic growth), the *capacity of other technologies* (i.e., all electricity-generating technologies capable of meeting electricity demand), and the *retiring capacity (all technologies)*. The *Federal or State Mandates for Technology Choices* variable represents the preference for a certain technology by the federal or local government. The renewable portfolio standard (RPS) is an example of such a preference where the push is toward renewable energy technologies to reduce carbon emissions in the electricity sector. The RPS mandates increase the demand for clean technology and decrease the demand for fossil-based technology.

Willingness to invest is affected by several economic, technical, and social factors. In a broader sense, the willingness of investors to invest in a new technology is directly influenced by the level of uncertainty of such an investment. The uncertainties are dependent on government support, represented by *federal incentives*—the stronger the support in terms of the incentive's scale and duration, the greater the willingness to invest. Another economic variable is the *competition price*, in which the attractiveness of a certain technology is measured against its competitors. In addition, the cost of energy generated by the new technology is affected by access to existing infrastructure (e.g., electrical grid for wind energy). The cost of the connection to the existing grid depends on the site's location and how much it would cost to connect the new site to the existing electrical grid, including new transmission lines and other infrastructure, permitting right-of-way rights, and other associated costs.

Social factors can be summarized as *public acceptance* where a given technology could experience either public support (e.g., recent strong support for clean technologies) or resistance (e.g., public resistance to nuclear energy after the Three Mile Island accident).

There are also some technical factors that could influence the attractiveness of a technology to investors. These are typically performance parameters like capacity factors or reliability, but these are considered endogenous to technological progress. However, supporting technologies, such as energy storage technologies for solar and wind generation, could either expedite or hinder the adoption of the technology of interest. This is represented by the *complementary technologies* variable.

Lastly, *federal R&D investment* is an exogenous variable supporting the learning-by-research loop, in which, in addition to the endogenous progress made by the industry by allocating a portion of their profit to R&D, the federal government provides additional external support, expediting technology maturation.

It is often the case in energy systems that the same variables could be considered either endogenous or exogenous depending on the selected system boundary. For example, in the case of the national electricity generation model, *federal incentives* would be an endogenous element, whereas here, this variable is exogenous.

4.3. Results of Model-Based Qualitative Assessments

As discussed previously, energy systems are very complex, with highly heterogeneous elements interconnected with each other. Yet, the model-based representation using CLDs, as shown in Figure 3, offers an intuitive, easy-to-understand way in graphical format for depicting complex interactions between system elements. In addition, the model-based system representation allows for additional benefits like traceability and automatic updates, which become increasingly important for larger models with dozens of feedbacks and hundreds of variables. For example, loops can be easily displayed, as presented in Figure 4, using a "causal chain" function, which helps communicate system behaviors to stakeholders. In this example, the learning-by-doing loop is automatically highlighted by the model.

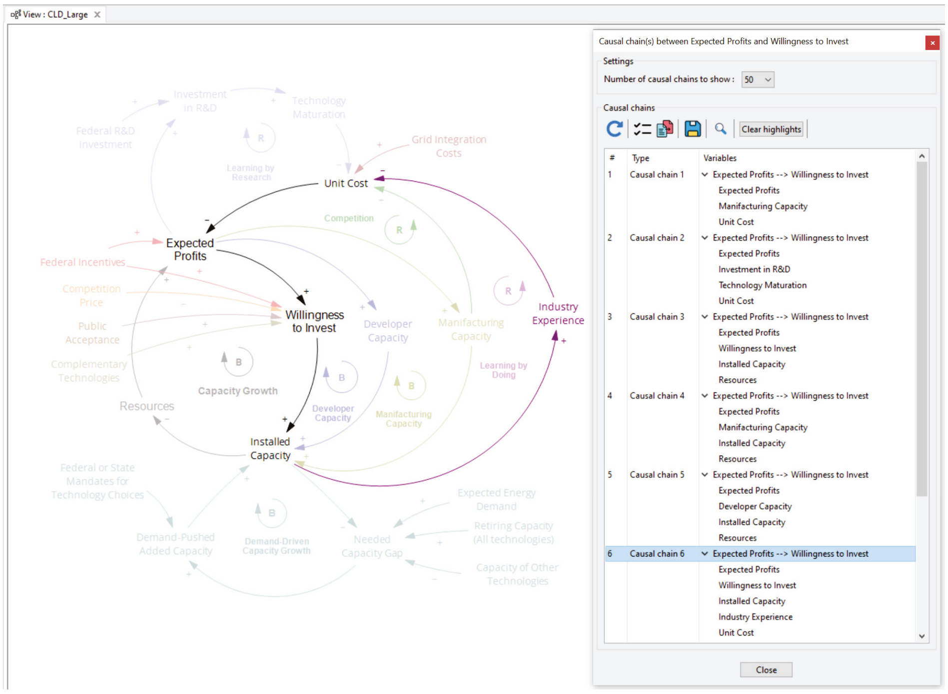

Figure 4. The "causal chain" function automatically highlights the **learning-by-doing** loop from Figure 3, illustrating the capability of model-based system dynamic models.

Another traceability option is to identify all influencing parameters for the variable of interest, either through a tree diagram or an N^2 matrix. Figure 5 shows all variables that influence the *installed capacity*.

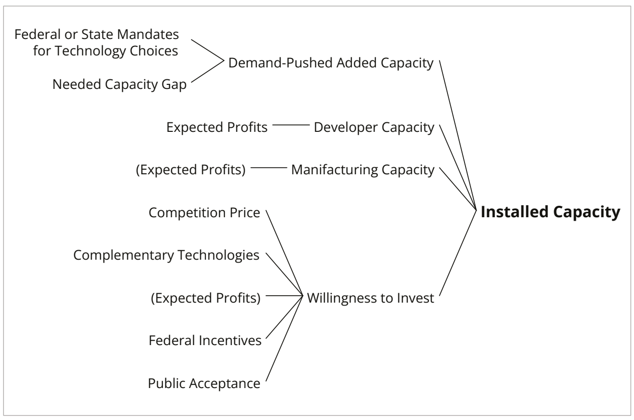

Figure 5. Identification of all influencing parameters for the *installed capacity* from Figure 3, illustrating another capability of model-based system dynamic models.

These capabilities become extremely important in supporting the decision-making process in a more straightforward, graphical manner, especially when systems are very large with hundreds of elements, thereby supporting scalability.

5. Quantitative Modeling of Energy System Commercialization Dynamics

While a qualitative depiction of energy system relationships and dynamics is valuable, it is not sufficient to support decision-making. For informed decision-making, understanding which parameters are the most influential is of critical importance. This understanding enables gauging levels of uncertainty and corresponding risks to the selected solutions, as well as developing strategies to best manage resources to increase the success of technology diffusion. As such, a qualitative approach is expanded to include a quantitative approach for energy system diffusion modeling, as discussed in the following subsections. The variables of the model, along with the data sources, are presented in Table 1.

Table 1. Variables and data sources for the wind model.

Submodel	Variable	Value	Data Source
Profitable Capacity	Historical and projected electricity price data:		
	Historical (1998–2023)	Data	[78]
	Projected (2024–2050)	Data	[79]
	PTC Lookup	Data	[80,81]
	ITC Lookup	Not used	
	Interest Rate	4%	[82]
	ROI	10%	
	Wind Supply Curve	Data	[83]
Technological Learning	Cumulative Global Capacity:		
	Historical (1998–2023)	Data	[3,84,85]
	Projected (2024–2050)	Data	[86]
	Initial Global Capacity—Total Globally Installed Capacity in 1998	10,200 MW	[84,85]
	Initial CapEx—Total Installed Costs in 1998	2824 USD/kW	[2]
	CapEx LR—Learning Rate for Total Installed Costs	0.1312	Estimated
	Initial OpEx—O&M Costs in 1998	98 USD/kW	[1]
	OpEx LR—Learning Rate for O&M Costs	0.09	[87]
	Initial Capacity Factor—Capacity Factor in 1998	0.255	[1]
	Capacity Factor LR—Capacity Factor Learning Rate	0.0517	Estimated
Developer Capacity Growth	Initial Developer Capacity in 1998	500 MW	[1]
	Maximum Growth Rate	40%	[59]
	Developer Capacity Adjustment Time	1 year	[59]
Capacity Growth	Permit Failure Rate	75%	[59]
	Permitting and PPA Decision Time Lookup	4–5 years	[88]
	Willingness to Invest	Data	Estimated
	Average Construction Time	1 year	[59]
	Average Project Lifetime	20–30 years	[89]
	Historical Installed Wind Capacity in the United States	Data	[1]
	Projected Wind Capacity in the United States	Data	[6]

5.1. Model Boundaries and Key Assumptions

An important step in modeling is problem articulation [55]. The purpose of the model is as follows: **To provide an understanding of factors affecting the trajectory of a new energy technology's commercialization to inform decision-making**. This purpose statement helps define the model's boundaries. Figure 3 demonstrates the key dynamics of a novel energy system, but the actual model should be as simple as possible to serve the purpose (i.e., provide valuable insights for the problem being examined). As such, we remove some of the dynamics from the detailed model to focus on the factors with the greatest influence on the energy system's market integration. The reason for model simplification is discussed below.

The importance of electricity demand to the success of novel energy technology integration is obvious. However, when the new technology is not expected to replace the incumbent technologies completely but rather take a somewhat smaller portion of the market, the overall electricity or energy demand is an exogenous variable that indirectly affects technology diffusion. This indirect effect is mostly related to market uncertainties in terms of the additional energy needs and whether such needs can be satisfied by the new technology.

In the current energy system landscape, novel energy technologies still represent a smaller portion of the market [90]. Fossil fuels account for approximately 60% of electricity generation, with nuclear energy providing 18% and all renewable sources contributing 21%. The share of renewable electricity generation has significantly increased over the past few decades, nearly doubling between 1990 and 2024. Nevertheless, individual novel technologies, such as utility-scale wind and solar, contribute only about 10% and 4%, respectively [90].

Given the substantial market demand relative to the small market share occupied by individual novel technologies, national electricity demand is not the key factor affecting technology diffusion. Consequently, the **demand-driven capacity growth** loop is excluded from the system dynamics model.

Multiple researchers have argued the need for better-defined learning curve models, specifically advocating for two-factor learning curves that account for both the effect of experience (i.e., "learning-by-doing" concept) and the impact of R&D (i.e., "learning by research" concept) [72,73,77,91,92]. Others have called for multifactor learning curves that include parameters beyond learning by doing and learning by research to enhance the understanding of technology cost reduction rates via multiple factors influencing them [93–96]. Results from studies on two-factor and multifactor learning curves indicate that installed capacity is the most influential factor in technological cost reduction, with the impact of R&D being the second. These studies also highlight the challenges in precisely estimating the contributions of learning by doing versus learning by research due to the integrated dynamics of these two processes. Furthermore, researchers have noted difficulties related to data availability for estimating the R&D contribution to overall technology cost reduction and warned that additional learning curve parameters may lead to overfitting, resulting in poor forecasts [97].

Given that the focus of this study is on technology commercialization rather than the specific factors driving cost reduction, it is reasonable to employ a simpler, single-factor learning curve in which cumulative installation is the primary driver of technology unit cost reduction. As such, the learning-by-research loop is not considered an individual driving factor, and cost reduction through experience is used as the cumulative learning factor.

Two balancing loops (the **developer capacity** and **manufacturing capacity** loops) are very similar—either or both can limit capacity growth due to restricted resources or uncertainties in the future energy market that dampen the desire to grow. The manufacturing sector, also referred to as the supply chain, has additional dynamics where competition can significantly affect component costs, which, in turn, directly impact the unit cost. The study described in [59] suggested that both developer and manufacturing capacities are crucial for the market uptake of novel energy systems and incorporated both dynamics into their model. Conversely, the study described in [28,29] included a single industry capacity factor, namely the "capacity of wind turbines construction industry", which aligns with the developer capacity concept in this study.

While there is agreement that both developer and manufacturer capabilities are vital for the diffusion of novel energy systems, it is unclear which is more significant for the adoption of an energy system within a specific context, such as a nation's electricity system. The ability to install utility-scale power plants is certainly dependent on domestic capabilities, whereas manufacturing capacity is a global factor since many manufacturers of novel technologies supply components globally. In fact, North American manufacturers represent a relatively small proportion of the total global manufacturers of wind components [98–100]. The U.S. share in solar energy component manufacturing is even smaller [101,102].

Several research studies [59,103] and industry assessments [104–106] have indicated that component costs are influenced by supply chain availability: increased backlog in orders typically drives up component markups, thereby increasing overall costs. However, establishing a clear correlation between individual manufacturing company order backlogs and price increases is complex due to limited access to company business information, variability in market strategies that affect pricing and markups, and multiple manufacturers in the market. Additionally, due to similar data limitations, the growth capability of manufacturing companies is difficult to predict since their growth is affected by local markets, policies, and individual business plans. Therefore, we excluded the **manufacturing capacity** loop from the system dynamics model for this study, and industry capacity growth is represented by the **developer capacity** loop.

Some of the exogenous variables shown in Figure 3 are integrated into endogenous variables in the model. Specifically, *grid integration cost* and *competition price* are accounted for as part of the available profitable resources concept, which is explained in Section 5.2. The *public acceptance* and *complementary technologies* variables are not included in the model since they are considered less important to technology diffusion; however, they could be incorporated into a more detailed model later.

The revised CLD is presented in Figure 6, representing the boundary of the system dynamics model built for this study, as described in Section 5.2.

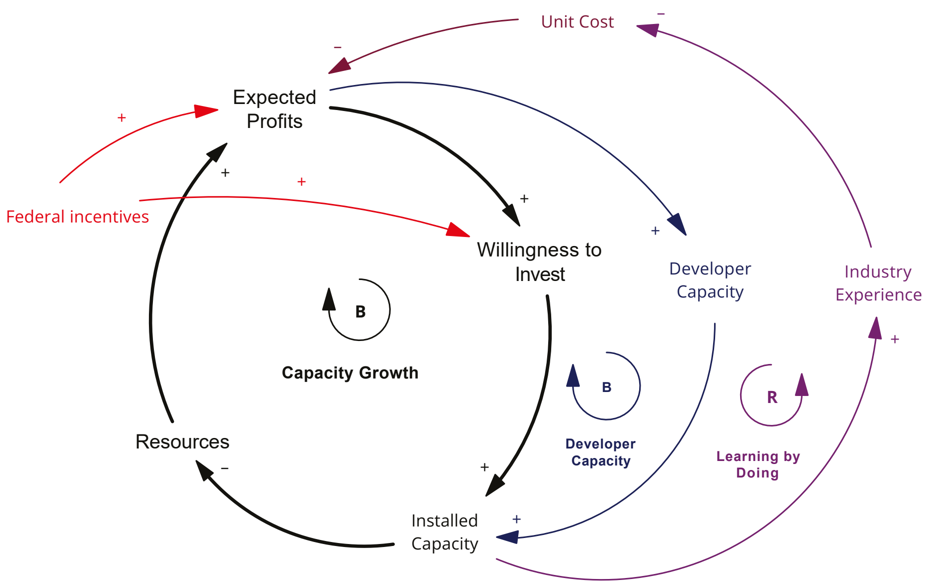

Figure 6. Causal-loop diagram of core dynamics of novel energy system deployment.

5.2. System Dynamics: Model Input Specification and Calibration

The model is built for onshore wind electricity generation technology with parameters and corresponding historical data. The core model consists of four submodels:

1. **Profitable capacity** models resources suitable for new energy system installations based on the total available resources, their portion available for installations, and a smaller portion of the available resources that is considered profitable;
2. **Technological learning** models improvements in performance and decline in cost as a function of cumulative installations;
3. **Developer capacity growth** describes factors that affect the industry's capability to scale and install the growing number of projects;
4. **Capacity growth** models the project's progress from the initial consideration to completion, including multiple factors that affect the process.

In this section, we describe each of the submodel structures, variables, and formulas. The model is built using Vensim Professional, version 10.2.2 [56], from Ventana Systems, Inc. It allows users to create graphical models with feedback loops, stocks and flows, and causal links, facilitating the exploration of how different variables in a system interact with each other. This software is often utilized in fields such as business, environmental science, public policy, and engineering for tasks like policy analysis, strategic planning, and resource management and has been used to model the dynamics of energy systems [59,65,77,107].

The diagrams in Figures 6–10 come directly from the Vensim model. The submodels and model variables (shown in *italicized text*) are described in the following subsections. The data sources for the model variables are shown in Table 1. Model inputs shown as <Variable> are modeled in submodel(s) other than the one depicted in the figure.

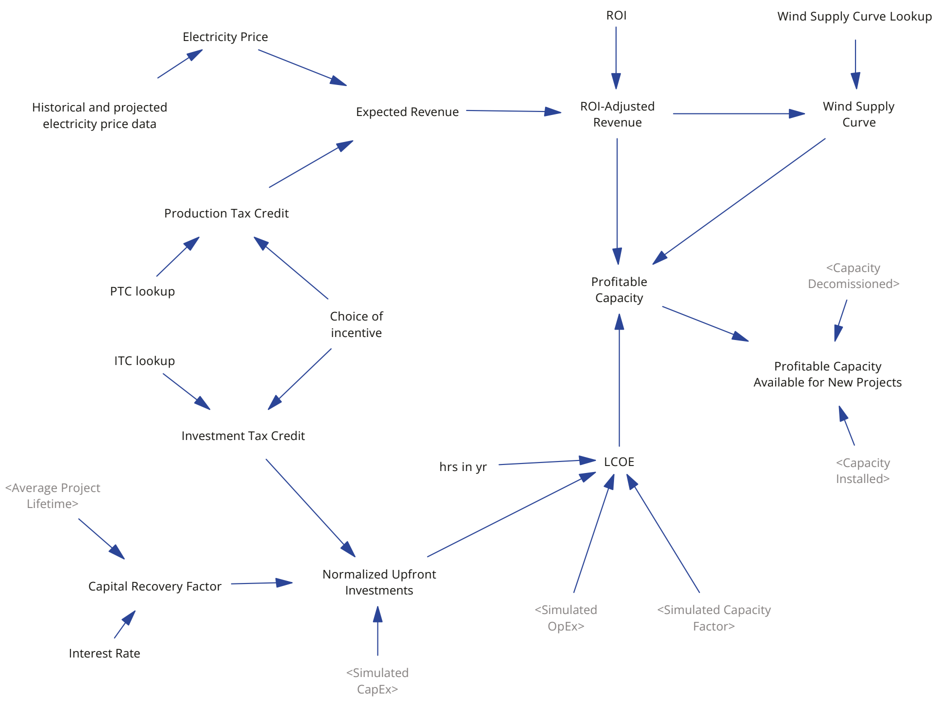

Figure 7. Profitable capacity model, representing the relationships between the *resources*, *expected profits*, and *federal incentives* variables in the **capacity growth** loop in Figure 6.

5.2.1. Profitable Capacity

For wind energy, the resource is the land available for installing wind projects. The most attractive sites are those with better wind quality (i.e., higher wind speeds and more frequent wind days). Developers first consider sites with the highest wind potential and sites closest to electrical grid infrastructure, as these sites are the most profitable. With increased installations, less profitable sites are considered next until no more profitable available land remains. The model calculates project expenses, expressed as levelized cost of energy (LCOE), and project revenue. The projects where the expected revenue exceeds estimated costs are considered profitable, and developers will be willing to proceed with installations. The submodel is presented in Figure 7.

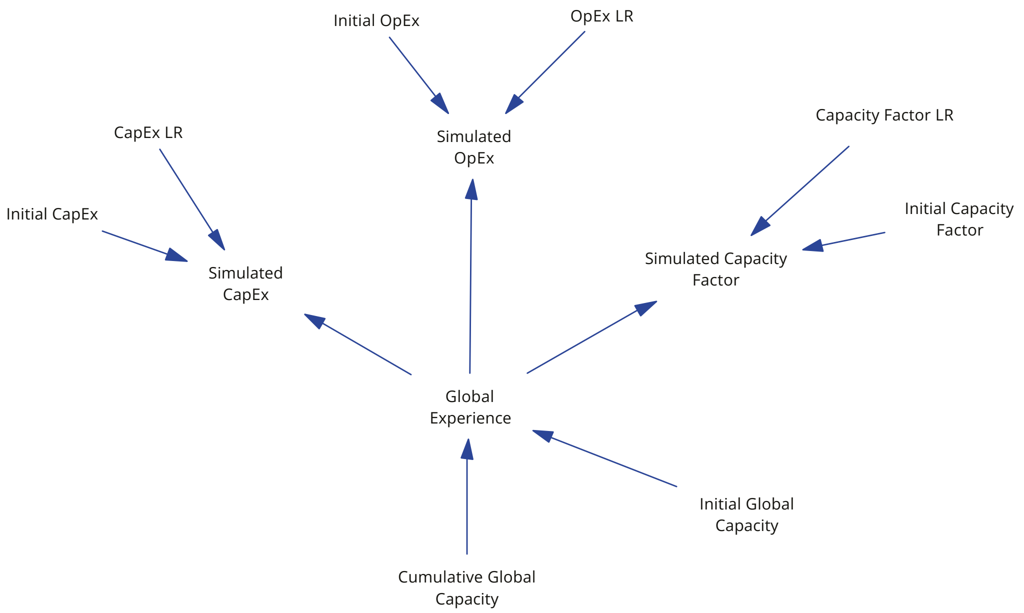

Figure 8. Technological learning model, representing the relationships between the *industry experience* and *unit cost* variables in the **learning-by-doing** loop in Figure 6.

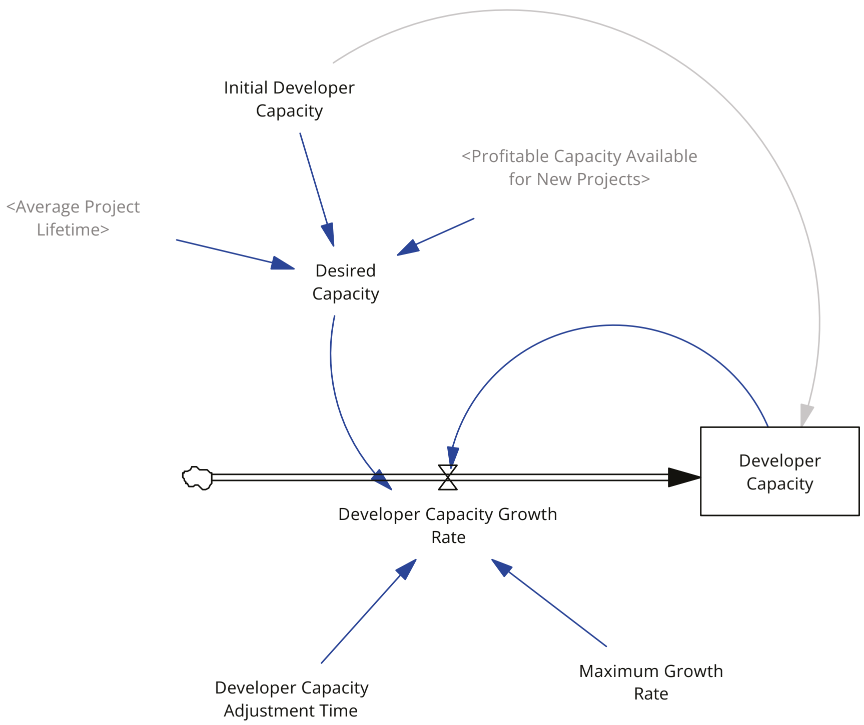

Figure 9. Developer capacity growth model, representing the **developer capacity** loop in Figure 6.

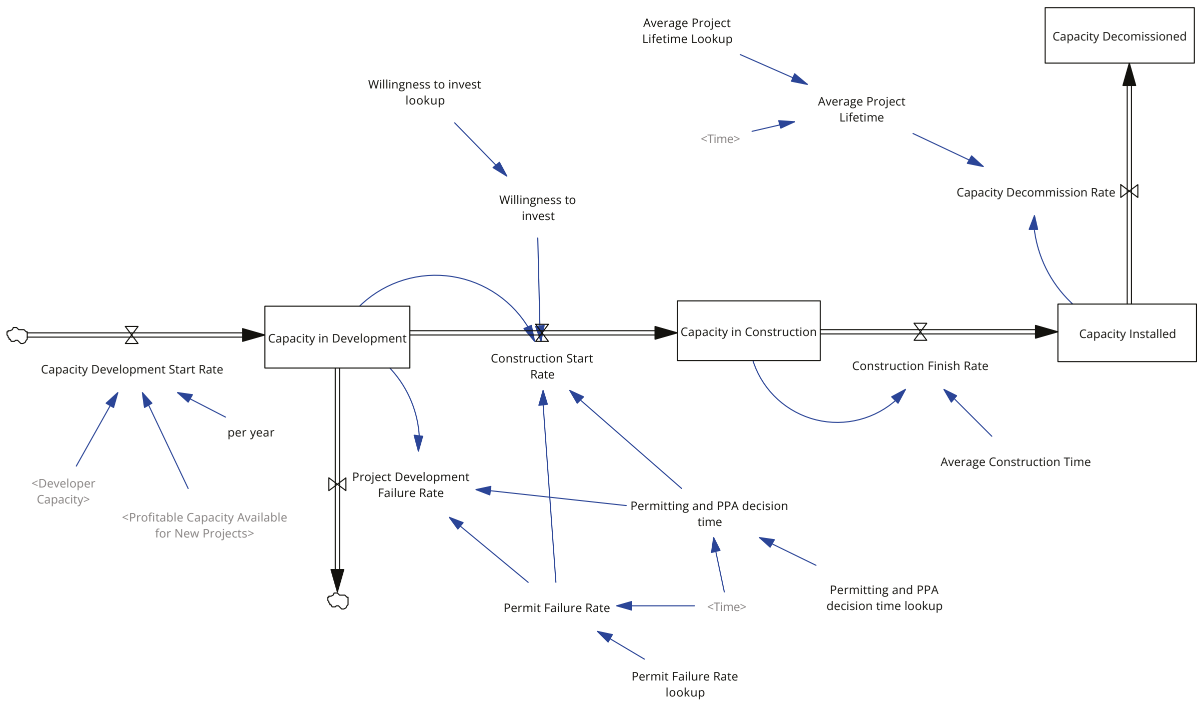

Figure 10. Capacity growth model representing the **capacity growth** loop in Figure 6.

The *expected revenue* is calculated as the sum of the *electricity price* and *production tax credit*. The *electricity price* is a value obtained from the *historical and projected electricity price data* for the corresponding modeled year.

The *choice of incentive* enables selecting the federal incentive, which is none, PTC, or investment tax credit (ITC). For the wind energy model, the PTC incentive is used, as this is the historically used incentive for wind projects in lieu of ITCs.

The *ROI-adjusted revenue* is the expected revenue considering a minimum return on investment (ROI) desired by the investors.

The *wind supply curve* represents the wind resource potential. Understanding the resource potential is fundamental to energy system modeling where cumulative deployment is resource-limited. We model the resource potential using the methodology developed by the National Renewable Energy Laboratory (NREL) [108]. This study evaluated the technical potential of onshore wind in terms of capacity, cost, performance characteristics, and grid interconnection costs. The combined metric, the LCOE, represents the overall project costs, including levelized transmission and plant costs.

The dataset for the wind supply curve for various siting regimes is available on the NREL Wind Supply Curve website [83], and data for the limited access siting regime was used in our model. The NREL wind supply curve data were translated into a supply curve with available wind capacity (measured in MW) for various levelized cost of energy (LCOE) (measured in USD/kWh) ranges. The land is considered profitable if the expected revenue is higher than the LCOE calculated for that land.

The LCOE is calculated using the same approach used in the NREL Simple Levelized Cost of Energy Calculator [109], using Equation (1):

$$\text{LCOE} = \frac{\text{Overnight Capital Cost} * \text{CRF} + \text{Fixed O\&M Cost}}{8760 * \text{Capacity Factor}} + \text{Fuel Cost} * \text{Heat Rate} + \text{Variable O\&M Cost} \tag{1}$$

where the overnight capital cost, also referred to as the normalized upfront investment, is measured in dollars per installed kilowatt (USD/kW); capital recovery factor (CRF) is the ratio of a constant annuity to the present value of receiving that annuity for a given length of time (dimensionless); the fixed operation and maintenance (O&M) cost is measured in dollars per kilowatt-year (USD/kW-year); the variable O&M costs are expressed in dollars per kilowatt-hour (USD/kWh); the capacity factor is a fraction between 0 and 1, representing the actual power being generated compared to the nominal installed full capacity (dimensionless); 8760 is the number of hours in a year; the fuel cost is expressed in dollars per million British thermal units (USD/MMBtu); and the heat rate is measured in British thermal units per kilowatt-hour (Btu/kWh) (the fuel cost is optional since some generating technologies like solar and wind do not have fuel costs).

The fixed and variable O&M costs are usually reported as all-in O&M costs, where variable costs reported in USD/kWh are converted to fixed costs based on capacity factors [87]. The fuel cost does not apply to wind energy technologies and is removed. These manipulations result in a shorter Equation (2), which is used by the model to calculate the LCOE:

$$\text{LCOE} = \frac{\text{Overnight Capital Cost} * \text{CRF} + \text{O\&M Cost}}{8760 * \text{Capacity Factor}} \tag{2}$$

The CRF is calculated based on the interest rate using Equation (3):

$$\text{CRF} = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{3}$$

The *profitable capacity* variable looks up the available capacity from the wind resource data *wind supply curve* when the *ROI-adjusted revenue* is greater than the *LCOE*; otherwise, the project is considered not profitable and the *profitable capacity* is set to zero.

Lastly, the *profitable capacity available for new projects* is calculated using Equation (4), accounting for the already installed capacity and decommissioned capacity becoming available for new installations:

$$\begin{aligned} \text{Profitable Capacity Available for New Projects} = {} & \text{Profitable Capacity} \\ & - \text{Capacity Installed} + \text{Capacity Decommissioned} \end{aligned} \tag{4}$$

5.2.2. Technological Learning

As discussed in Section 4, technological learning and innovation represent a key reinforcing feedback loop affecting energy technology uptake by the market. This dynamic is modeled as a **learning-by-doing** loop, as shown in Figure 6. Gained experience results in cost reductions, including upfront investments for purchasing and installing equipment, referred to as capital expenses or CapEx, as well as O&M expenses, referred to as OpEx. In addition, technological improvements and innovations lead to improved technology performance through improved reliability, improved availability, and increased energy output. For wind energy, increased turbine size, rotor diameter, and hub height result in a significant increase in energy outputs from a single unit. These performance improvements can be cumulatively described via a capacity factor, which is the ratio of the actual energy generated to the installed capacity. The technological learning submodel is presented in Figure 8.

The capacity factor is a complex, aggregated parameter influenced by multiple contributing factors. The most significant contributor is the wind resource quality at the site selected for the wind project. Technological advancements, particularly increased hub height and larger rotor diameter, also substantially impact the power output from wind turbines [1,59,110] and, consequently, the capacity factor. With the proliferation of wind installations, technological innovations and learning have led to increased capacity factors. However, the quality of wind resources is gradually declining, as the best sites were utilized first, leaving sites with lower wind quality for subsequent projects. This creates a dichotomy—while technological improvements drive an increase in the capacity factor, diminishing resource quality exerts a negative influence. Despite this, the overall trend in the capacity factor is upward, as reported in the Land-Based Wind Market Report [1], indicating that technological advancements are outpacing the decline in wind resource quality.

A detailed analysis of the dynamics affecting the capacity factor could involve modeling individual contributors, such as rotor diameter, hub height, and wind resource quality. However, this study opts to use an aggregate capacity factor as a variable. This approach aligns with the research focus on higher-level factors, such as the capacity factor itself, which influence technology adoption, rather than on the specifics of technological improvements.

The model employs a standard learning curve formulation [70] to describe the reduction in CapEx and OpEx, as well as improvements in the capacity factor. The learning rate is the rate at which the system improves (in the case of capacity factors) or reduces costs (in the case of CapEx and OpEx) as a function of cumulative experience. Historical data are used to estimate learning rates through Excel's Goal Seek function to minimize the sum of least-squared errors. The model uses the ratio of total global capacity installation experience to the capacity installed globally in 1998. Since learning is a global process, focusing solely on the U.S. experience would underestimate technology scaling and cost reductions. Therefore, global cumulative capacity is used as an exogenous input to the model.

5.2.3. Developer Capacity Growth

As discussed in Section 4, the deployment and diffusion of novel energy systems could be limited by the capabilities of developers to install energy projects. This factor is modeled as a **developer capacity** loop, as shown in Figure 6. The developer capacity growth submodel is presented in Figure 9.

The *developer capacity* is modeled as a stock variable, where capacity growth is increased at a rate equal to the *developer capacity growth rate*. It is assumed in this model that the gained developer capacity does not reduce, so there is no outflow from the stock. The *developer capacity growth rate* is calculated using Equation (5):

$$\begin{aligned} &\text{Developer Capacity Growth Rate} = \min[\#1, \#2] \\ &\#1 = \frac{\text{Desired Capacity} - \text{Developer Capacity}}{\text{Developer Capacity Adjustment Time}} \\ &\#2 = \text{Developer Capacity} * (1 + \text{Maximum Growth Rate}) \end{aligned} \tag{5}$$

where the *desired capacity* is calculated using Equation (6):

$$\begin{aligned} &\text{Desired Capacity} = \max[\#3, \#4] \\ &\#3 = \text{Initial Developer Capacity} \\ &\#4 = \frac{\text{Profitable Capacity Available for New Projects}}{\text{Average Project Lifetime}} \end{aligned} \tag{6}$$

5.2.4. Capacity Growth

As discussed in Section 4 and shown in Figure 6, capacity growth is the key dynamic of technology diffusion and adoption.

Energy project developers are the main drivers of the diffusion of energy technology since they, with the support of investors, decide how many projects are feasible to build given the market conditions and developers' resources. Energy-generating plant development follows a standard process, including site and plant development, construction, and commissioning [59]. After the plant lifetime ends, the capacity is either decommissioned or refurbished and placed back into operation (which is not modeled). The capacity growth submodel is presented in Figure 10.

The *capacity development start rate* is the smaller value of either the *profitable capacity available for new projects* or the *developer capacity*. The *capacity in development* is a stock variable representing how many projects are in development. The development stage includes project site selection, power plant design, the permitting process, and securing a power purchase agreement (PPA). The *capacity in development* is calculated as the integral between the inflow rate (i.e., *capacity development start rate*) and the outflow rates (i.e., *construction start rate* and *project development failure rate*).

The *project development failure rate* is calculated using Equation (7):

$$\text{Project Development Failure Rate} \quad = \quad \frac{\text{Capacity in Development} * \text{Permit Failure Rate}}{\text{Permitting and PPA Decision Time}} \tag{7}$$

The *permit failure rate* is 75% for wind projects (i.e., every three out of four wind projects fail) [59]. Projects can fail because of environmental or other permit issues, public pushback from communities unwilling to have wind projects installed (i.e., a not-in-my-backyard situation) or because they fail to secure a PPA. It is assumed that failure rates for very early wind projects had a much lower failure rate due to the urgency of wind installations driven by the oil crisis in the 1980s and an overall easier permitting process since environmental concerns and public pushback were not prominent issues at the time; however, failure rates rose to 75% by 2000. It is also assumed that this rate will likely remain the same moving forward.

The *permitting and PPA decision time* is estimated to be about 4.5 years today (in 2024) according to the American Clean Power fact sheet [88], an increase from 4 years in the 2000s [59]. It is expected that the permitting time will gradually increase to 5 years by 2050 and is modeled accordingly.

The *construction start rate* is calculated by taking the portion of not failed projects and adjusting it by the *willingness to invest* factor. Factors such as willingness to invest, perceived value, satisfaction, or attractiveness are so-called soft variables, and they are the most complicated to model since they are typically an aggregate of multiple contributing factors and data are either unavailable or extremely sparse [111–113]. However, despite the difficulties, soft variables should be included in the model if they are important for the dynamics of the system. As Sterman pointed out, "data are not only numerical data, that 'soft' (unmeasured) variables should be included in our models if they are important to the purpose" [113].

Willingness to invest is an important parameter in the diffusion and market uptake of a novel energy system. A similar parameter, expressed as the willingness of investors, investors' investment strategies, or relative attractiveness investment capacity, has been included in multiple studies of energy system dynamics [29,77,114].

The adoption of wind energy in the United States has been significantly impacted by government support policies, namely PTC incentives. Dykes and Sterman [30] pointed out that inconsistent policies have resulted in large volatilities, so-called boom-and-bust cycles. More recently, Frazier et al. explored the impact of PTCs and ITCs on wind and solar deployment [10]. The study found that policy uncertainty created a volatile market characterized by boom-and-bust cycles in wind deployment. Several independent organizations and researchers have pointed out the significance of federal incentives to the success of U.S. wind energy deployment [4,115–117]. Figure 11 shows a timeline correlation between PTCs and incremental wind capacity additions.

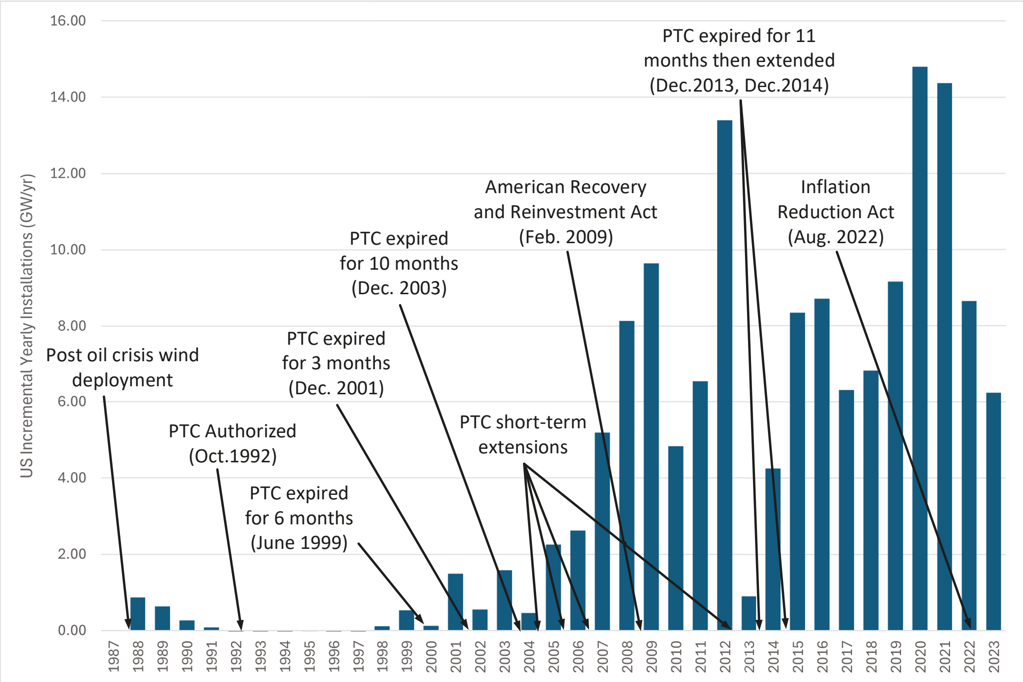

Figure 11. Timeline of PTCs with wind capacity additions in the United States (adopted from [10]).

Every time the PTC expired, industry dramatically reduced wind project development, choosing to wait until the credit was renewed. The tax credit incentives created a unique investment opportunity for companies with large tax obligations, allowing a high ROI due to tax credits. The investors had much less interest in investing in energy projects when the incentives were under threat of being removed.

Besides federal incentives, several states have implemented their own initiatives to boost renewable energy production. These initiatives, known as renewable portfolio standards (RPSs), mandate that retail electricity providers source a certain percentage or quantity of their electricity from eligible renewable sources. Although RPS programs aim to increase the proportion of renewable energy, there is still a lack of consistent empirical evidence regarding their effectiveness and whether they actually drive investments in renewable capacity [118].

Research by Deschenes et al. [118] revealed that states with RPSs had higher average levels of wind and solar capacity installed by 1990 compared to those without RPSs, but these differences were not statistically significant. The study also indicated that while RPS policies increased investment in wind generation capacity within these states, they had no effect on investments in solar generation. In summary, although RPS programs influence the deployment of renewable energy sources, their impact is much smaller compared to federal incentives. As such, the model does not explicitly include RPSs as a variable.

In our study, we model *willingness to invest* as a coefficient based on the availability of PTCs, both historical and projected.

The *capacity in construction* represents the amount of capacity in the construction stage, modeled as a stock variable and calculated as an integral between the inflow and outflow rates—the *construction start rate* and *construction finish rate*, respectively.

The *construction finish rate* is calculated by dividing the *capacity in construction* by the *average construction time*, which is set at 1 year based on recent industry experience, with construction taking between 6 and 18 months on average.

The *installed capacity* represents the amount of commissioned capacity after the plant is constructed and connected to the grid. It is modeled as a stock variable and calculated as an integral between the *construction finish rate* and the *capacity decommission rate*, with the initial installed capacity being the total installed capacity in the United States in 1998 [1].

The *capacity decommission rate* is calculated by dividing the *installed capacity* by the *average project lifetime*. The wind project lifetime has increased from 20 years in the early 2000s to 25 years in the mid-2010s and to 30 years more recently [89], which is how it is modeled in our study.

Lastly, the *capacity decommissioned*, which is also a stock variable, is calculated as an integral of the *capacity decommission rate*.

5.3. Results of Model-Based Quantitative Assessment

The outcome of this research is a model that simulates the trajectory of the wind energy system's capacity growth based on multiple factors that affect system deployment. The model also informs the user about potential scenarios of the system's behavior given the potential variations in the variables, as well as the sensitivity of a given parameter to the input variables.

To demonstrate the validity of the model, the simulated installed capacity based on the SD model from the previous section was compared to the historical installed wind capacity in the United States [1] and the projected wind capacity [6]. Figure 12 shows this comparison. The SD model-simulated installed capacity shows a reasonable fit with both the historical data (1998–2023) and projected capacity (2024–2050). Focusing on the initial historical portion, the final installed capacity values are nearly the same at 160 GW, with a GW/yr rate of about 9.1. However, the initial capacity growth from 2000 to 2006 was slower in the SD model. For future projections, a similar increasing trend was observed between [6] and the SD model's results, including capturing a key inflection point around 2034. However, the forecasted results from the SD model follow two fairly linear segments, which start to show more significant deviations toward the end of the explored timeline. These differences warrant further exploration to support specific claims regarding the level of fidelity of the model beyond capturing important features. Still, the overall general agreement in shape and magnitude demonstrates that the SD model captures the important features driving the dynamics of this energy technology's development.

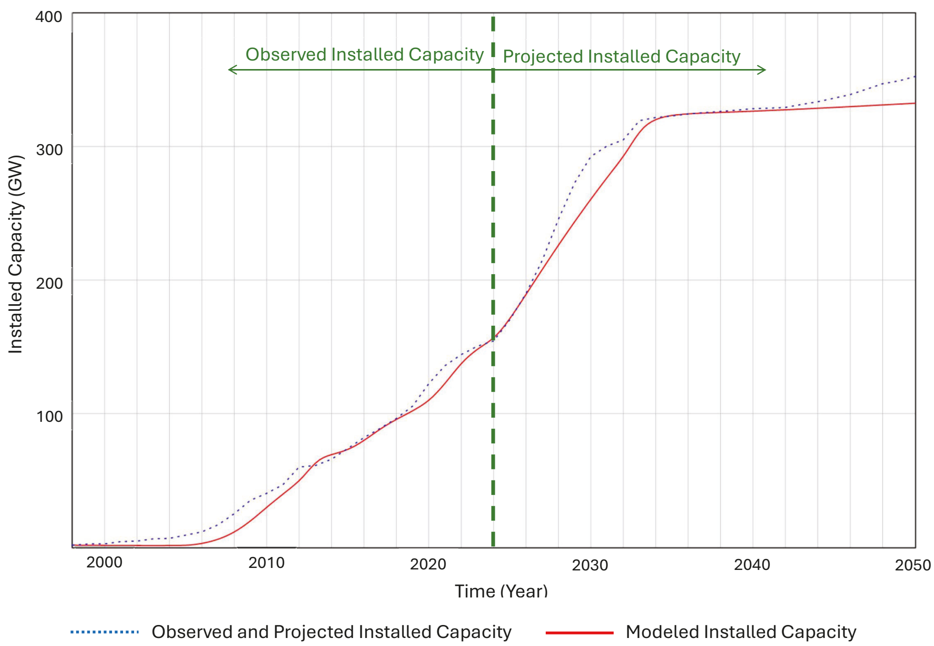

Figure 12. SD model-simulated installed capacity versus observed installed capacity [1] and projected installed capacity [6].

5.3.1. Sensitivity Studies

Additional insights about the model and the represented energy system were obtained through sensitivity studies. Figure 13 presents a tornado chart showing the sensitivity of capacity growth to various elements. It shows that capacity growth is most sensitive to the availability of resources, represented as a *supply curve*. The second most influential parameter is *willingness to invest*. These insights are not surprising since the total capacity of the potential wind energy is directly affected by the available and profitable land to build wind installations. As discussed in Section 4.2, investors' willingness to fund wind energy projects is one of the key factors affecting the overall deployment of wind installations and total capacity growth. The next most influential factors are economic variables, namely the *initial capacity factor*, *electricity price*, *initial CapEx*, and *average project lifetime*. This is also an expected finding since the feasibility of wind installation deployment is determined using these economic parameters. The model is less sensitive to other variables representing the ability of the developers to grow their capacity and to factors affecting learning rates.

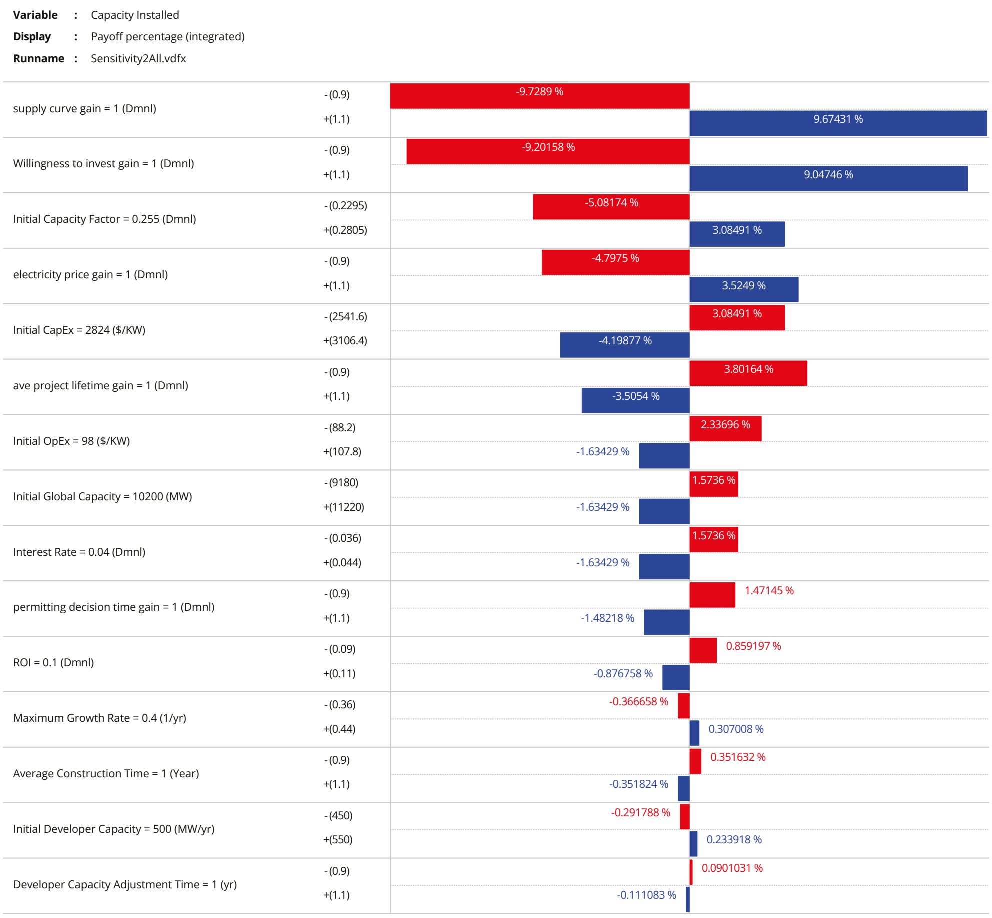

Figure 13. Sensitivity of capacity growth to modeled variables.

Similarly, Figure 14 illustrates the sensitivity of the LCOE to the various model inputs. In this case, the focus is on variables affecting the cost of energy rather than capacity growth potential. The results confirm the expectation: the largest influencing factor is the *capacity factor*, since even small changes dramatically affect the resulting cost of energy. The rest of the economic variables have a smaller but still measurable impact on energy cost.

The outcomes of the sensitivity studies confirm the general dynamics of energy system diffusion presented in Figure 6 by demonstrating the dependencies between variables within and between the loops.

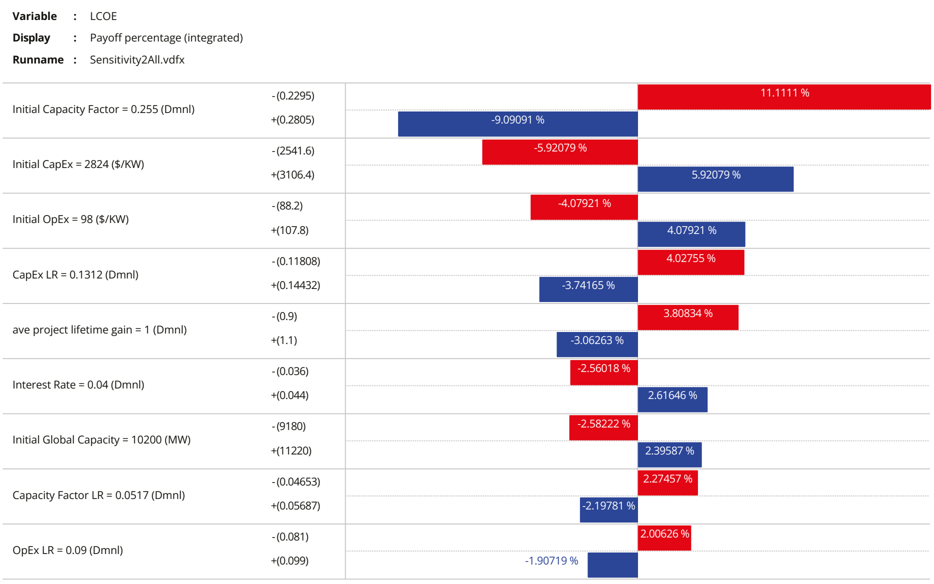

Figure 14. Sensitivity of the LCOE to modeled variables.

5.3.2. Scenario Analysis

We also further explored the impact of influential parameters, namely resource availability, the presence of PTCs, and technological learning. Figure 15 shows the capacity growth outcomes for reduced resources (left) and the availability of PTCs (right).

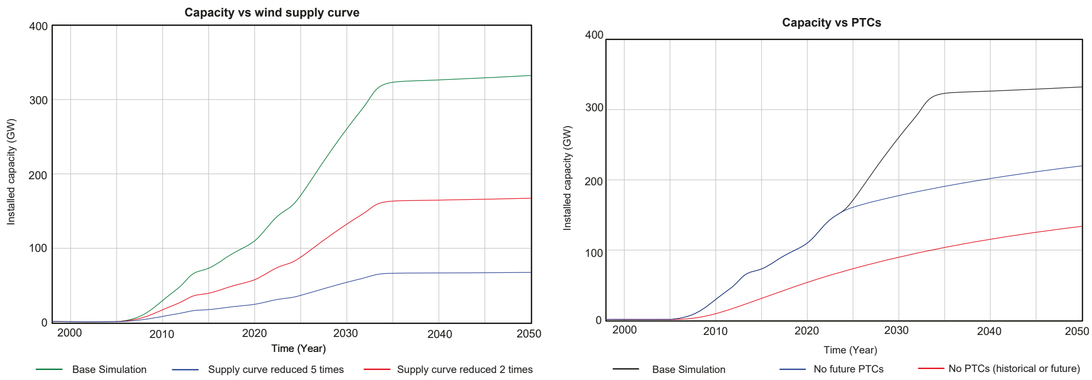

Figure 15. Capacity growth versus available wind supply (**left**). Capacity growth versus PTCs (**right**).

The sensitivity studies showed the strong influence of the wind supply curve on capacity growth, which was confirmed by the scenario analysis. Reducing resources by 5× and 2× greatly reduced the modeled installed capacity, as shown in Figure 15. This is consistent with the findings in [108], in which the authors point out that siting restrictions could dramatically reduce the overall wind energy growth. The wind growing capacity modeled up to 2050 has not reached the available resource potential, so increasing the available resources would have little to no impact on the modeled installed capacity.

The scenario simulations of the availability of PTCs confirmed the importance of the incentives: both cases where incentives were not available showed a significantly smaller total installed capacity than the base model.

Figure 16 shows the impact of technological learning on capacity growth (left) and the LCOE (right) based on modeled scenarios with reduced and increased learning. As expected, a reduction in learning, represented by reduced learning rates, slows capacity growth, while an increase in technological learning accelerates technology adoption. Although the impact on capacity growth is not significant, the effect on the LCOE is dramatic.

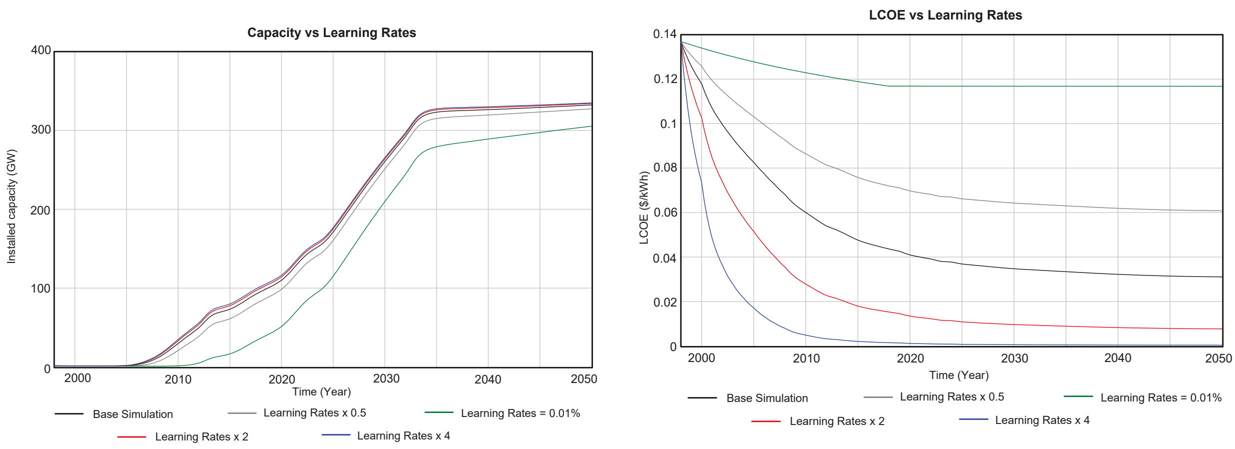

Figure 16. LCOE versus technological learning (**left**). Capacity growth versus technological learning (**right**).

This observation highlights a model limitation, where willingness to invest is modeled as an exogenous variable primarily dependent on federal incentives. In reality, willingness to invest is a much more complex parameter that dynamically depends on many factors beyond incentives, including the LCOE, available resources, cost and availability of competing technologies, and social factors like public acceptance.

In a comprehensive energy system model that includes all energy generation technologies, consumption, and demands, willingness to invest would be an endogenous variable. However, this study specifically focused on the diffusion dynamics of individual energy technologies, necessitating limited model boundaries and treating willingness to invest as an exogenous variable.

Future work could expand this study to model willingness to invest more accurately. Although data for such a model are limited, surveys and expert solicitation techniques could be employed. More detailed modeling would require broadening the system boundaries to include additional variables, such as the costs of competing technologies and energy demands, which could remain exogenous while willingness to invest becomes an endogenous variable. This approach would provide a better understanding of the effect that willingness to invest has on capacity growth.

6. Discussion

In this research, we hypothesized that the dynamics of novel energy system adoption by the energy market are influenced by multiple factors. We explored these factors by examining the history of electricity generation using land-based wind technologies and developed a system dynamics model to investigate the relationships between wind growth capacity and the elements influencing this growth process. The sensitivity analyses and scenario analyses are presented in Section 5.3.

The significance of this research lies in its contribution to addressing the urgent need to tackle energy security and resiliency in the United States while ensuring the feasibility of new energy technologies. By developing a comprehensive model that captures the behavior of new energy technologies within the existing energy system, this research provides valuable insights into the dynamics of technology diffusion and adoption. The successful validation of this model with mature energy systems like wind and solar indicates its potential applicability to emerging technologies such as hydrogen generation from electrolysis and more. The research contributes to novel methodologies for informed decision-making for investments in novel energy systems and aids in the development of effective policies for technology deployment. By highlighting key factors influencing market uptake, such as resource availability, federal incentives, and technological learning, this work supports the transition to a more diverse and resilient energy future.

The scientific novelty lies in the integrated approach for evaluating novel energy technologies where multiple disciplines are considered. The methodology and tool developed in this research support the integration of technological, economic, and social factors to enable informed decisions. This outcome is different from typical analyses that focus primarily on one of the areas, often economics, for investment decision-making.

The model developed in this research provides an intuitive understanding of the underlying complex dynamics of the wind energy system and identifies the most significant factors influencing energy system deployment.

However, there are several limitations in the developed model. First, while the model is intended to be generic and applicable to a diffusion analysis of many novel energy technologies, the model presented in this research was specifically validated with onshore wind energy. As such, the model must be adjusted for the specifics of other technologies. Second, the scope of this research and, as a result, the model boundaries, is limited to factors that are considered the most influential to the commercialization trajectory of novel energy systems. Lastly, as part of limiting the scope of the research, an important parameter, *willingness to invest*, was modeled as an exogenous variable. However, this variable would be better modeled as an endogenous variable since factors like technological learning, cost reduction, and total deployed capacity impact willingness to invest and vice versa. Future research could refine the model to overcome these limitations.

Future Research

Further research should, in particular, extend the same model to other novel energy technologies, such as utility-scale solar photovoltaic, using technology-specific parameters and historical data while maintaining the model's structure. Future research also could apply a similar model to battery storage systems. Such research would test the hypothesis that the deployments of novel energy technologies follow a similar trajectory and that the core dynamics and influencing factors remain consistent across different technologies. Lastly, future research could explore in greater detail the willingness to invest factor, i.e., what influences investors' decisions to fund energy technologies in general and specific technologies in particular. It is desirable to understand both quantitative values, e.g., return on investment, and soft parameters, e.g., perceived risk, to develop more detailed models simulating factors that could support better-informed decision-making.

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Data Availability Statement: The data employed in this paper were taken from openly available documents as indicated throughout the paper. The system dynamics model developed in this research is available in the open-source GitHub repository: https://github.com/lawrencesv/Dynamics-of-new-energy-system-deployment_SD-Model, accessed on 29 March 2025. This research used data from U.S. government publications in the public domain [5,6,119] that are not subject to copyright protection. Source: U.S. Energy Information Administration (March 2025).

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Abbreviations

CLD	causal loop diagrams
CRF	capital recovery factor
ITC	investment tax credit
LCA	life cycle assessment
LCOE	levelized cost of energy
MBSE	model-based systems engineering
O&M	operation and maintenance
PPA	power purchase agreement
PTC	production tax credit
R&D	research and development
ROI	return on investment
RPS	renewable portfolio standard
SD	system dynamics
SE	systems engineering

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Review

Reinforcement Learning in Energy Finance: A Comprehensive Review

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Abstract: The accelerating energy transition, coupled with increasing market volatility and computational advances, has created an urgent need for sophisticated decision-making tools that can address the unique challenges of energy finance—a gap that reinforcement learning methodologies are uniquely positioned to fill. This paper provides a comprehensive review of the application of reinforcement learning (RL) in energy finance, with a particular focus on option value and risk management. Energy markets present unique challenges due to their complex price dynamics, seasonality patterns, regulatory constraints, and the physical nature of energy commodities. Traditional financial modeling approaches often struggle to capture these intricacies adequately. Reinforcement learning, with its ability to learn optimal decision policies through interaction with complex environments, has emerged as a promising alternative methodology. This review examines the theoretical foundations of RL in financial applications, surveys recent literature on RL implementations in energy markets, and critically analyzes the strengths and limitations of these approaches. We explore applications ranging from electricity price forecasting and optimal trading strategies to option valuation, including real options and products common in energy markets. The paper concludes by identifying current challenges and promising directions for future research in this rapidly evolving field.

Keywords: reinforcement learning; energy finance; option value; stochastic optimization; machine learning; risk management

1. Introduction

1.1. Overview

The intersection of energy markets and financial engineering has allowed for the rise of a specialized field known as energy finance. This domain encompasses the valuation of energy commodities, derivatives pricing, risk management, and investment decisions in energy infrastructure. The complexity of energy markets stems from several distinctive characteristics: high volatility, significant seasonality, mean-reversion tendencies, extreme price spikes, regulatory influences, and the physical constraints of energy production and delivery systems [1]. These complexities make conventional financial modeling approaches insufficient for many applications in energy finance.

Simultaneously, recent advances in artificial intelligence, particularly reinforcement learning (RL), have opened new avenues for addressing complex decision-making problems under uncertainty. RL differs from other machine-learning paradigms in its focus on sequential decision-making and delayed rewards, making it particularly suitable for financial applications where decisions unfold over time and outcomes become apparent only in the future [2]. Unlike supervised learning, which requires labeled examples of optimal decisions, RL algorithms can learn through interaction with an environment, gradually improving their decision policies based on the rewards received.

The application of RL to energy finance represents a convergence of these two complex domains. The inherent volatility and structural complexities of energy markets create an ideal testing ground for RL methodologies, while the limitations of traditional approaches in capturing these complexities create a clear need for more sophisticated techniques. This review paper aims to systematically analyze how RL has been applied to various problems in energy finance, with particular attention to derivatives valuation and trading strategies.

While both reinforcement learning and energy finance represent active research areas individually, the intersection of these fields warrants dedicated review due to their rapid evolution and the unique challenges that arise in this convergence. Several excellent reviews exist in adjacent areas. Specifically, Fischer (2018) [2] surveyed reinforcement learning applications in general financial markets, focusing primarily on stock trading and portfolio optimization. In addition, Weron (2014) [3] comprehensively examined forecasting methodologies in electricity markets without a specific focus on reinforcement learning. However, a comprehensive review focusing specifically on reinforcement learning applications in energy finance, particularly in derivatives valuation and risk management, is notably absent from the literature. This gap is significant due to the distinctive characteristics of energy markets that create unique challenges and opportunities for reinforcement learning methodologies.

The need for this review is particularly timely for several reasons. First, energy markets globally are undergoing fundamental transformation driven by decarbonization policies, technological advances in renewable generation, and the emergence of distributed energy resources. These changes have introduced new sources of uncertainty and complexity that traditional modeling approaches struggle to address adequately. Second, recent advances in reinforcement learning, particularly deep reinforcement learning and its variants, have demonstrated remarkable success in complex decision domains with characteristics similar to those found in energy markets. Third, energy derivatives and structured products continue to evolve in complexity, creating both challenges for valuation and opportunities for novel methodological approaches. The convergence of these trends creates a compelling need for systematic assessment of how reinforcement learning can address the distinctive challenges of energy finance.

This review makes several specific contributions to the literature. First, it provides a unified conceptual framework for understanding reinforcement learning applications in energy finance, establishing clear connections between RL methodologies, energy market characteristics, and financial applications. Second, it systematically analyzes the distinctive features of energy markets—such as extreme price dynamics, physical constraints, and market incompleteness—that make them particularly suitable for reinforcement learning approaches while challenging for traditional methodologies. Third, it comprehensively examines current reinforcement learning methodologies applied to energy finance problems, critically evaluating their strengths, limitations, and comparative advantages over conventional approaches. Fourth, it identifies significant research gaps and promising future directions, providing a roadmap for researchers and practitioners seeking to advance this emerging field.

This comprehensive review is targeted at several key audiences. First, researchers in financial engineering and machine learning will find a systematic overview of how reinforcement learning techniques are being adapted to the unique challenges of energy markets, highlighting methodological innovations and performance benchmarks [4]. Second, energy market practitioners—including traders, risk managers, and investment analysts—will gain insights into cutting-edge quantitative tools that may enhance decision-making in increasingly complex and volatile markets. Third, policy makers and regulators concerned with energy market design and systemic risk will benefit from understanding how advanced algorithmic approaches may influence market behavior and efficiency. Finally, graduate students and early-career researchers entering this interdisciplinary field will find this review provides essential background knowledge and identifies promising research directions. By bridging theoretical foundations with practical applications, this paper aims to foster collaboration between academic research and industry practice in advancing reinforcement learning solutions for energy finance challenges.

The remainder of this paper is organized as follows: Section 2 provides the theoretical foundations of RL and its relevance to financial applications. Section 3 examines the specific characteristics of energy markets that make them suitable candidates for RL approaches. Section 4 reviews the literature on RL applications in energy price forecasting and trading strategy optimization. Section 5 focuses on derivatives valuation in energy markets using RL, including options pricing and real options analysis. Section 6 discusses implementation challenges and methodological considerations when applying RL to energy finance problems. Section 7 discusses option value in power systems, particularly regarding smart grid technologies. Section 8 concludes the paper with a synthesis of key findings and perspectives on the future evolution of this field.

1.2. Illustration

Figure 1 presents the conceptual framework that organizes our comprehensive review of reinforcement learning applications in energy finance. The framework illustrates the three fundamental pillars of our analysis: reinforcement learning foundations, energy market characteristics, and application domains.

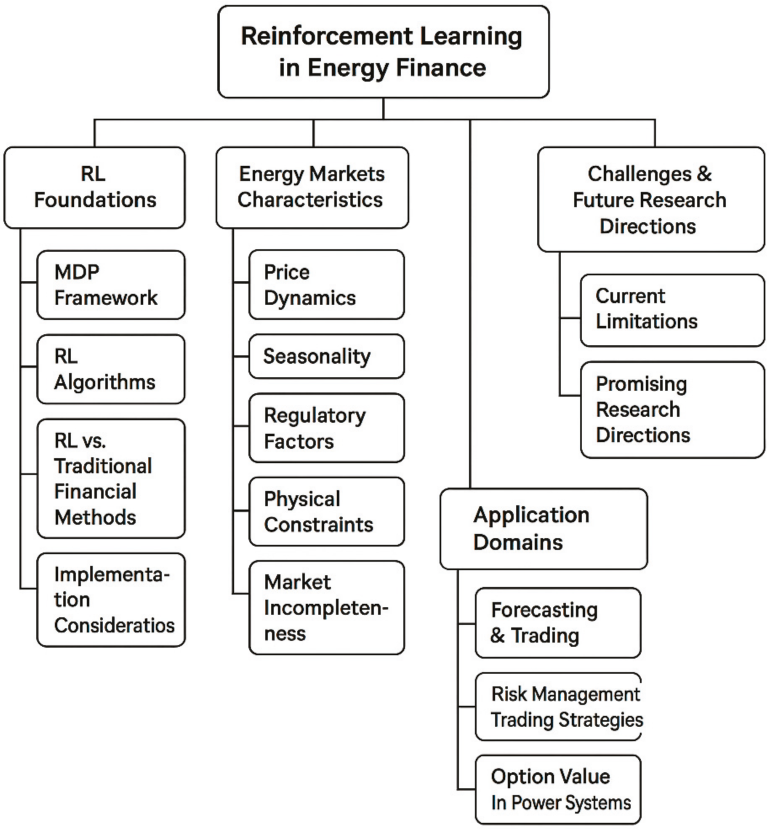

Figure 1. Conceptual framework of reinforcement learning applications in energy finance.

The first pillar, RL Foundations, encompasses the theoretical underpinnings of reinforcement learning methodologies relevant to energy finance. The Markov Decision Process (MDP) framework provides the mathematical structure for sequential decision-making under uncertainty, including states, actions, transition probabilities, reward functions, and discount factors that form the basis of RL algorithms. We review key RL algorithms applicable to energy finance problems, from classical methods like Q-learning to advanced approaches such as deep reinforcement learning. The framework also highlights comparisons between RL and traditional financial methods, emphasizing the distinctive advantages of RL in handling complex, non-linear dynamics. Implementation considerations address practical aspects of applying RL to energy finance, including data requirements, computational needs, state and action space design, and reward function formulation.

The second pillar, Energy Markets Characteristics, identifies the distinctive features that make energy markets particularly suitable for RL applications. These include complex price dynamics (volatility, mean-reversion, jumps), multi-layer seasonality patterns, regulatory and market structure factors, physical constraints of energy assets, and market incompleteness challenges. These characteristics create both challenges for traditional modeling approaches and opportunities for RL methodologies.

The third pillar organizes the application domains into three major categories. The first category, Forecasting and Trading, covers RL applications in energy price prediction and optimal trading strategy development, including risk management approaches. The second category, Derivatives Valuation, examines RL methods for pricing various energy options and analyzing real options embedded in physical assets. The third category, Option Value in Power Systems, focuses on applications specific to electricity systems, including VaR/CVaR approaches for system reliability and valuation of flexibility provided by smart grid technologies.

The framework concludes with Challenges and Future Research Directions, identifying current limitations in applying RL to energy finance and promising avenues for future research. This comprehensive structure provides a roadmap for understanding how reinforcement learning is transforming analysis and decision-making in energy finance while highlighting areas where further methodological development is needed.

1.3. Literature Review and Research Gaps

This section systematically reviews the existing literature at the intersection of reinforcement learning and energy finance, identifying key research streams and critical gaps that motivate this paper.

1.3.1. Reinforcement Learning in Financial Markets

Reinforcement learning has gained significant traction in financial applications over the past decade. Fischer (2018) [2] provided a comprehensive survey of reinforcement learning applications in general financial markets, focusing primarily on equity trading, portfolio optimization, and traditional asset classes. This work established RL's potential for sequential decision-making under uncertainty but concentrated predominantly on conventional securities markets rather than commodity or energy-specific applications.

Similarly, foundational work on reinforcement learning methodologies by Sutton and Barto (2018) [5] established theoretical frameworks applicable across domains but did not address the specific challenges of energy markets. The ability of RL algorithms to learn optimal policies through interaction with complex environments, as demonstrated by Mnih et al. (2015) [6] in other contexts, suggests particular promise for energy finance applications, though this connection remains underdeveloped in the existing literature.

1.3.2. Energy Finance Modeling Approaches

Traditional energy finance approaches have evolved to address sector-specific challenges but often struggle with the full complexity of modern energy markets. Eydeland and Wolyniec (2003) [1] developed foundational frameworks for energy and power risk management, identifying distinctive characteristics that include high volatility, significant seasonality, mean-reversion tendencies, extreme price spikes, regulatory influences, and physical constraints. However, their methodologies primarily relied on parametric models and conventional stochastic processes that face limitations in capturing the full complexity of energy market dynamics.

In the specific area of electricity price forecasting, Weron (2014) [3] comprehensively examined various methodologies, including time series models, artificial intelligence techniques [7–20], and fundamental approaches. While this work acknowledged the unique challenges of electricity markets, it did not specifically explore reinforcement learning's potential for addressing these challenges or connect forecasting to broader financial decision-making frameworks.

Energy derivatives valuation has received attention from researchers, including Carmona and Coulon (2014) [21], who examined structural models for electricity prices, and Benth et al. (2008) [22], who developed stochastic modeling approaches for electricity markets. These works established sophisticated mathematical frameworks but generally relied on closed-form solutions or Monte Carlo methods rather than learning-based approaches capable of handling market incompleteness and complex constraints.

1.3.3. Energy System Operations with Learning-Based Methods

A separate research stream has focused on optimization and learning methods for energy system operations.

The operational challenges of power generation assets have been examined by researchers, including Conejo et al. (2010) [23], who developed decision-making frameworks under uncertainty, and Thompson et al. (2009) [24], who studied energy storage valuation and optimization. These works established the complex optimization problems inherent in energy systems but generally treated financial considerations as secondary to technical constraints and reliability objectives.

More recently, smart grid technologies have introduced new flexibility options into energy systems, as demonstrated by Konstantelos et al. (2017) [25], Giannelos et al. (2018) [26], and other works focused on option value and stochastic optimization [27]. While these studies incorporate uncertainty and flexibility valuation, they typically employ conventional stochastic optimization methods rather than reinforcement learning approaches.

1.3.4. Research Gaps and Contributions

Based on this literature review, several critical research gaps emerge at the intersection of reinforcement learning and energy finance:

Gap 1: Lack of an integrated conceptual framework. While separate bodies of literature address reinforcement learning for finance and optimization methods for energy systems, a comprehensive framework connecting RL methodologies to the specific characteristics of energy markets is notably absent. This paper addresses this gap by establishing clear connections between RL methodologies, energy market characteristics, and financial applications, providing a unified conceptual structure (as illustrated in Figure 1) that bridges previously disconnected research streams.

Gap 2: Insufficient analysis of energy market features requiring specialized RL approaches. The existing literature has not systematically analyzed which distinctive features of energy markets—such as extreme price dynamics, physical constraints, and market incompleteness—make them particularly suitable for reinforcement learning approaches. This paper provides this analysis in Section 3, establishing a foundation for understanding why conventional methods may fall short and how RL can address these limitations.

Gap 3: Limited comparative assessment of RL methodologies for energy finance applications. While various RL algorithms have been applied to isolated energy finance problems, a comprehensive assessment of their relative strengths and weaknesses across different application domains is missing. This paper addresses this gap in Section 2.2 and throughout application-specific sections, evaluating algorithm suitability for different energy finance challenges.

Gap 4: Absence of a comprehensive review of real options analysis with RL in energy systems. Despite the significant embedded optionality in energy assets and infrastructure, the existing literature lacks a comprehensive treatment of how RL can enhance real options valuation in this context. This paper fills this gap in Sections 5.3 and 6, connecting option theory with reinforcement learning to provide new perspectives on flexibility valuation.

Gap 5: Fragmented understanding of option value in power systems. The literature on option value in power systems, particularly regarding smart grid technologies, has developed separately from the RL literature, limiting cross-fertilization between these fields. This paper bridges this divide in Section 6, examining how RL methods can enhance option valuation for smart grid investments.

By addressing these gaps, this paper makes several novel contributions to the literature. First, it provides the first comprehensive review specifically focused on reinforcement learning applications in energy finance, creating a reference point for researchers and practitioners working across these domains. Second, it establishes a conceptual framework that organizes existing and future research, clarifying how different RL methodologies align with specific energy finance challenges. Third, it systematically evaluates the comparative advantages of RL approaches over traditional methods across multiple application domains. Finally, it identifies promising research directions and methodological improvements that could further advance this emerging field.

This review is particularly timely due the accelerating energy transition [1,2,4,21,23,26–89], which is creating new sources of uncertainty and complexity in energy markets that conventional modeling approaches struggle to address adequately. Simultaneously, recent advances in reinforcement learning, particularly deep reinforcement learning and its variants, have demonstrated remarkable success in complex sequential decision domains with characteristics similar to those found in energy markets.

2. Theoretical Foundations of Reinforcement Learning in Energy Finance

2.1. Reinforcement Learning Framework

A comprehensive review of reinforcement learning applications in energy finance is both timely and necessary for several compelling reasons. First, research at this intersection has grown exponentially in recent years but remains fragmented across multiple disciplines, including finance, computer science, energy systems, and operations research. This fragmentation creates barriers to knowledge transfer and impedes the identification of common methodological challenges and solutions. Second, the rapid evolution of both reinforcement learning techniques and energy market structures means that practitioners and researchers often lack awareness of the full spectrum of available approaches and their relative strengths for specific energy finance problems. Third, energy markets worldwide are undergoing fundamental transformation driven by decarbonization policies, technological change, and increasing penetration of renewable resources, creating new valuation and risk management challenges that traditional methods struggle to address. Finally, the practical implementation of reinforcement learning in energy finance requires interdisciplinary expertise that is rarely found within a single research group or company, highlighting the need for a synthesized review that bridges these knowledge domains.

By reviewing the theoretical underpinnings of reinforcement learning in a financial context, this section provides the foundational understanding necessary to appreciate the unique advantages RL offers for addressing the complex decision-making challenges in energy markets. The remainder of this section examines the core components of reinforcement learning and their specific relevance to financial applications.

Reinforcement learning is a computational method for learning how to make optimal decisions through interactions with an environment (Sutton and Barto, 2018) [51]. The core framework of RL is the Markov Decision Process (MDP), which includes:

- A set of states S representing the environment
- A set of actions A available to the agent
- Transition probabilities $P(s'|s,a)$ defining how actions lead to new states
- A reward function $R(s,a,s')$ providing feedback on action quality
- A discount factor γ determining the relative importance of immediate versus future rewards

In this framework, an agent learns a policy π that maps states to actions, with the goal of maximizing the expected cumulative discounted reward over time (Sutton and Barto, 2018) [51]. The value function $V^{\pi}(s)$ represents the expected return starting from the state s and following policy π thereafter:

$$V^{\pi}(s) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty}\gamma^{t}R_{t+1}|S_0 = s\right]$$

Similarly, the action–value function $Q^{\pi}(s,a)$ represents the expected return starting from the state s, taking action a, and following policy π thereafter:

$$Q^{\pi}(s,a) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty}\gamma^{t}R_{t+1}|S_0 = s, \quad A_0 = a\right]$$

The optimal policy π maximizes these value functions, yielding the optimal value function V^{s} and optimal action–value function $Q^{*}(s,a)$.

2.2. RL Algorithms Relevant to Financial Applications

The application of reinforcement learning to finance has been facilitated by several classes of algorithms, each with distinct characteristics that make them suitable for different financial problems.

Value-based methods focus on learning the value function or action-value function from which a policy is derived. Q-learning, introduced by Watkins and Dayan (1992) [90], and its neural network extension, Deep Q-Networks (DQN) [6], have found significant applications in financial domains. These approaches excel in environments with discrete action spaces, such as binary trading decisions or discrete investment choices, due to their ability to estimate the expected return of each possible action precisely.

Policy gradient methods, in contrast, directly parameterize and optimize the policy without explicitly computing a value function. This category includes algorithms such as REINFORCE [91], Trust Region Policy Optimization (TRPO) [92], and Proximal Policy Optimization (PPO) [93]. The strength of these methods lies in their ability to handle continuous action spaces effectively, making them particularly valuable for portfolio allocation, hedging decisions, and other financial applications requiring nuanced control.

Actor–critic methods represent a hybrid approach that maintains both a value function approximator (the critic) and a separate policy representation (the actor). Prominent examples include Advantage Actor–Critic (A2C) and Deep Deterministic Policy Gradient

(DDPG) [11]. These methods have demonstrated effectiveness in complex financial environments by combining the stability of value-based methods with the capability to handle continuous actions. This dual structure allows for more efficient learning in the intricate and often non-stationary conditions characteristic of financial markets.

Model-based RL algorithms learn an explicit model of the environment's dynamics to facilitate planning and decision-making. Notable implementations include Dyna-Q [94] and more recent approaches such as Model-based Policy Optimization (MBPO) [84]. The data efficiency of these methods presents a significant advantage in financial applications, where data acquisition may be limited or costly. By learning to predict market behavior, these algorithms can simulate potential outcomes of different strategies without requiring actual market interaction, potentially reducing both risk and the data requirements for effective learning.

2.3. RL vs. Traditional Financial Modeling Approaches

Financial modeling and decision-making have historically relied on several well-established methodologies, each with distinct characteristics and limitations when applied to complex markets such as those in the energy sector.

Dynamic programming and stochastic control techniques, formalized through the Hamilton–Jacobi–Bellman equation, provide mathematically rigorous frameworks for sequential decision-making under uncertainty. Despite their theoretical elegance, these approaches typically require explicit specification of system dynamics and reward functions, rendering them computationally intractable for high-dimensional problems or systems with complex transition dynamics [95]. This limitation is particularly relevant in energy markets, where multiple interacting factors influence price dynamics.

Monte Carlo simulation methods have been widely employed to address uncertainty in financial modeling by generating numerous random scenarios to estimate expected outcomes. While effective for many applications, these techniques generally necessitate a predefined model of the underlying stochastic processes, potentially introducing model risk when the specified processes deviate from actual market behavior [68].

Parametric models, such as the Black–Scholes framework for option pricing or GARCH models for volatility forecasting, rely on specific assumptions about the underlying stochastic processes. Although these models offer computational efficiency and interpretability, their underlying assumptions—including normality of returns, constant volatility, or specific mean-reversion properties—often fail to capture the complex dynamics observed in energy markets [80].

Reinforcement learning presents several comparative advantages in addressing these limitations. First, the model-free nature of many RL algorithms enables learning optimal policies without requiring explicit specification of environmental dynamics, a valuable characteristic when these dynamics are complex, unknown, or difficult to parameterize. Second, RL approaches, particularly when implemented with deep neural networks, demonstrate superior capacity for capturing non-linear relationships that resist effective parametric modeling [96]. Third, RL frameworks inherently accommodate adaptability through continuous policy updates based on new observations, allowing them to respond to evolving market conditions. Finally, RL methodologies can naturally incorporate complex constraints and multiple objectives that may prove challenging to formulate within closed-form optimization problems.

However, these advantages must be weighed against certain trade-offs involving interpretability, data requirements, and computational complexity—considerations that will be examined in subsequent sections of this review.

3. Characteristics of Energy Markets Relevant to RL Applications

Energy markets possess several distinctive characteristics that make them both challenging for traditional modeling approaches and suitable candidates for RL applications.

3.1. Price Dynamics and Volatility

Energy commodities (electricity, coal, natural gas, crude oil, etc.) exhibit distinctive price dynamics that differentiate them from conventional financial assets (stocks, bonds, currencies, etc.), presenting unique challenges for modeling and trading strategies. These dynamics can be characterized by several key features that make traditional financial models often inadequate.

Energy markets display exceptional volatility, particularly in electricity markets, where price amplitudes significantly exceed those observed in conventional securities markets. While typical financial assets may experience annual volatility of 20–30%, electricity prices can undergo fluctuations of several hundred percent within equivalent timeframes [3]. This extraordinary volatility is primarily attributable to the limited storability of electricity and the necessity for instantaneous balance between supply and demand. The 2021 Texas winter storm provides a striking illustration, with wholesale electricity prices reaching the market cap of USD 9000/MWh, representing an approximately 9000% increase from typical levels [97].

Unlike many financial assets that follow random walk processes, energy prices typically exhibit mean-reverting behavior. This tendency to return to fundamental equilibrium levels occurs because energy prices are intrinsically linked to production costs. When prices deviate significantly from these costs, market mechanisms induce corrective movements—excessive prices stimulate increased production, while depressed prices lead to supply contraction. The mean-reversion rate varies considerably across energy commodities, with electricity prices potentially reverting within hours, while natural gas might require months to return to equilibrium levels [98].

A distinctive characteristic of energy markets, particularly electricity, is the occurrence of extreme price spikes. These episodic events manifest as transient but dramatic price increases, potentially orders of magnitude above normal levels. Such spikes typically result from supply constraints, extreme weather events, or technical failures in generation or transmission infrastructure. During the aforementioned 2021 Texas winter storm, the confluence of increased heating demand and widespread generation outages produced price spikes reaching the market cap [97]. These non-normally distributed events present significant challenges for conventional modeling approaches while creating opportunities for adaptive algorithms capable of recognizing precursory patterns [83].

Energy price dynamics operate across multiple overlapping timescales, creating complex temporal structures. These include intraday patterns reflecting diurnal demand fluctuations, weekly cycles distinguishing between workdays and weekends, seasonal variations driven by weather-dependent consumption, and long-term trends reflecting technological and regulatory evolution [99]. This multi-layered temporal structure necessitates modeling approaches capable of simultaneously capturing short-term fluctuations and long-term evolutionary patterns.

These complex dynamics exceed the capabilities of traditional parametric models, which typically rely on simplifying assumptions inappropriate for energy markets. This limitation creates a compelling opportunity for reinforcement learning approaches, which can learn directly from empirical data without imposing restrictive structural assumptions.

These theoretical price dynamics are vividly illustrated by several historical events in electricity markets. During the 2021 Texas winter storm, wholesale electricity prices in ERCOT reached the market cap of USD 9000/MWh, representing an approximately

9000% increase from typical levels of around USD 20–30/MWh [50,100]. This extreme price spike reflected both the physical non-storability of electricity and supply–demand imbalance when approximately 48.6% of generation capacity was forced offline due to weather conditions, while heating demand simultaneously surged. Following this crisis, prices rapidly reverted to normal levels once generation facilities were restored and demand normalized, demonstrating the mean-reverting characteristic discussed above.

The Australian National Electricity Market provides another instructive example of complex price dynamics. Specifically, Higgs and Worthington (2008) [76] documented that this market exhibited mean-reverting behavior with both intraday and seasonal patterns, but it also experienced frequent extreme price spikes. Their analysis showed that these spikes followed distinct statistical distributions that conventional models struggled to capture, highlighting the challenge for traditional pricing approaches.

Natural gas markets demonstrate different temporal dynamics but similar complexity. In their comprehensive analysis, Nick and Thoenes (2014) [101] showed that European natural gas prices exhibit mean-reversion at multiple time scales—short-term reversions following supply disruptions or weather events, and longer-term reversions toward production costs. Their study documents how these dynamics interact with seasonality patterns and storage levels to create complex price behaviors that cannot be adequately modeled by conventional stochastic processes.

3.2. Seasonality and Cyclicality

Energy markets exhibit pronounced temporal patterns across multiple timescales, creating complex cyclical structures in price formation. These patterns manifest through intraday fluctuations reflecting diurnal demand variations, with peak consumption hours typically commanding price premiums. Weekly cycles emerge from the distinct consumption profiles of weekdays versus weekends, while seasonal variations are predominantly driven by weather-dependent demand—heating requirements during winter months and cooling demand during summer periods in most regions. Certain energy commodities, particularly natural gas, display marked annual cyclicality attributable to storage injection–withdrawal cycles and seasonal consumption patterns.

The interaction of these temporal components creates a multi-layered structure that evolves dynamically in response to changing consumption behaviors, technological advancements, and regulatory modifications. Reinforcement learning methodologies offer the potential to capture these intricate temporal dependencies without necessitating explicit parameterization of individual cyclical components.

These theoretical patterns are clearly observable in empirical data across energy markets. Examining the PJM electricity market, Knittel and Roberts (2005) [102] documented pronounced diurnal patterns with peak/off-peak price differentials averaging 25–45%, depending on the season. Their analysis identified predictable load patterns driving these cycles, with price peaks typically occurring between 4–7 pm on weekdays. Beyond daily patterns, they found weekly cycles, with Sunday prices averaging 15–30% below Tuesday–Thursday levels due to lower commercial and industrial activity.

Natural gas markets provide a striking illustration of annual seasonality. Analyzing the Henry Hub benchmark, Suenaga et al. (2008) [103] documented how the injection–withdrawal cycle creates predictable price patterns, with late-summer-to-early-fall prices (during peak storage injection) historically averaging 10–15% below winter prices (during peak withdrawal). This seasonality interacts with storage inventory levels—Brown and Yücel (2008) [104] showed that when storage levels fall significantly below 5-year averages, winter price premiums can expand dramatically, sometimes exceeding 50% above summer prices.

European energy markets demonstrate how these cyclical patterns can evolve with changing consumption behaviors. Particularly, Paraschiv et al. (2015) [105] analyzed German electricity markets following substantial renewable integration, finding that traditional seasonality was increasingly overlaid with renewable generation cycles. Their research documented how solar generation created midday price depressions (sometimes resulting in negative prices) that altered the traditional peak/off-peak pattern, demonstrating how technological change can reshape fundamental market dynamics.

3.3. Regulatory and Market Structure Considerations

Energy markets operate within complex regulatory frameworks that substantially influence price formation mechanisms and market dynamics. Market design varies significantly across jurisdictions, ranging from fully liberalized structures to partially regulated environments, each with distinctive price formation processes [87]. Many electricity markets incorporate separate capacity mechanisms that provide supplementary revenue streams for generators, further complicating asset valuation and investment decision-making [40].

Renewable energy integration policies, including subsidies, feed-in tariffs, and priority dispatch provisions, significantly alter market dynamics and can precipitate negative price episodes [106]. Additionally, carbon pricing mechanisms and environmental regulations introduce further complexity to energy price formation [48]. These regulatory factors create regime-dependent dynamics that traditional modeling approaches struggle to accommodate. The adaptive learning capabilities of reinforcement learning algorithms are particularly suited to navigating these regulatory complexities.

The impact of regulatory frameworks on energy price formation is clearly illustrated by comparing market designs and policy impacts across different jurisdictions. Comparing the PJM and ERCOT electricity markets, Potomac Economics and Electric Reliability Council of Texas (2020) [107] documented how their structural differences created divergent price dynamics despite similar underlying fundamentals. While both markets use locational marginal pricing, PJM's capacity market provides generators with a separate revenue stream beyond energy prices, resulting in less extreme price volatility during scarcity conditions compared to ERCOT's energy-only design. During comparable reserve shortage events, maximum real-time prices reached significantly higher levels in ERCOT than in PJM, demonstrating how market design fundamentally shapes price behavior.

The impact of renewable energy policies is evident in Germany's electricity market transformation. Specifically, Ketterer (2014) [106] empirically analyzed how Germany's renewable integration policies, particularly solar subsidies and priority dispatch provisions, fundamentally altered market dynamics. Her econometric analysis documented a 36% reduction in average daily price levels between 2006–2012 attributable to solar and wind penetration, along with increased volatility. Furthermore, the study identified 40 negative price episodes during that period, a phenomenon virtually non-existent before these policies.

Carbon pricing mechanisms provide another example of regulatory impacts on energy markets. Analyzing the EU Emissions Trading System, Fabra and Reguant (2014) [48] found that power producers passed through approximately 80% of carbon prices to wholesale electricity prices, demonstrating how environmental regulations directly influence price formation. Their study showed that pass-through rates varied significantly across market conditions and generator types, creating complex interactions between carbon and electricity price dynamics.

3.4. Physical Constraints and Real Options

Energy assets are subject to substantial physical constraints that generate embedded optionality in their operation. Power generation facilities face operational limitations, including minimum and maximum output thresholds, ramp rate restrictions, and startup/shutdown costs that create complex optimization problems [23]. Energy storage facilities, such as natural gas storage or hydroelectric reservoirs, operate under capacity constraints, injection/withdrawal rate limitations, and cycle efficiency losses [24]. Additionally, transmission infrastructure constraints can induce locational price differentials and restrict arbitrage opportunities [77].

These physical constraints create real options that present significant valuation challenges for traditional methodologies. The sequential decision-making framework inherent in reinforcement learning approaches aligns naturally with the temporal exercise of these real options, offering advantages over conventional valuation techniques.

The operational constraints of power generation units create complex optimization challenges with significant economic implications. In their analysis of gas-fired power plants, Staffell and Green (2016) [108] documented how start-up costs ranged from GBP 3000–GBP 30,000 per start (approximately USD 4000–USD 40,000), depending on plant size and technology, while ramp rates limited output changes to 2–7% of capacity per minute. These constraints transformed the simple spark spread calculation into a complex optionality valuation problem that traditional methodologies struggle to accurately capture.

Transmission constraints frequently create locational price differentials that reflect embedded real options in the energy system. In a comprehensive analysis of the PJM market, Woo et al. (2011) [109] documented congestion-driven price differences exceeding USD 50/MWh between neighboring nodes during approximately 15% of hours studied. These differentials reflect the option value of transmission capacity, which varies with system conditions, demand patterns, and generation availability—a complexity well-suited to reinforcement learning approaches.

Energy storage facilities operate under multi-dimensional constraints that generate sophisticated optionality. Analyzing grid-scale battery storage, Staffell and Rustomji (2016) [110] detailed how cycle degradation (0.2–0.5% capacity loss per full cycle), depth-of-discharge limitations, and round-trip efficiency losses (15–25%) created complex trade-offs between short-term revenue opportunities and long-term asset value. These characteristics create real options that require advanced modeling techniques to value appropriately, particularly as storage technologies evolve and market services expand.

3.5. Market Incompleteness and Liquidity Constraints

Energy markets exhibit characteristics of financial incompleteness that impede comprehensive risk management. Basis risk emerges when standardized trading instruments fail to match the temporal or locational specificity of physical energy exposures. This mismatch between available hedging instruments and actual physical positions creates inherent inefficiencies, necessitating risk premiums to compensate for unhedgeable exposures [1].

Liquidity constraints represent a related challenge, as many energy derivatives markets exhibit limited depth. Restricted participation results in widened bid–ask spreads, elevated transaction costs, and potential price impacts from large transactions. This thin trading environment undermines a fundamental assumption of risk-neutral valuation—continuous portfolio rebalancing without price impact. The inability to establish and maintain cost-effective perfect hedges compromises the theoretical foundation of traditional pricing models, necessitating additional risk premiums that cause deviations from theoretical values.

Furthermore, energy markets encompass heterogeneous participants with divergent objectives, operational constraints, and risk preferences. This diversity in market participation leads to complex price formation dynamics that may not conform to standard equilibrium assumptions [111]. These market imperfections challenge traditional valuation methodologies predicated on no-arbitrage principles and market completeness. Reinforcement learning approaches offer alternative methodologies capable of incorporating transaction costs, liquidity constraints, and participant heterogeneity.

Basis risk in energy hedging creates significant challenges that illustrate market incompleteness. Examining natural gas markets, Brinkmann and Rabinovitch (1995) [112] documented basis risk between Henry Hub futures and 28 delivery locations, finding correlations ranging from 0.42 to 0.96. This incomplete correlation meant that even "hedged" positions retained substantial exposure, with risk reduction ranging from 18% to 92% across locations. Their analysis demonstrated how geographical specificities prevented perfect hedging even with standardized instruments.

The liquidity constraints in energy derivatives markets significantly impact trading costs and risk management. In their analysis of electricity forward markets, Frestad et al. (2010) [51] found bid–ask spreads in the Nordic electricity market (Nord Pool) ranging from 0.5% for front-month contracts to over 4% for quarters beyond 1 year. These transaction costs materially impacted hedging effectiveness and implied that continuous portfolio rebalancing—a key assumption in many valuation models—was economically infeasible beyond short time horizons.

Market participant heterogeneity further contributes to energy market incompleteness. Analyzing the UK electricity market, Karakatsani and Bunn (2008) [113] documented how different categories of participants (generators, suppliers, financial traders) systematically valued forward contracts differently based on their physical positions and risk preferences. Generators consistently valued forward contracts at a 5–12% discount to expected spot prices, while suppliers paid a 3–8% premium, creating a persistent risk premium that violated risk-neutral pricing assumptions. This heterogeneity demonstrates how energy markets operate with multiple subjective valuations rather than the single risk-neutral measure assumed by complete market theory.

4. RL for Energy Price Forecasting and Trading Strategies

Before examining specific applications in detail, Table 1 provides a systematic classification of reinforcement learning implementations in energy trading and forecasting. This classification organizes the literature by algorithm type, application domain, data characteristics, and key findings, offering a structured framework for understanding the evolving landscape of RL applications in energy markets. The table highlights the progression from traditional RL algorithms toward more sophisticated approaches, including distributional and multi-agent frameworks, reflecting the increasing complexity of energy market challenges being addressed. This classification also reveals patterns in methodological choices for different problem types, with value-based methods predominating in forecasting applications and policy-based approaches showing particular strength in trading strategy development. As the subsequent sections elaborate on these applications, this classification serves as a reference point for identifying methodological trends and comparative performance across different market contexts.

Table 1. Classification of Reinforcement Learning Applications in Energy Trading and Forecasting. This table categorizes key studies by algorithm type, application domain, data characteristics, and principal findings, illustrating the diverse approaches to implementing RL in energy market prediction and trading strategy development (2018–2024).

Study	RL Algorithm	Energy Application	Data Characteristics	Key Findings
Jiang and Powell (2018) [85]	Value iteration with function approximation	Ensemble forecasting of electricity prices	PJM hourly price data	RL-based ensembles adapt better to regime changes than static ensemble methods
Boukas et al. (2020) [114]	Proximal policy optimization	Intraday electricity trading	Nord Pool intraday market	RL strategy outperforms benchmark strategies by 15–28% in risk-adjusted returns
Du et al. (2021) [46]	Multi-agent DQN	Bidding strategy in day-ahead markets	ERCOT market data	Multi-agent approach effectively approximates Nash equilibrium solutions
Moti (2022) [115]	Q-learning	Electricity price prediction in blockchain-based grid	Simulated smart grid environment	RL framework mediates operator–consumer interactions for price prediction
Pannakkong et al. (2023) [116]	Double deep Q-network	Peak electricity demand forecasting	Thailand's electricity demand data	DDQN outperformed individual ML models by dynamically selecting optimal models
Guo and Wang (2020) [72]	Deep Q-network	Adaptive model selection for price forecasting	ISO New England data	RL framework reduced MAPE by 18% compared to the best individual model
Cao et al. (2023) [30]	Deep distributional RL	Options portfolio hedging	Simulated & empirical energy data	Outperformed delta hedging by 22–30% in managing non-linear risks
Mulliez (2021) [117]	Q-learning	Dynamic hedging with basis risk	Natural gas basis spreads	Adaptive hedging outperformed traditional approaches under time-varying risks
Chen et al. (2020) [34]	Hybrid RL + supervised learning	Energy portfolio hedging	Futures and spot price data	Cross-learning improved profit-risk tradeoffs vs. static hedging
Karimi Madahi et al. (2024) [118]	Distributional RL	Battery storage arbitrage	UK imbalance settlement prices	Captured asymmetric risk profiles better than expected value methods

4.1. Energy Price Forecasting with RL

Accurate price forecasting constitutes a fundamental component of energy trading and risk management. Traditional forecasting methodologies in energy markets encompass time series models (ARIMA, GARCH), fundamental models based on supply–demand balances, grey system theory models, and conventional machine-learning approaches, including neural networks and support vector machines [3]. The grey system theory, introduced by Deng (1982) [43], offers prediction methods particularly suited for systems with limited and uncertain information—characteristics often present in energy markets. Grey prediction models, notably GM (1, 1) and its variants, have demonstrated effectiveness in electricity price forecasting by requiring minimal historical data while maintaining reasonable accuracy [119,120]). These methods are especially valuable when dealing with non-stationary series and limited samples, complementing traditional statistical approaches. Grey models have been further enhanced through hybrid approaches, combining them with wavelets, neural networks, or residual correction mechanisms to improve forecasting performance across different time horizons (Zhao et al., 2015) [121]. Reinforcement learning offers a distinctive paradigm for addressing forecasting challenges by reformulating prediction as a sequential decision-making problem rather than a static estimation task.

Energy forecasting methodologies have evolved significantly in recent years, with numerous innovations emerging in 2024–2025. Specifically, Mystakidis et al. (2024) [122] provided a comprehensive review of energy forecasting techniques across different time horizons, highlighting how deep-learning approaches are increasingly outperforming traditional methods in capturing complex patterns in energy data. Several noteworthy advances have emerged in neural network architectures optimized for energy forecasting. Also, Majeske et al. (2025) [17] introduced dynamic attention neural networks (A-RNN) for industrial energy forecasting, demonstrating how attention mechanisms can capture spatiotemporal dependencies in multi-device systems while providing interpretability through learned feature importance. This approach shares conceptual similarities with attention-based reinforcement learning algorithms, suggesting potential integration paths between these methodologies.

Hybrid decomposition techniques combined with deep learning have shown remarkable results in renewable energy forecasting. Boucetta et al. (2024) [123] developed a novel approach combining Variational Mode Decomposition (VMD) with CNN-LSTM architectures for photovoltaic power forecasting, significantly outperforming conventional deep-learning methods. Similarly, Famoso et al. (2024) [49] integrated Artificial Neural Networks with stochastic dependability modeling for wind power forecasting, achieving substantial accuracy improvements by accounting for operational uncertainties like turbine failures. These approaches demonstrate the value of incorporating domain-specific knowledge into forecasting models, a principle that reinforcement learning naturally extends by learning optimal forecasting policies through environment interaction.

Optimization of neural network architectures has emerged as another promising direction. Specifically, Hosseini et al. (2025) [78] proposed a hybrid GA-PSO approach that optimizes Deep Neural Networks for energy consumption and photovoltaic production forecasting, achieving up to 27% accuracy improvements over traditional methods. This evolutionary optimization shares conceptual similarities with policy optimization in reinforcement learning, suggesting potential cross-fertilization between these approaches.

In their survey of medium- and long-term energy forecasting methods, Rodrigues Dos Reis et al. (2025) [124] highlighted the progressive shift toward advanced computational intelligence that can handle increasingly complex data and environment interactions. This trend aligns with the reinforcement learning paradigm discussed in this review, which reformulates forecasting as a sequential decision-making process rather than a static prediction task. As these forecasting techniques continue to evolve, their integration with reinforcement learning frameworks presents a compelling research direction, potentially combining the predictive power of specialized neural architectures with the adaptive decision-making capabilities of RL agents.

Several research streams have emerged in the application of reinforcement learning to energy price forecasting. The direct forecasting approach employs RL algorithms to predict future prices by learning from historical patterns and market feedback. Specifically, Pannakkong et al. (2023) [116] developed a framework utilizing Double Deep Q-Networks (DQN) to dynamically select optimal ensembles of machine-learning models for peak electricity demand forecasting. Their approach demonstrates how reinforcement learning can integrate model selection directly into the forecasting process, thereby improving prediction accuracy while adapting to evolving demand patterns in real-time environments.

Adaptive forecasting strategies represent another promising application of RL methodologies. Specifically, Guo et al. (2020) [72] proposed an adaptive reinforcement learning framework for electricity price forecasting that dynamically selects from a portfolio of forecasting models based on prevailing market conditions. In their implementation, the state space incorporates recent price trajectories and exogenous variables, while the action space consists of candidate forecasting models. This meta-learning approach demonstrated superior performance compared to individual forecasting methodologies, particularly during regime transitions in market behavior.

The application of reinforcement learning to feature selection and engineering has also yielded promising results. Specifically, Moti (2022) [115] introduced a novel framework employing Q-learning within blockchain-based smart grid environments for electricity price prediction. Their approach implements a Stackelberg game-theoretic framework mediating interactions between grid operators and consumers to optimize pricing mechanisms in real time, illustrating the potential of RL methodologies in dynamic, multi-agent environments.

Ensemble methods leveraging reinforcement learning have demonstrated particular efficacy in energy price forecasting. In particular, Jiang and Powell (2018) [85] developed an ensemble approach that combines multiple forecasting models with an RL algorithm determining optimal model weights based on recent performance metrics and prevailing market conditions. This methodology exhibited a remarkable capacity to adapt to regime changes in energy markets, consistently outperforming static ensembles and individual forecasting models during periods of market transition.

Traditional forecasting methodologies in energy markets encompass time series models (ARIMA, GARCH), fundamental models based on supply–demand balances, grey system theory models, and conventional machine-learning approaches, including neural networks and support vector machines [3]. The grey system theory, introduced by Deng (1982) [43], offers prediction methods particularly suited for systems with limited and uncertain information—characteristics often present in energy markets. Grey prediction models, notably GM (1, 1) and its variants, have demonstrated effectiveness in electricity price forecasting by requiring minimal historical data while maintaining reasonable accuracy [119]. These methods are especially valuable when dealing with non-stationary series and limited samples, complementing traditional statistical approaches. Reinforcement learning offers a distinctive paradigm for addressing forecasting challenges by reformulating prediction as a sequential decision-making problem rather than a static estimation task.

4.2. Optimal Trading Strategies

The implementation of effective trading strategies in energy markets requires addressing unique challenges, including high volatility, complex seasonality patterns, and distinctive price dynamics. Reinforcement learning methodologies have emerged as promising approaches for developing adaptive trading strategies capable of navigating these market complexities.

In day-ahead electricity markets, Du et al. (2021) [46] proposed a multi-agent deep reinforcement learning framework for optimizing bidding strategies. Their approach approximated Nash equilibrium solutions whereby market participants, represented as autonomous agents, learned optimal bidding policies through iterative interaction within simulated market environments. This methodology demonstrated particular effectiveness in capturing strategic behaviors in oligopolistic market structures where participants must consider competitors' potential actions.

Concerning shorter-term trading horizons, Boukas et al. (2020) [114] developed a reinforcement learning framework, specifically addressing intraday electricity trading challenges. Their implementation utilized the Proximal Policy Optimization algorithm with a comprehensive state representation incorporating recent price trajectories, order book information, and temporal features. Empirical evaluation demonstrated the framework's capacity to exploit intraday price patterns, particularly short-term price reversals and momentum effects. The authors noted that their approach exhibited superior adaptability to changing market conditions compared to traditional rule-based trading strategies.

More recently, Seyed Soroush Karimi Madahi et al. (2024) [118] advanced the application of reinforcement learning to energy storage arbitrage by implementing a distributional reinforcement learning framework. Their approach focused specifically on optimizing battery operation for profit maximization within imbalance settlement mechanisms in electricity markets. The authors' key contribution lies in their modeling of complete return distributions rather than merely expected values, enabling enhanced decision-making under uncertainty. This distributional perspective proved particularly valuable in capturing the asymmetric risk profiles characteristic of imbalance markets, where price volatility exhibits pronounced skewness and kurtosis [67].

These studies collectively demonstrate the evolution of reinforcement learning applications in energy trading, from strategic bidding in structured markets to tactical exploitation of short-term price dynamics and sophisticated risk management in storage optimization.

4.3. Risk Management Applications

The application of reinforcement learning to risk management in energy trading has garnered increasing attention, particularly in the domains of hedging, portfolio optimization, and risk measurement. Several recent studies have demonstrated the efficacy of RL-based approaches in addressing the unique challenges of energy markets.

Value at Risk (VaR) represents a fundamental cornerstone of financial risk management in energy markets, quantifying the maximum potential loss over a specified time horizon at a particular confidence level [88]. Traditional VaR methodologies in energy finance include historical simulation, parametric approaches, and Monte Carlo simulation, each with distinct advantages and limitations in capturing the complex dynamics of energy price behavior [125]. In this context, Halkos and Tsirivis (2019) [73] demonstrated the importance of employing advanced GARCH-type models for VaR estimation in energy portfolios, highlighting how these approaches can better quantify capital at risk due to the distinctive volatility patterns of energy commodities. The application of neural networks to VaR estimation has shown particular promise, with Wang, Liu, and Yao (2024) [126] developing an explainable quantile regression neural network (QRNN) method for VaR forecasting in energy markets that addresses both accuracy and interpretability concerns [127].

Conditional Value at Risk (CVaR), which measures the expected loss exceeding VaR, has found significant applications in power system reliability assessments. In particular, Zhang et al. (2023) [128] developed a CVaR-based reserve assessment model for power systems that explicitly accounts for primary energy supply risks, demonstrating how advanced risk metrics can enhance reliability in systems with high renewable penetration. These developments in VaR and CVaR methodologies provide important foundations for reinforcement learning applications in energy risk management, as RL frameworks can potentially learn to dynamically adjust risk measures based on evolving market conditions.

Specifically, Cao et al. (2023) [30] developed a deep distributional reinforcement learning framework for options portfolio hedging that has direct applicability to energy derivatives. Their methodology extends beyond conventional delta hedging by incorporating gamma and vega exposure management through quantile regression techniques. This approach enables more comprehensive risk-aware decision-making by modeling the entire distribution of potential outcomes rather than merely expected values. Empirical evaluations demonstrated that their framework consistently outperformed benchmark strategies in managing non-linear risks across diverse market scenarios, suggesting significant potential for application in the complex derivatives structures common in energy markets.

The challenge of basis risk—a persistent issue in energy hedging due to imperfect correlation between physical exposures and available hedging instruments—was addressed by Mulliez (2021) [117] through an innovative Q-learning framework. This study demonstrated how reinforcement learning methodologies can dynamically adapt hedging strategies in environments characterized by structural pricing mismatches. Comparative analysis revealed superior performance relative to traditional analytical hedging approaches, particularly in scenarios where the underlying and hedging instruments exhibit time-varying correlation structures—a common occurrence in regional energy markets with transmission constraints.

Particularly, Chen et al. (2020) [34] proposed a hybrid methodology combining reinforcement learning with supervised learning techniques specifically tailored to the dynamic nature of energy portfolios. Their cross-learning framework effectively captured temporal patterns in energy price dynamics while supporting adaptive strategy generation in response to changing market conditions. Performance evaluations indicated improved profit–risk trade-offs compared to both static hedging protocols and purely statistical methodologies, highlighting the advantages of RL's sequential decision-making paradigm in volatile energy markets.

Specifically, Trabelsi et al. (2025) [129] investigated tail risk transmission between crude oil and clean energy stock indices using a Time-Varying Parameter Vector Auto-Regressive model integrated with a Conditional Autoregressive Value-at-Risk approach. Their findings highlighted how crises like the COVID-19 pandemic intensified volatility spillovers between these markets, providing crucial insights for risk management strategies. These findings underscore the potential value of reinforcement learning approaches that can adapt to such regime shifts in market behavior, learning optimal risk management policies across different market states.

In examining broader portfolio construction considerations, Barrera–Rivera and Valencia–Herrera (2022) [130] developed an integrated framework combining machine-learning techniques with conditional risk measures for energy asset portfolios. Their research explored the construction of efficient frontiers under dynamic conditions and leveraged scenario simulations to enhance decision robustness. The implementation of machine-learning models provided particular advantages in forecasting non-linear dependencies characteristic of energy price behavior, enabling more effective hedging strategy formulation under uncertainty.

The integration of reinforcement learning with VaR and CVaR methodologies presents a promising frontier for energy risk management. The ability of RL algorithms to learn complex, non-linear relationships and adapt to changing market conditions aligns naturally with the challenges of risk quantification in volatile energy markets. As demonstrated by applications in related fields [69,131], the combination of advanced risk metrics with learning-based approaches offers potential to enhance both the accuracy and adaptability of risk management strategies in energy markets.

Collectively, these studies demonstrate reinforcement learning's significant potential in addressing the complex risk management challenges endemic to energy trading environments, where traditional models often prove inadequate due to market incompleteness, basis risk, and extreme price dynamics.

5. RL for Derivatives Valuation in Energy Markets

5.1. Option Pricing Fundamentals

Derivatives valuation in energy markets presents distinctive challenges that differentiate these instruments from their counterparts in conventional financial markets. These challenges arise from several fundamental characteristics of energy commodities and their corresponding markets.

The non-storability of certain energy commodities, particularly electricity, represents a significant departure from traditional financial assets. Unlike securities or even physical commodities such as precious metals, electricity cannot be economically stored in substantial quantities. This characteristic violates a fundamental assumption underpinning traditional arbitrage-based pricing models—the ability to construct replicating portfolios through buying and holding the underlying asset [44].

Energy price processes exhibit complex stochastic behavior that extends beyond the relatively simple dynamics assumed in standard financial models. These processes frequently incorporate features such as mean-reversion, reflecting the tendency of prices to return to production cost levels; discontinuous jumps, capturing sudden supply or demand shocks; and regime-switching, representing distinct market states with different underlying dynamics. These complex behaviors necessitate sophisticated stochastic modeling approaches that extend well beyond conventional geometric Brownian motion assumptions [21].

Market incompleteness presents another substantial challenge for derivatives valuation in energy markets. The inability to construct perfect replicating portfolios—due to non-storability, limited market depth, or the absence of liquid trading in certain risk factors—undermines the theoretical foundation of risk-neutral valuation. This incompleteness introduces an unavoidable element of subjectivity in pricing, as different market participants may assign different values to non-hedgeable risks [22].

Many energy derivatives incorporate embedded optionality regarding delivery specifications, further complicating their valuation. These contingent features may include flexibility in delivery location, timing, or quantity. For instance, natural gas swing contracts permit buyers to vary daily consumption within specified limits, while power transmission rights grant optionality regarding the utilization of transmission capacity [1].

Despite these challenges, several methodological approaches have been developed to address energy derivatives pricing. Extended Black–Scholes frameworks modify the standard geometric Brownian motion assumption to incorporate mean-reversion, jumps, and other features characteristic of energy price dynamics [75,98]. Monte Carlo simulation techniques provide numerical solutions through the simulation of price paths based on specified stochastic processes, particularly valuable for path-dependent derivatives or contracts with complex exercise features [14]. Partial differential equation methods offer numerical solutions to the governing equations of derivative prices under specific assumptions about the underlying price process, though their application becomes increasingly challenging as the dimensionality of the problem increases [132].

Following our examination of option pricing fundamentals, Table 2 classifies significant research applying reinforcement learning methodologies to energy derivatives valuation. This classification organizes studies by valuation problem type, RL methodology, energy market focus, and key contributions. The table illustrates how different RL approaches address specific challenges in energy derivatives pricing and real options analysis, providing a framework for understanding the comparative advantages of these methods over traditional approaches.

Table 2. Summary of reinforcement learning applications in energy derivatives valuation, highlighting methodologies, energy domains, and key contributions.

Study	Valuation Problem	RL Methodology	Energy Focus	Key Contribution
Halperin (2019) [74]	General option pricing	Q-learning	Energy options	Model-free approach deriving pricing functions directly from empirical data
Buehler et al. (2019) [133]	Hedging under market frictions	Deep reinforcement learning	Options hedging	Framework accommodating transaction costs and market incompleteness
Becker et al. (2019) [134]	Optimal stopping	Deep Q-Network	American-style options	Direct learning of exercise policies without explicit continuation values

Table 2. *Cont.*

Study	Valuation Problem	RL Methodology	Energy Focus	Key Contribution
Becker et al. (2020) [135]	Gas swing option valuation	Deep reinforcement learning	Natural gas contracts	RL approach superior to LSMC for contracts with complex constraints
Marzban et al. (2023) [18]	Risk-aware option pricing	Actor-critic with risk measures	Energy derivatives	Incorporation of expectile risk measures for risk-averse valuation
Song (2022) [136]	Computationally efficient pricing	Deep RL with high-performance computing	Energy option pricing	Real-time pricing under dynamic market conditions
Carbonneau (2021) [29]	Equal risk pricing	Neural networks with RL	Energy derivatives	Pricing framework reflecting actual hedging costs and residual risks
Dalal et al. (2016) [41]	Generation asset valuation	Deep Deterministic Policy Gradient (DDPG)	Power generation	Operating policies maximizing value under technical constraints
Boogert and de Jong (2008) [137]	Gas storage valuation	Q-learning	Natural gas storage	Capturing complex intertemporal tradeoffs in storage operations
Lee et al. (2023) [10]	CCU investment valuation	RL with real options	Carbon capture	Framework for identifying optimal investment timing under uncertainty
Caputo and Cardin (2022) [31]	Waste-to-energy system valuation	Deep RL for flexibility analysis	Energy systems	DRL models improved economic outcomes by up to 69% vs. traditional approaches
Cheraghi et al. (2024) [38]	Energy transition investment	RL for sustainable planning	Renewable energy	Dynamic optimization considering environmental and regulatory uncertainty

5.2. RL Approaches to Option Pricing and Applications

Reinforcement learning methodologies offer promising alternatives to traditional derivatives valuation techniques, potentially addressing several limitations of conventional approaches. These methods have demonstrated particular utility in the context of energy derivatives, where complex market dynamics and incompleteness present significant modeling challenges.

Particularly, Halperin (2019) [74] developed a model-free approach to option pricing using reinforcement learning frameworks. This methodology enables an agent to learn pricing functions by directly interacting with a simulated market environment, circumventing the need for explicit specification of the underlying price process. The approach derives pricing functions directly from empirical data, thereby avoiding potentially restrictive parametric assumptions. When applied to energy options, this technique demonstrated notable efficacy, particularly for instruments with complex features that resist conventional parametric modeling. The flexibility of this approach proves especially valuable in energy markets, where price dynamics exhibit distinctive characteristics including extreme volatility, mean-reversion, and regime-switching behavior.

The deep hedging framework proposed by Buehler et al. (2019) [133] represents another significant application of reinforcement learning to derivatives pricing. This approach employs deep reinforcement learning to determine optimal hedging strategies that minimize hedging error under realistic market conditions. When extended to energy derivatives, this methodology naturally accommodates market frictions, including transaction costs, liquidity constraints, and market incompleteness—features that traditional risk-neutral pricing approaches struggle to incorporate. By optimizing hedging decisions directly, rather than deriving them from theoretical price processes, deep hedging provides more robust risk management strategies for complex energy derivatives.

Specifically, Becker et al. (2019) [134] applied deep reinforcement learning techniques to optimal stopping problems, which have particular relevance for American-style options and swing options commonly traded in energy markets. Their methodology employed a Deep Q-Network (DQN) architecture to learn optimal exercise policies directly, eliminating the need for explicit modeling of continuation values that traditional approaches require. When applied to gas storage contracts with complex exercise constraints, their reinforcement learning approach demonstrated superior performance compared to conventional least-squares Monte Carlo methods. This performance advantage stems from the ability of reinforcement learning algorithms to capture complex exercise boundaries without restrictive functional form assumptions.

The valuation of energy derivatives presents unique challenges that traditional approaches struggle to address effectively. Electricity's non-storability, complex price dynamics, and the presence of operational constraints create an incomplete market where perfect hedging is impossible. RL offers a model-free framework that can learn optimal pricing and hedging strategies directly from market data without requiring explicit specification of the underlying stochastic processes.

Particularly, Marzban et al. (2023) [18] extend deterministic actor–critic reinforcement learning to incorporate time-consistent recursive expectile risk measures, addressing the risk-averse nature of energy market participants. Their approach accommodates complex hedging problems even when only historical asset data are available, generating nearly optimal hedging policies for energy derivatives without requiring full knowledge of asset dynamics. This is particularly valuable in electricity markets where price processes exhibit regime-switching behavior and extreme events that parametric models struggle to capture.

Also, Song (2022) [136] addresses the computational intensity of option pricing in energy markets by integrating high-performance computing with deep reinforcement learning. This approach enables real-time pricing of complex energy derivatives under dynamic market conditions, incorporating challenges like random interest rates and transaction costs that are prevalent in energy markets. The shift from analytical models to data-driven, computation-heavy frameworks aligns well with the realities of modern energy derivatives that often lack closed-form solutions.

The concept of equal risk pricing, explored in depth by Carbonneau (2021) [29], offers a promising framework for energy derivatives where market incompleteness makes traditional risk-neutral pricing problematic. By modeling hedging strategies as neural networks trained via deep reinforcement learning, this approach can generate fair prices for energy derivatives that reflect the actual hedging costs and residual risks faced by market participants. The ability to incorporate multiple hedging instruments is particularly relevant for energy markets where cross-commodity hedging is common practice.

The distinctive characteristics of energy markets have allowed for the rise of specialized option structures that present unique valuation challenges, prompting researchers to explore reinforcement learning approaches for these instruments.

Swing options represent a significant application domain in energy markets, particularly in natural gas and electricity contracts. These instruments afford holders the flexibility to determine both the timing and volume of delivery, subject to cumulative constraints over the contract period. This optionality is particularly valuable due to the volatile nature of energy prices and varying demand patterns. Also, Meinshausen and Hambly (2004) [19] pioneered the application of reinforcement learning to this valuation problem, implementing Q-learning algorithms to determine optimal exercise policies that respect both local and global constraints. Building upon this foundation, Becker et al. (2020) [135] employed deep reinforcement learning methodologies to value swing options in natural gas markets, demonstrating performance advantages over traditional least-squares Monte Carlo approaches. Their research revealed particularly significant improvements for contracts with complex constraint structures and during periods of high market volatility, where the adaptive nature of reinforcement learning offers distinct advantages.

Spread options, particularly spark spreads (electricity price minus gas price multiplied by heat rate) and dark spreads (electricity price minus coal price multiplied by heat rate), constitute fundamental instruments for managing generation asset exposure in energy portfolios. These instruments derive their value from the margin between output and input commodity prices, incorporating the efficiency factor of the conversion process. In addition, Carmona and Coulon (2014) [21] elucidated the challenges inherent in valuing these instruments using traditional methods, noting, particularly, the complex correlation structures and regime-switching behaviors that characterize the relationship between fuel and electricity prices. The application of reinforcement learning to spread option valuation remains an evolving research domain, with recent studies suggesting promising results in capturing the non-linear dependencies between underlying commodities. The multi-factor nature of these options presents both challenges and opportunities for reinforcement learning approaches, as the high-dimensional state space benefits from the RL's capacity to learn complex value functions.

Locational spread options emerge from transmission constraints that create price differentials between geographic regions within interconnected energy networks. These instruments derive value from arbitraging price disparities between locations when transmission capacity permits. Particularly, Oren (2001) [138] articulated the difficulties in applying conventional valuation techniques to these instruments, highlighting the impact of network topology and congestion patterns on option values. Recent applications of reinforcement learning to this domain have demonstrated advantages in incorporating the complex network constraints and contingency scenarios that influence locational spread values. The stochastic nature of both congestion patterns and regional supply–demand dynamics creates a particularly suitable application for reinforcement learning methodologies, which can adapt to changing network conditions without requiring explicit modeling of all contingencies. Furthermore, the integration of increasing volumes of location-dependent renewable generation has enhanced the importance and complexity of these instruments, creating additional incentives for advanced valuation methodologies.

These specialized energy options illustrate the diversity of challenges in energy derivatives valuation and highlight the potential advantages of reinforcement learning approaches over traditional techniques, particularly when handling complex constraints, high-dimensional state spaces, and regime-dependent dynamics that characterize modern energy markets.

5.3. Real Options Analysis

Real options analysis provides a framework for valuing operational flexibility and managerial discretion embedded in physical assets and investment decisions in energy markets. Unlike traditional discounted cash flow methods, real options approaches explicitly account for the value of flexibility under uncertainty. Reinforcement learning methodologies offer a natural computational framework for addressing these complex sequential decision problems that often resist closed-form solutions.

The valuation of power generation assets represents a prominent application domain, as these facilities can be conceptualized as real options to transform fuel inputs into electricity when economically advantageous. Specifically, Tseng and Barz (2002) [139] articulated the limitations of conventional valuation methodologies in this context, particularly their inability to adequately incorporate technical constraints and operational characteristics. Advancing this research direction, Dalal et al. (2016) [41] implemented deep reinforcement learning techniques for generation asset valuation, developing operating policies that maximized economic value while respecting technical constraints. Their methodology employed a Deep Deterministic Policy Gradient algorithm with a multidimensional state space encompassing fuel prices, electricity prices, and plant operational status variables. This approach demonstrated superior performance compared to traditional methods, particularly in capturing the value of operational flexibility under complex market conditions.

Energy storage facilities, including natural gas storage, pumped hydroelectric systems, and battery installations, represent sophisticated real options with multi-dimensional constraints. Specifically, Boogert and de Jong (2008) [137] applied classical reinforcement learning techniques to natural gas storage valuation, demonstrating how these methods could capture the complex intertemporal trade-offs inherent in storage operation. Subsequent research has extended these approaches to incorporate additional constraints and market characteristics.

Investment timing decisions in energy infrastructure development involve embedded timing options that significantly impact project valuation. Also, Chronopoulos et al. (2016) [39] examined these timing options specifically within the context of renewable energy investments, highlighting how policy uncertainty affects optimal investment strategies. Reinforcement learning approaches offer particular advantages in this domain due to their ability to incorporate multiple uncertainties simultaneously, including regulatory changes, technological learning curves, and market condition evolution.

Recent literature has significantly advanced the integration of reinforcement learning with real options analysis in energy markets. Specifically, Nadarajah and Secomandi (2023) [140] provide a comprehensive review of real options applications across various energy domains, including electricity, natural gas, and crude oil, highlighting the evolving role of machine-learning techniques in capturing value under uncertainty. Their survey establishes a foundation for understanding how computational approaches are transforming valuation methodologies in energy finance, building upon the earlier works while identifying emerging research directions.

The application of reinforcement learning to environmentally significant energy technologies has emerged as a particularly active research area. Specifically, Lee et al. (2023) [10] developed a framework merging real options theory with reinforcement learning to evaluate the commercial viability of carbon capture and utilization (CCU) technologies. Their approach models uncertain factors such as market prices and policy shifts, identifying optimal investment timing and highlighting the value of flexibility in energy project deployment under deep uncertainty. Similarly, Alqubaisi (2023) [141] applied deep-learning methods to value real options in renewable energy projects, developing a framework that captures non-linear dependencies and offers a scalable approach to handle complex valuation under stochastic conditions.

Methodological advancements in applying reinforcement learning to real options have also progressed significantly. Furthermore, Caputo and Cardin (2022) [31] proposed a deep reinforcement learning approach to assess flexibility in engineering systems, tested on a waste-to-energy system. By comparing DRL models with traditional decision rule approaches, they demonstrated that DRL-enhanced models improved economic outcomes by up to 69%, generalizing across scenarios and supporting better-informed strategic design under uncertainty. Moreover, Lawryshyn (2023) [9] further emphasized the limitations of classical option pricing models in capturing multidimensional uncertainties and proposed RL-based solutions for adaptive decision-making, providing valuable insights into training RL agents for investment strategies with embedded flexibility.

Looking toward future energy systems, Cheraghi et al. (2024) [38] explored the use of reinforcement learning in planning and investment for sustainable energy transitions. Their work introduces RL algorithms that dynamically optimize energy systems considering environmental and regulatory uncertainty, positioning RL as a crucial tool to unlock value creation in decarbonized energy strategies. This research direction highlights how reinforcement learning can address the complex, multi-objective decision problems inherent in energy transition investments.

The application of reinforcement learning to real options valuation in energy markets remains an active research frontier with substantial opportunities for methodological advancement. Future research directions include the development of hybrid approaches that combine the interpretability of traditional real options models with the flexibility of reinforcement learning, and the extension of these methods to address multi-agent decision environments that better reflect competitive market dynamics.

6. Option Value in Power Systems

6.1. Real Options Framework for Smart Grid Technologies

The concept of option value has found significant applications in power systems, particularly in economically evaluating smart grid investments under uncertainty [142]. In this context, the option value of deploying a smart grid technology represents the difference in total expected system costs between cases with and without the technology deployment [81]. This approach recognizes that smart grid investments create flexibility to deal with future sources of uncertainty, which has economic value beyond traditional deterministic cost–benefit analysis [143].

Several smart grid technologies have demonstrated significant option value when captured using a stochastic optimization framework [25]. Dynamic Line Rating (DLR) captures the variable transmission capacity based on real-time conditions rather than static conservative ratings, generating option value from deferred transmission investments and improved congestion management [144]. In this context, Giannelos et al. (2018) [63] quantified the option value of DLR in transmission systems, showing that DLR can lead to expensive network reinforcements being deferred or displaced.

Energy storage systems provide multiple services, including arbitrage, capacity deferral, ancillary services, and renewable integration. Their option value stems from the ability to charge/discharge load in response to price signals, system needs, and renewables output—all subject to significant uncertainty [145]. Also, Giannelos et al. (2020) [60] developed a methodology to quantify the contribution of energy storage to the security of supply through the F-Factor approach, capturing additional option value beyond traditional energy arbitrage applications.

Demand-Side-Response (DSR) programs create option value by providing network operators with flexibility to modify load profiles in response to supply constraints or price signals. This flexibility is particularly valuable during extreme events or unexpected system conditions, as shown by Papadaskalopoulos and Strbac, 2017 [146]. Also, Giannelos et al., 2018 [26] and Giannelos et al., 2018 [64]) analyzed the option value of the demand-side response under decision-dependent uncertainty, demonstrating the significant option value of DSR technology under endogenous uncertainty, using stochastic optimization.

Advanced Network Management Systems that enable greater observability and controllability of distribution networks create option value by allowing network operators to defer traditional reinforcement costs while maintaining reliability under uncertain load growth and distributed generation adoption [47]. In their comprehensive framework, Giannelos, Borozan, Konstantelos et al. (2024) [57] quantified the option value, investment costs, and deployment levels for various smart grid technologies, providing a systematic approach to evaluating these investments.

Electric Vehicle Smart Charging creates significant option value by coordinating charging patterns to support grid requirements [147]. Specifically, Giannelos, S., Borozan, S., and Strbac, G. (2022) [55] developed a backwards induction framework that quantifies both the option value of smart charging and the risk of stranded assets under uncertainty. Their analysis demonstrated how smart charging strategies can significantly reduce network investment costs while accommodating growing EV penetration. Additionally, in two studies, Borozan, Giannelos, and Strbac [148,149]) integrated EV smart charging as an investment option within strategic network expansion planning, demonstrating substantial option value through deferred network reinforcements. Similarly, Giannelos, S., Borozan, S., Strbac, G. et al. (2024) [58] focused on vehicle-to-grid applications, quantifying their contribution to security of supply using the F-Factor methodology, capturing additional option value beyond traditional V2G applications. Moreover, the option value of smart charging portfolios is presented in Giannelos, Borozan, Moreira et al. (2023) [59].

Soft Open Points, power electronic devices that enable flexible network reconfiguration in distribution systems, have also demonstrated significant option value [52,86]. The paper by Lu et al. (2019) [16] proposes a multi-layer planning model for deploying Soft Open Points in active distribution networks, integrating a demand response to enhance grid flexibility and reduce operational costs. SOPs are used to control power flow and mitigate issues arising from high penetration of distributed generation, while demand response is modeled using time-of-use pricing to shift loads cost-effectively. The model, solved using an improved particle swarm optimization algorithm, shows through IEEE-33 node simulations that this combined planning approach improves both economic performance and operational feasibility.

A similar analysis is presented in Giannelos, Konstantelos et al. (2019), where soft open point technology is combined with energy storage [150].

6.2. Stochastic Optimization Approach to Quantifying Option Value

The quantification of option value for smart grid technologies typically employs stochastic optimization methods in a two-stage process. In the first stage, a stochastic optimization problem is solved without the smart grid technology under future uncertainty. The objective function typically minimizes total system costs, including operational costs and investment costs. The result is the expected system cost without the technology. In the second stage, the same stochastic optimization problem is solved with the smart grid technology considered for deployment in the system [71]. This yields the expected system cost with the technology. A list of smart technologies and their formulations is presented in Giannelos, Borozan, and Aunedi (2023) [56].

The difference between these expected costs represents the option value of the technology. A positive difference indicates that the technology creates value by providing flexibility to deal with uncertainty. Key uncertainties typically modeled in such stochastic optimization models include renewable generation output, load growth and profiles, fuel prices, equipment outages, policy and regulatory changes, and technology costs. These uncertainties represent the primary factors that affect the valuation of smart grid technologies and must be adequately characterized to produce meaningful option value estimates.

Mathematically, this can be formulated as:

$$OV = E[C_{without}] - E[C_{with}]$$

where OV is the option value, $E[C_{without}]$ is the expected cost without the technology, and $E[C_{with}]$ is the expected cost with the technology, each quantified via stochastic optimization.

Specifically, Giannelos, Konstantelos et al. (2017) [62] developed a new class of planning models for option valuation of storage technologies under decision-dependent innovation uncertainty. Their approach incorporated how deployment decisions affect future technology costs and capabilities, showing that traditional models undervalue early adoption of promising technologies.

In particular, Zhao et al. (2015) [121] applied this approach to evaluate energy storage systems in a system with high renewable penetration. Their analysis showed that traditional deterministic approaches significantly undervalued storage by failing to capture its ability to mitigate the uncertainty of renewable generation.

Also, Giannelos, Jain, and Borozan (2021) [61] apply stochastic optimization to long-term expansion planning of the transmission network in India under multi-dimensional uncertainty. Their framework captures complex interactions between different sources of uncertainty, demonstrating how flexible investment strategies create substantial option value in rapidly evolving power systems. Building on this work, Giannelos, Zhang et al. (2024) [66] developed methods for Pareto frontier sensitivity analysis in power systems, enabling decision-makers to understand how economic value changes across different configurations.

Moreover, Dong, Zhang, et al. (2024) [45] examined how coordinated control of space heating across multiple buildings can enhance urban energy system flexibility. Using optimization models that incorporate building thermal dynamics and occupant comfort constraints, they demonstrated substantial option value from heating flexibility.

6.3. Methodological Considerations for RL-Based Option Valuation

Applying RL to quantify the option value of smart grid technologies involves several methodological considerations. To accurately determine option value, the baseline (without technology) scenario must use the same RL algorithm and reward structure, differing only in the availability of the technology. This ensures a fair comparison of expected costs. The scenarios used for training and evaluation should properly represent the underlying uncertainties. Techniques like importance sampling, scenario reduction, and generative models can help create representative scenario sets without excessive computational burden.

The reward function should accurately reflect the total system costs, including operation and investment costs. Improperly specified reward functions can lead to biased option value estimates. Smart grid investments typically have multi-decade lifespans. RL approaches must properly account for long-term effects, either through appropriate discount factors or explicit modeling of long-term scenarios. RL-based valuation typically requires significant computational resources for training.

Techniques like transfer learning, model-based RL, and distributed computing can help address this challenge, similar to decomposition methodologies applied to stochastic optimization frameworks as in Borozan, Giannelos et al. (2024) [151], which present a machine-learning-enhanced Benders decomposition approach for multi-stage stochastic transmission expansion planning that significantly improves computational efficiency while capturing the full option value of smart grid investments [35].

These models could support more accurate scenario generation for RL-based option valuation. Similarly, Giannelos, Zhang, Pudjianto et al. (2024) [65] compared strategic versus incremental planning approaches in electricity distribution grids, providing insights into how different planning horizons affect option values—a key consideration when designing RL reward functions for long-term investment decisions.

6.4. Future Research Directions

Several promising research directions could further enhance RL-based option valuation in power systems. Most studies focus on individual technologies, but real power systems deploy portfolios of complementary smart grid technologies. Research on RL-based valuation of technology portfolios could identify synergistic combinations (Charousset-Brignol et al., 2021) [33] that create greater option value than the sum of individual technologies. Rather than learning expected values, distributional RL learns the full distribution of returns. This approach could provide more comprehensive information about the option value distribution under extreme events and rare scenarios. Different stakeholders have different risk preferences when evaluating smart grid investments. Research on risk-sensitive RL could provide option valuations tailored to specific risk preferences, such as risk-averse utility regulators. Smart grid deployments can influence market prices and regulatory decisions, creating feedback effects not captured in current models. Research on RL approaches that model these feedback effects could provide more accurate option valuations. Regulatory approval of smart grid investments typically requires transparent justification. Research on explainable RL could make option valuation results more interpretable and trustworthy for regulators and other stakeholders.

7. Conclusions: Limitations, Future Directions, and Policy Limitations

This review has examined how reinforcement learning can be applied to energy finance, highlighting applications ranging from price forecasting and trading strategies to derivatives valuation and option value assessment in power systems. As this field continues to evolve, it is important to recognize current limitations, identify promising research directions, and consider policy implications.

7.1. Current Limitations of RL in Energy Finance

Despite demonstrating significant potential, the application of reinforcement learning methodologies to energy finance encounters several substantial challenges that merit careful consideration.

Interpretability remains a primary concern in the deployment of RL techniques within financial contexts. Deep reinforcement learning models frequently operate as “black boxes”, with decision-making processes that resist straightforward human interpretation. This opacity presents significant impediments for risk management protocols and regulatory compliance frameworks that typically require transparent justification of trading strategies and investment decisions. While recent research has explored techniques such as attention mechanisms and feature importance analysis to enhance model interpretability [152], these approaches have yielded only incremental improvements. The development of inherently interpretable RL architectures that maintain competitive performance represents a critical avenue for future research, particularly as financial regulators increasingly scrutinize algorithmic decision-making systems.

Sample complexity constitutes another significant limitation. RL algorithms characteristically require extensive data for effective policy learning, a requirement that proves problematic in energy finance applications where historical data may be insufficient, particularly for rare events or emerging market structures. This limitation becomes especially pronounced when modeling extreme price events or evaluating strategies under novel regulatory frameworks. Current approaches addressing this constraint include model-based reinforcement learning, which leverages environment models to reduce data requirements; transfer-learning techniques that apply knowledge from related domains; and synthetic data augmentation [153]. However, the effectiveness of these methods remains constrained when the target domain exhibits substantial structural differences from available training data. The integration of domain knowledge and physics-informed constraints into RL frameworks offers a promising direction for improving sample efficiency in energy applications.

The challenge of generalization across distinct market regimes is particularly salient in energy finance. Reinforcement learning agents trained under specific market conditions frequently struggle to maintain performance when confronted with regulatory changes, technological disruptions, or structural market shifts. This limitation is particularly relevant in energy markets, which regularly experience significant policy interventions and infrastructure evolution. While meta-learning approaches have demonstrated promise for adapting to changing environments [13], these techniques remain in the nascent stages of development for financial applications. Robust evaluation methodologies that specifically assess RL algorithm performance across regime changes could provide valuable insights for practitioners implementing these systems in dynamic energy markets.

Computational requirements present practical implementation barriers, particularly for smaller market participants. Contemporary deep reinforcement learning methods typically demand substantial computational resources during both training and, in some cases, inference phases. This resource intensity creates asymmetric advantages for larger institutions with greater technological capabilities. Although algorithmic improvements and optimization techniques have somewhat mitigated these requirements, computational efficiency remains a significant concern [154]. The development of more efficient algorithmic formulations and hardware-specific optimizations could democratize access to advanced RL techniques across a broader spectrum of energy market participants. Additionally, federated learning approaches may offer pathways to collaborative model development while maintaining data privacy, potentially addressing both computational and data scarcity challenges simultaneously.

Finally, the field suffers from benchmarking difficulties that impede systematic evaluation and comparison of different methodologies. The absence of standardized benchmarks and evaluation protocols makes objective assessment of competing RL approaches, complicating both research progress and practical implementation decisions. The development of common benchmarks specifically designed for energy finance applications, incorporating realistic market constraints and evaluation metrics aligned with practitioner objectives, represents an important direction for future research [155]. These benchmarks should ideally capture the multifaceted nature of energy markets, including physical constraints, regulatory frameworks, and the multiple time scales characteristic of energy price dynamics discussed in earlier sections.

7.2. Promising Research Directions

The intersection of reinforcement learning and energy finance presents fertile ground for innovative research. Below, we identify key research directions organized by methodological advancements, application domains, and comparative studies that warrant further exploration in this rapidly evolving field.

7.2.1. Methodological Advancements for Energy Finance

Explainable RL for Energy Investment Decisions: Developing interpretable reinforcement learning models represents a critical research priority. For smart grid investments, transparency in decision processes, in particular, is essential for regulatory approval and stakeholder acceptance. Future research should focus on methods that balance performance with comprehensibility, perhaps through attention mechanisms that highlight which factors most influence investment timing and operational decisions in energy assets [79].

Multi-agent Reinforcement Learning Frameworks: As energy systems become increasingly decentralized, understanding strategic interactions becomes essential. Multi-agent reinforcement learning presents a compelling direction, particularly for optimizing distributed energy resources across smart grid ecosystems [156]. Research in this area could address how decentralized decision-making impacts financial returns across different stakeholders and potentially reveal emergent properties that centralized valuation methods might miss.

Transfer Learning and Domain Adaptation: Energy markets exhibit significant regional variations in regulations, market structures, and resource availability. Research on transferring knowledge from data-rich to data-sparse markets could enable more efficient application of RL techniques. This is particularly relevant for emerging energy technologies where historical data may be limited, but analogous applications exist in other domains.

7.2.2. Enhanced Valuation of Energy Assets and Flexibility

Valuation of Operational Flexibility: Traditional real options valuation often struggles to capture the complex interdependencies between multiple flexibility options in smart grid technologies. Reinforcement learning algorithms, with their ability to learn optimal policies through interaction with dynamic environments, offer promising mechanisms to value these interconnected flexibilities more accurately. Such research could bridge the gap between theoretical option value and practical implementation challenges in smart grid investments.

Long-duration Energy Storage Valuation: Deep reinforcement learning techniques show promise for addressing the complex valuation of long-duration energy storage assets within smart grid systems. These assets present particular challenges in balancing short-term operational decisions with long-term strategic value creation. Research applying deep reinforcement learning methods to capture these temporal dependencies could overcome limitations of traditional valuation methods that often oversimplify the strategic dimension of energy storage.

Renewable Integration Flexibility: Methods for accurately valuing flexibility in high-renewable energy systems remain underdeveloped. Research applying distributional reinforcement learning to capture the full range of outcomes under renewable uncertainty could provide more accurate valuations of flexible assets like batteries, demand response, and dispatchable generation. This research is particularly relevant as energy systems worldwide transition toward higher renewable penetration.

7.2.3. Uncertainty Modeling and Risk Assessment

Regulatory Uncertainty: Energy markets face continuous regulatory evolution, creating significant uncertainty for investors. Research developing reinforcement learning algorithms that explicitly model and adapt to regulatory changes could help energy investors maintain option value in unstable policy environments. This is particularly relevant for smart grid technologies, which often rely on evolving market structures and incentive mechanisms.

Climate Risk Integration: Future research should explore integrating climate risk factors into reinforcement learning frameworks for energy investments. This includes modeling physical risks (extreme weather impacts on infrastructure) and transition risks (policy and technology shifts) within RL environments. Models that capture these complex, interacting uncertainties could significantly improve long-term energy investment decisions under climate change scenarios [56].

Cross-market Risk Dependencies: Energy markets exhibit strong interdependencies with other commodities and financial markets. Developing reinforcement learning approaches that capture these cross-market dynamics represents a promising research direction with significant implications for comprehensive risk management in energy investment portfolios.

7.2.4. Comparative Analysis of Decision-Making Frameworks

Comparative analysis of decision-making frameworks represents a critical research opportunity. By systematically evaluating reinforcement learning, stochastic optimization, and least-worst-regret approaches [36] for energy investment decisions, researchers can establish clearer guidelines for when each methodology excels. Smart grid technologies often involve multiple uncertainties across varying time horizons, making the selection of appropriate decision frameworks crucial. This comparative research could yield practical decision roadmaps for energy finance practitioners facing complex investment choices.

Each methodology offers distinct advantages in handling uncertainty, computational requirements, and interpretability. By advancing understanding of their relative strengths in the energy finance context, researchers can develop more robust decision-support tools for smart grid investment and operation. Standardized benchmarks and case studies would further enhance the practical utility of such comparative analyses.

The advancement of open-source implementations, standardized problem formulations, and common datasets would accelerate progress across these research directions. Addressing these complex challenges at the intersection of reinforcement learning and energy finance will require interdisciplinary collaboration between financial engineering, computer science, energy systems, and policy research communities.

7.2.5. Sustainable Communities and Energy Equity

The application of reinforcement learning to energy finance extends beyond technical optimization and economic efficiency to address pressing social challenges. There is growing recognition that energy systems must support sustainable communities by combating energy poverty [54,157–159] and ensuring equitable distribution of benefits [160]. This section examines how reinforcement learning methodologies can be leveraged to promote pragmatic solutions that balance technical, economic, and social dimensions of energy transitions [8].

Social Innovation in Community Energy Transitions: Energy transitions are increasingly viewed through the lens of social innovation and community participation rather than purely technological change. Alaize Dall–Orsoletta et al. (2022) [161] conducted a systematic review of how social innovations promote community-driven energy transitions, identifying major themes, including citizen participation, institutional support, and the role of cooperatives in renewable energy deployment. The authors highlighted practical examples of successful transitions facilitated through collective action, providing a foundation for understanding how reinforcement learning frameworks could be designed to support community-based decision processes [162,163].

Building on this foundation, Pillan et al. (2023) [164] proposed conceptual frameworks to help communities better understand and contribute to sustainable energy transitions, emphasizing the role of education and participatory design in fostering local energy initiatives. Their work suggests that reinforcement learning models could be developed to incorporate community preferences and knowledge, creating more robust and socially accepted energy optimization strategies. Similarly, Neij et al. (2025) [165] reviewed experiences of energy communities across Europe, identifying key success factors, including strong local engagement, supportive regulations, and diversified revenue streams—factors that could be parameterized within RL frameworks to better reflect community priorities.

Energy Poverty Assessment and Alleviation: Energy poverty—inadequate access to affordable, reliable energy services—remains a critical challenge globally. Recent advances in machine-learning applications for energy poverty have opened new avenues for addressing this issue. López–Vargas et al. (2022) [15] examined how AI methods are being applied to energy poverty contexts, noting that relatively few studies have explored AI solutions specifically for energy poverty and suggesting future directions for AI-based detection, prediction, and policy design.

More concretely, Gawusu et al. (2024) [53] used spatial data and predictive modeling to identify energy poverty hotspots and inform targeted policy measures, demonstrating how spatial analytical techniques could enhance the precision of interventions. Abbas et al. (2022) [166] employed machine learning to measure and predict extreme forms of energy poverty based on multiple socio-economic factors, identifying critical determinants such as income, education, and geographic variables. These advancements in prediction and classification provide foundations that reinforcement learning frameworks could build upon to optimize dynamic resource allocation for energy poverty alleviation programs [167].

Che et al. (2021) [37] proposed an integrated evaluation framework for global energy poverty, stressing availability and affordability of energy as primary obstacles to alleviation. Their emphasis on regional disparities as barriers for global policy coordination highlights the need for adaptive solutions that reinforcement learning is well-positioned to provide. Complementing this work, Lippert and Sareen (2023) [12] explored how transitioning to low-carbon energy infrastructures can help reduce energy poverty, using big data analytics to identify systemic changes needed in infrastructure and agency behavior. Their finding that mere technological fixes are insufficient without systemic policy shifts aligns with the need for reinforcement learning approaches that can navigate both technical and institutional complexities.

Democratized Energy Markets and Community Participation: Reinforcement learning shows particular promise in enabling more inclusive participation in energy markets. Piras et al. (2024) [168] presented an open-source AI/ML-based tool designed to facilitate the automated creation of renewable energy communities, demonstrating that AI can directly enhance social coordination in energy system development. By integrating advanced energy modeling and citizen participation frameworks, such tools support a decentralized and democratic energy transition—an application area where reinforcement learning's sequential decision-making capabilities could prove particularly valuable.

The concept of a "just energy transition" has gained prominence in policy discussions, with del Guayo and Cuesta (2022) [42] critically examining this concept within European policy frameworks. Their analysis of the Just Transition Fund highlighted its emphasis on supporting coal-dependent regions while critiquing its narrow scope. The authors argued that energy justice challenges extend beyond coal closures to issues like lithium mining, rural environmental impacts, and growing energy poverty—complex trade-offs that reinforcement learning methodologies could help navigate by incorporating multiple objectives and constraints.

Equity-Aware Reinforcement Learning Frameworks: A critical challenge in applying RL to energy finance is ensuring that optimization objectives incorporate equity considerations. Chen et al. (2024) [36] addressed this challenge directly, focusing on how bias in ML models can exacerbate existing inequities in energy systems. They proposed technical and governance frameworks to mitigate biases and promote fairness across energy distribution networks, providing a crucial blueprint for ensuring AI-driven energy systems uphold principles of energy justice. These insights could inform the development of fairness-aware reward functions in reinforcement learning models for energy systems.

Kaur et al. (2024) [169] explored how AI, particularly machine learning and data analytics, can improve the sustainability and resilience of energy systems while emphasizing stakeholder engagement, such as involving local communities in solar energy initiatives. Their argument that AI must be socially inclusive to fully realize sustainable energy transitions suggests the need for reinforcement learning frameworks that explicitly incorporate distributional impacts and fairness constraints, similar to how risk constraints are integrated into financial optimization models.

Ethical Considerations in AI-Driven Energy Systems: The ethical dimensions of AI deployment in energy systems have received increasing attention. Chauhan et al. (2024) [32] reflected on ethical concerns surrounding AI and ML deployment in clean energy systems, particularly regarding fairness and social impact. Their discussion of the tension between rapid technological advancement and ensuring equitable outcomes highlights the need for careful design of reinforcement learning objectives and constraints in energy applications. Similarly, Jain and Mitra (2025) [82] advocated for human-centered AI systems that prioritize marginalized groups when supporting sustainable development goals, including energy access.

Nalli et al. (2025) [170] proposed frameworks for energy equity through intelligent system design, highlighting AI's role in enabling inclusive energy transitions at the community level. Their work on optimizing energy systems while ensuring equitable access to affordable power provides conceptual groundwork for reinforcement learning applications that balance efficiency with equity considerations.

Research Directions and Implementation Challenges: Despite growing interest in integrating social considerations into energy system optimization, implementing equity-aware reinforcement learning faces several challenges: defining appropriate fairness metrics, obtaining representative data across diverse communities, and balancing potentially competing objectives of efficiency and equity.

Alturif et al. (2024) [171] discussed using AI tools for poverty prediction and strategic alleviation, reviewing various machine-learning models and their policy applications. While focused broadly on poverty, their work highlights the transformative potential of AI in identifying at-risk populations—a capability that could be enhanced through reinforcement learning's ability to optimize interventions across time.

Future research should focus on developing reinforcement learning frameworks that explicitly incorporate community values and preferences, equity metrics, and distributional impacts. Multi-objective reinforcement learning approaches that simultaneously optimize for technical efficiency, economic viability, and social equity represent a particularly promising direction. As energy systems continue to evolve toward greater decentralization and complexity, reinforcement learning approaches that can navigate these multidimensional trade-offs will become increasingly valuable for creating truly sustainable energy futures.

7.3. Policy Recommendations

Based on the findings of this review, several policy recommendations emerge for regulatory bodies, market operators, and industry participants seeking to harness the potential of reinforcement learning in energy finance.

Regulatory Framework for Algorithmic Trading: As reinforcement learning adoption increases in energy markets, regulatory bodies should develop frameworks specifically addressing algorithmic trading that balance innovation with market stability. These frameworks should include disclosure requirements for trading entities using RL systems, stress testing protocols for extreme market scenarios, and circuit breaker mechanisms designed to prevent cascading algorithmic reactions during market stress. Importantly, regulations should be technology-neutral, focusing on outcomes and risk profiles rather than specific algorithmic approaches.

Market Design Considerations: Market operators should evaluate how current market rules and structures might be impacted by widespread RL adoption. Auction mechanisms, price formation processes, and market clearing rules may require reconsideration to ensure they remain robust in environments with significant algorithmic participation. In particular, operators should consider how information disclosure policies influence RL-based strategies and whether current market structures provide sufficient incentives for beneficial flexibility provision while discouraging manipulative behavior.

Transparency and Interpretability Standards: Industry associations and regulators should collaborate to develop standards for transparency and interpretability of RL systems in energy markets. These standards could include requirements for documenting model limitations, reporting backtest methodologies, and providing simplified explanations of decision processes for significant trading actions. Such standards would enhance stakeholder trust while providing a framework for responsible innovation.

Public Research Infrastructure: Government agencies and academic institutions should invest in creating public research infrastructure for energy finance RL applications. This infrastructure could include anonymized market data repositories, standardized simulation environments reflecting realistic market conditions, and benchmark problem sets that enable objective comparison of different approaches. Such resources would democratize research opportunities, accelerate methodological advances, and support more robust model evaluation.

Workforce Development: Educational institutions and industry stakeholders should prioritize developing interdisciplinary training programs that combine energy systems knowledge, financial engineering, and machine-learning expertise. The complexity of RL applications in energy finance requires professionals who understand both the technical nuances of advanced algorithms and the distinctive characteristics of energy markets. Targeted educational initiatives would help address the talent gap in this emerging field.

7.4. Synthesis and Outlook

While significant work remains to address the limitations outlined in this review, the promising results to date suggest that RL will increasingly transform how we value, trade, and manage energy assets and contracts in the coming years. The ongoing energy transition—characterized by increasing renewable penetration, storage deployment, and market decentralization—will likely accelerate this transformation by creating greater complexity and optionality that traditional approaches struggle to capture. By combining the adaptive learning capabilities of reinforcement learning with domain-specific knowledge of energy systems, researchers and practitioners can develop more sophisticated tools for navigating the evolving energy finance landscape.

8. Conclusions

This review has examined how reinforcement learning can be applied to energy finance. We have highlighted applications ranging from price forecasting and trading strategies to derivatives valuation and option value assessment in power systems.

Energy markets have unique features that make them challenging to model. These markets show extreme price swings, seasonal patterns, and complex regulations. Energy assets like power plants and storage facilities also have physical limitations that create special types of options. Traditional financial models often struggle with these complexities.

Reinforcement learning offers several important advantages for addressing these challenges. First, RL can learn directly from data without needing simplified assumptions about price behavior. Second, RL handles non-linear relationships well, which are common in energy markets. Third, RL adapts to changing market conditions, a crucial feature in evolving energy systems. Fourth, RL naturally incorporates complex constraints that are difficult to include in traditional models.

The ability of RL to capture option value is particularly important. Smart grid technologies, energy storage systems, and demand response, all create significant option value—the net economic benefit of having flexibility under uncertainty. This option value represents the difference in expected system costs between the cases with and without the deployment of the flexible smart grid technology. RL methods are well-suited to quantify this value because they can learn optimal decision policies across many possible future scenarios and capture the sequential nature of energy system operations. Current approaches to quantifying option value have relied primarily on stochastic optimization methods, which, while effective, often become computationally intractable for high-dimensional problems with many uncertainty sources and struggle to capture complex, non-linear relationships and sequential decision processes. In this context, RL provides several advantages over stochastic optimization for option valuation.

Despite these advantages, several challenges remain in applying RL to energy finance. Interpretability concerns make it difficult for decision-makers to trust complex RL models. Data limitations can be problematic since RL algorithms typically need large training datasets. Generalization across different market conditions remains difficult. Computational requirements can be extensive, especially for complex energy systems. Finally, the lack of standardized benchmarks makes it hard to compare different approaches objectively.

Future research directions include developing more explainable RL methods for energy applications, creating robust approaches that perform well under extreme market conditions, exploring multi-agent frameworks that capture strategic interactions among market participants, sector coupling (Goyal et al., 2024) [70], and integrating RL with traditional models. The integration of RL with traditional stochastic optimization methods represents a particularly promising direction as well. Hybrid approaches could combine stochastic optimization with the RL's ability to discover complex non-linear policies. For example, stochastic optimization could define scenario structures and boundary conditions, while RL determines detailed operational policies within these frameworks.

In conclusion, reinforcement learning represents a powerful approach for addressing the unique challenges of energy finance, particularly in capturing the option value created by flexible technologies and operating strategies [172]. While significant work remains to make these methods fully practical for industry applications, the promising results to date suggest that RL will increasingly transform how we value, trade, and manage energy assets and contracts in the coming years.

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Directions of the Energy Transition in District Heating: Case Study of Poland

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Abstract: In light of the ongoing discussion concerning the energy transition of the heating sector, primarily focused on district heating and shaped by heating corporations towards an incremental transformation, an alternative direction for the energy transition of the heating sector towards electroheating—a breakthrough transformation—is presented in this paper, along with a justification of its rationale. Arguments "for" and "against" both transformation paths are provided. Analyses of the costs of transforming district heating systems along both trajectories are conducted. The opportunities of a breakthrough transformation are characterized. An alternative approach to the energy transformation of district heating systems will provoke resistance and opposition from representatives of institutions operating within the current model. Transforming the existing heating model without changing its structure will burden society with high transformation costs through demands for government guarantees to cover these expenses. The analysis presented in this paper shows that these costs can be significantly reduced if the approach to the generation and distribution of district heat is changed.

Keywords: district heating; electroheating; energy transformation; incremental and breakthrough transformation; electrification

1. Introduction

The European Commission has adopted the "European Green Deal" [1], with detailed implementation measures outlined in the "Fit for 55" package [2]. These initiatives form part of the European Union's energy policy, which emphasizes energy security, sustainability, and the integration of energy markets across member states.

Regardless of ongoing political and ideological debates, EU member states are preparing for current and forthcoming changes in legislation.

Buildings account for approximately 40% of the EU's total energy demand [3], with the majority of this energy required for heating and domestic hot water. In Poland, legacy district heating systems are predominantly based on coal-fired boiler plants, which are currently being modernized, most commonly through the replacement of coal boilers with gas-fired units [4]. However, the question arises whether such an energy transition will be sufficient under the constraints of the Fit for 55 package. If carbon dioxide emission limits are upheld, it may become necessary to move toward the concept of electrical monism [5].

Electrical monism is a theoretical concept in which all energy demands (including heating and transportation) are met exclusively through electricity, while minimizing overall electricity consumption [5].

Under such a scenario, building heating systems would be based on electric energy. This assumption forms the starting point for the analysis presented in this article. The authors do not question whether the implementation of electrical monism is technically or economically feasible, nor do they attempt to estimate whether individual member states are capable of producing or transmitting the required amounts of electric energy.

Instead, the article examines issues related to the cost of transitioning from conventional district heating to electric-based heating systems—referred to as electroheating. This term is used here to describe district heating systems in which electricity serves as the sole source of thermal energy.

The study considers a scenario in which a municipality is required to modernize its district heating network and where, due to regulatory constraints (e.g., environmental legislation), electricity must be used as the heat source. The simplest approach appears to be a direct replacement of coal-fired boilers with electric boilers—a process referred to in the article as incremental transformation. However, is this the optimal solution [4,6,7]?

The authors explore an alternative approach termed breakthrough transformation, in which heat is generated directly at the point of consumption. Although this approach appears rational, most of the current public discourse and media suggest a focus on incremental transformation.

The authors therefore performed calculations, based on available data, to compare the costs associated with both transformation models. These calculations are intended to provide a basis for further discussion regarding the pathways and prospects for district heating transformation in Poland.

The motivation for this study stems from published estimates indicating high costs associated with the heating sector's transition [8,9]. The research aimed to address the following key questions:

- Does the energy transformation of district heating into electroheating need to be as costly as assessments of the state of district heating in Poland indicate?
- Do heating bills from electric energy need to be "nightmare bills", as suggested in the media?
- Does the transformation of district heating in Poland need to burden the state budget?

Does the current generation, which is shaping an expensive "incremental" energy transformation of district heating, have the moral right to pass these costs on to future generations, especially when the dynamic technological development of renewable energy sources, storage technologies, and heat sources allows for a cheaper "breakthrough transformation"?

The chosen path of energy transformation will have far-reaching consequences for future generations, both financially and technologically [4,10]. These factors will determine whether the transformation will be either a breakthrough or incremental transformation [5,11,12]. An incremental transformation would amount to nothing more than an expensive cosmetic modification of existing solutions.

Public awareness among both heat producers and consumers regarding the transformation of district heating to electroheating differs depending on the type of heat source—whether in individual households, network-based district heating, or industrial/technological heating systems, which may be networked or off-grid.

In individual households, electroheating is a natural consequence of the rise of electroprosumerism [5,11,12]: a personal photovoltaic micro-power plant, a heat pump, an electric energy storage system, a thermal energy storage unit, and an energy management controller together justify the shift toward electric heating. The goal of the transformation in this sector should be the maximization of self-consumption.

Network-based district heating, on the other hand, constitutes a specific sectoral market of electroprosumerism and is closely tied to the adopted pathway of energy transformation [4,10]. An incremental transformation [5,11,12] is characterized by the preservation of the existing central district heating distribution infrastructure. It focuses solely on replacing current fossil fuel-based heat sources with renewable energy sources, without fundamentally rethinking the underlying system architecture.

A prosumer (from producer + consumer) is an energy user who both consumes and produces energy, typically from renewable sources. Prosumers are usually individual households, businesses, or housing cooperatives that generate electricity—most often via solar panels, wind turbines, or other renewable technologies—and use it for their own needs. Any surplus energy can often be fed back into the grid. An electroprosumer is a more specific type of prosumer who not only produces and consumes electricity but also actively uses electricity for technologies that traditionally rely on other energy sources, especially for heating (e.g., replacing gas or coal with heat pumps, electric boilers, or induction heaters). Electroprosumers thus electrify their energy demand while producing their own electricity, often from renewables [5,12].

A breakthrough transformation [5,11,12] is based on the distribution of energy via the electrical grid and its conversion into heat at the point of use.

What logic of transformation should be adopted under the assumption that, by the year 2050, we will have achieved electric monism and a zero-emissions economy?

The logic of technological transformation can be better understood through historical paradigms that illustrate how innovation dynamics—especially the interplay between technological potential, incumbent resistance, and market forces—shape system evolution. Table 1 presents three paradigms relevant to understanding today's energy transitions.

Table 1. Historical paradigms of technological transformation.

Pattern	Transformation Description	Key Features	Lessons for Energy Transition
1. Factory and Workstation Drives	Steam engines and belt-driven torque systems gave way to electric motors. Eventually, individual electric drives replaced centralized mechanical distribution [13].	Gradual evolution; legacy resistance; eventual obsolescence of transmission belts.	Decentralization of energy use; technology shifts may initially preserve legacy formats before transforming system-wide logic.
2. Telecommunications	Wired telephony was rapidly overtaken by mobile wireless systems [14].	Rapid transformation; user-driven demand; market outpaces regulation.	Innovation aligned with user behavior can accelerate systemic change. Policy and infrastructure must adapt quickly.
3. Transport and Electromobility	Fossil-fuel lobbies delayed electric vehicle development despite superior electric motor performance [15].	Negative example of innovation resistance; historical and modern suppression of alternatives.	Market interests can hinder beneficial innovation; policy intervention may be needed to overcome entrenched resistance.

Is the current situation in Poland not analogous, particularly regarding the development of prosumer-based energy systems? Lobbying efforts in favor of centralized corporate energy solutions are strikingly visible and, unfortunately, act as a brake on innovation in the renewable energy sector.

Following the logic that governed the transformation of industrial drive systems and telecommunications, one can conclude that if electricity is to become the primary energy carrier, it would, perhaps, be rational to deliver energy in the form of electricity directly to the end user and convert it into heat at the point of use.

To embrace this logic by the market, electricity should become a true market commodity, and the following conditions should be met:

Condition 1: Minimization of electricity distribution costs. It is beneficial when the electricity used in electroheating originates from local renewable energy sources (RES) and electroprosumer systems—in other words, from a decentralized power grid. Transmitting electricity over long distances through the National Power System (KSE), for example, from the north to the south of the country, only to convert it into heat, is expensive. The transmission and infrastructure investment costs associated with such long-distance transport significantly increase the fixed costs of heat derived from electricity. Decentralized RES sources installed by investors in local government units or industrial zones can form local "direct networks" or "green medium/low-voltage electroprosumer networks," along with electroprosumer settlement platforms. These structures can relieve the burden on national transmission and distribution networks (KSE), thereby reducing the need for costly grid investments—investments for which the traditional energy and district heating sectors currently seek public funding;

Condition 2: Exergetic optimization of buildings [3,11]. Electroheating must be integrated with the minimization of thermal losses in buildings and should be introduced only after all feasible energy efficiency measures have been exhausted. Only then does its implementation make thermodynamic and economic sense. The authors did not consider the thermal modernization of buildings in the calculations because this will be carried out regardless of the adopted path of energy transformation, in accordance with [3]. Regardless of whether the transformation is incremental or breakthrough, it will be difficult without the exergetic optimization of buildings. Electroprosumerism inherently promotes energy-conscious thinking, which translates into optimal energy use management—including in the heating sector. It is also crucial to store heat when RES generation exceeds immediate demand;

Condition 3: Minimization of heat distribution costs (fixed costs). The reduction in heat distribution costs has the greatest impact on the final price of heat. Below is a summary of factors influencing the cost of distribution in the two models discussed:

A. **Incremental Transformation**
   1. **Heat loss costs in distribution networks—**associated with the transmission of high-parameter heat (high temperature and pressure);
   2. **Heat loss costs in heat exchange stations—**due to the lack of regulation, incorrect controller settings, or poor maintenance. Heat distributors are typically not incentivized to optimize heat consumption, but rather to maximize heat sales;
   3. **Costs associated with failures in district heating networks**;
   4. **Maintenance costs of the heat distribution network**.

B. **Breakthrough Transformation**
   1. **No heat distribution losses—**heat is generated directly at the point of use from electricity;
   2. **Automatic optimal regulation** of space heating and domestic hot water consumption through the control system of the electric heat source;
   3. **Electroheating node is owned by the building owner—**creating an incentive for energy conservation;
   4. **No failures in district heating networks—**the centralized heat distribution system is eliminated;
   5. **Optimized digital energy management** from a centralized dispatch point (e.g., a housing cooperative's management office or electroheating utility operator);

6. **Lower maintenance costs for district heating networks or centralized heat exchange stations**—the infrastructure is decentralized and simplified.

The logic behind incremental approaches to heating sector transformation must be seriously reconsidered. District heating in Poland is developed on a scale unmatched globally, except within the former Eastern Bloc [4]. The Warsaw district heating system is the third largest in the world, following those in Moscow and St. Petersburg. While system-based heating was technically and economically justified in the past era, it is now a legacy solution that requires a thorough analysis of whether its continued operation—and especially its further development—makes sense in light of the high modernization costs [8,9].

Even though it is a declining solution, this decline will unfold gradually and should follow economically rational principles. The transformation of the energy sector, particularly with respect to heating, should be a breakthrough in nature. It also presents an opportunity for municipal heating companies (PEC) willing to embrace disruptive transformation in the heating sector.

1.1. Breakthrough Transformation

A breakthrough transformation of network-based district heating into electroheating (i.e., electroprosumer-based heating) will lead to the gradual and partial phase-out of the central heating network, as it becomes technically obsolete. In areas where it is technically and economically justified, the district heating infrastructure will be replaced by the electrical grid and decentralized electric heat sources such as heat pumps and induction boilers. As the load on the central heating network decreases, the temperature of the medium in this network can be reduced, which will reduce heat losses. However, this requires a reduction in the energy transmitted through this network, because current networks were designed for high parameters. This would also require replacing equipment on the recipient side.

Upon disconnecting a building's heat exchange station from the central district heating network, the heat supply is taken over by on-site heat pumps and induction boilers, supported by local (distributed) heat storage systems, as shown on Figure 1, where red crosses symbolize disconnected part of network.

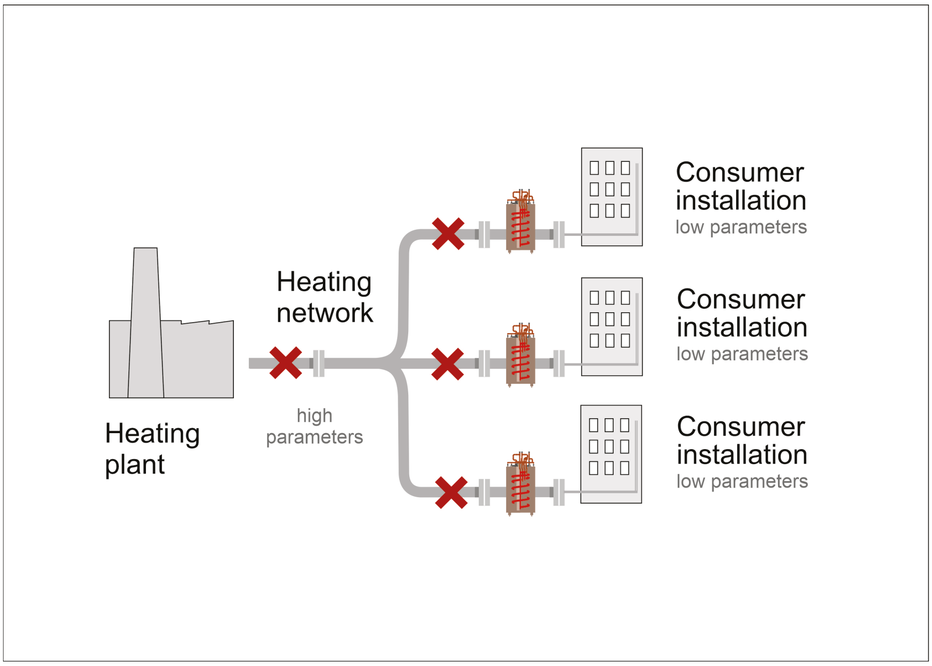

Figure 1. Diagram of the heating network at the point of disconnection of facilities from the network and connection of an electric heat source.

Local heat pumps and induction boilers can be powered by a combination of building-integrated photovoltaic systems, and, optionally, wind power systems, electricity storage units, bioelectric power stations, hydrogen or gas-fueled cogeneration units (with temporary use of oil-fired systems if necessary), and hydrogen electrolyzers. These resources can be managed by a centralized energy management system. In practice, energy sources will depend on local conditions. Generally, it is optimal when energy sources are local, which reduces the costs of transmission and expansion of the energy grid

An enterprise operating under this model, referred to as Electro-PEC, can function as an energy island (self-sufficient microgrid) or be connected to the local KSE (National Power System) distributor, depending on its level of energy self-sufficiency. The management center consists of a computer system and an IT specialist performing monitoring, service coordination, and billing functions. An example of the organizational structure of Electro-PEC is presented on Figure 2.

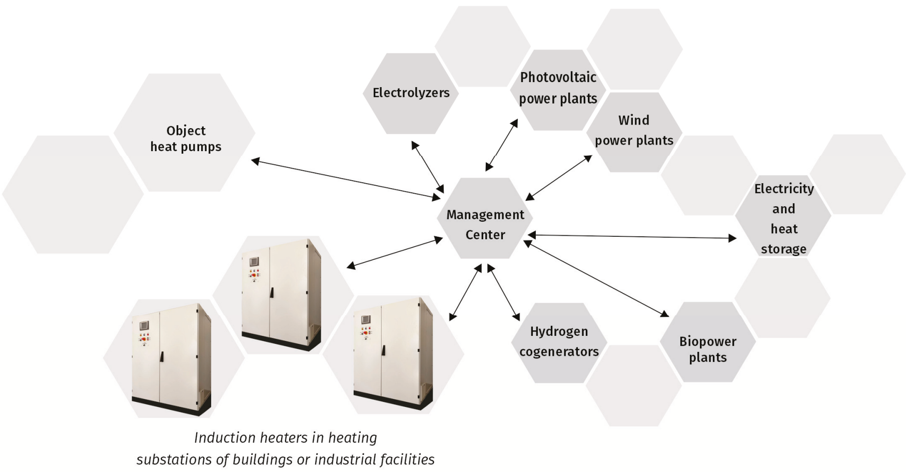

Figure 2. An example of the organizational structure of a modern heating company, Electro-PEC.

The task of Electro-PEC can be taken over by a housing cooperative, enabling it to become energy-independent. The feasibility of this transformation depends on the cooperative's investment capacity in energy transformation, particularly in heating and renewable energy systems (RES). The technical possibilities are already available, with heat pumps and induction boilers (Figure 3) offering the potential for optimal heat management.

(**a**) (**b**)

Figure 3. 100 kW induction boiler: (**a**) induction boiler in the heating center of Energo-Complex company; and (**b**) general view of the induction boiler.

1.2. Breakthrough Transformation—Induction Heating Boiler in a Multi-Family Building

The induction boiler is an alternative heat source in the transformation of district heating towards electroheating. The induction boiler is proposed as an alternative heat source in the transformation of conventional district heating systems to electroheating, serving as an alternative to heat pumps. In the context of multi-family housing, induction boilers with capacities exceeding 100 kW, installed in thermal substations, may be applicable. These boilers feature continuous control of heating power and their integrated control systems enable optimal operation of the substation. The operational characteristics and advantages of induction boilers, particularly in comparison to resistive electric boilers, are described in the literature [16,17].

Induction boilers are particularly relevant in cases where the use of heat pumps is technically or economically unjustified. Such circumstances include:

- Large-area buildings not connected to a district heating system, such as schools, public offices, hotels, commercial facilities, places of worship, or buildings occupied by SMEs. Here, the induction boiler may function either as the primary or supplementary heat source;
- Large-area buildings in city centers, often renovated or historic, where the repair of district heating network failures is economically unfeasible;
- Small- to medium-scale thermal energy storage systems (e.g., facility-based, cooperative-based, or energy community-owned), supplied by RES, for storing surplus renewable energy in the form of heat;
- Large-scale heat storage systems, charged with heat generated by heat pumps, where the induction boiler is used to increase the temperature of stored heat;
- Waste heat recovery systems, such as from wastewater, where induction boilers can be used to boost the temperature of heat recovered by heat pumps;
- Dynamic air-based heating systems for industrial halls, where rapid and responsive heating is required;
- Emergency electroheating systems, acting as backup heat sources in cases of the failure of primary systems;
- Temperature stabilization in industrial processes, such as in the production of food items, bituminous materials, resins, protective films, etc.

The cost of electric heating using induction boilers is approximately twice as high as heating with heat pumps. Therefore, the price of electricity is a critical factor. Of particular importance is the local generation of renewable electricity through distributed energy systems and prosumer-based production, which are not burdened by distribution costs. Prosumer electricity should be transmitted via local "green networks" within economic zones or municipal areas (LGU). An additional factor in optimizing the cost of heat is the presence of a local thermal energy storage system.

2. Methodology

To estimate the costs of transitioning from conventional district heating to electric-based heating systems (electroheating), two analyses were conducted, as presented on flowchart on Figure 4.

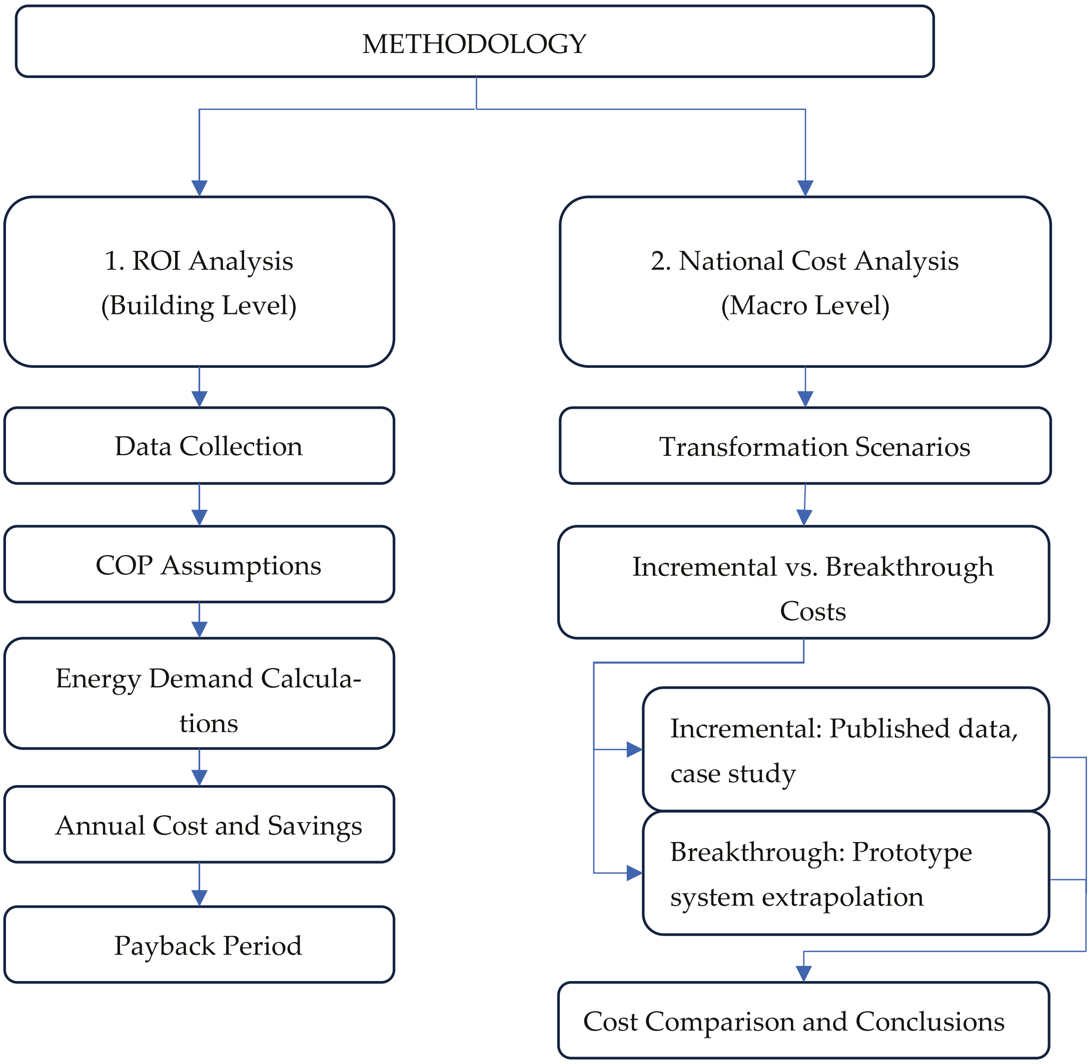

Figure 4. Flowchart of the methodology.

2.1. Analysis of Investment Costs and Return on Investment for Individual Multi-Family Buildings

This analysis focused on estimating investment costs, subsequent operational costs, and the return on investment (ROI) for an individual multi-family residential building. The estimation was based on data available to the authors from a case study described in a publication [18]. As some of the building data were based on design assumptions, the authors conducted additional analysis using empirical heat demand data from a similar building. These data were obtained directly from the property owner [16] and assumed a higher heating demand.

For the analyzed building, data were collected on the residential floor area, heat demand, pre-retrofit heating costs, and the investment cost associated with replacing the heat source.

Since heat pumps were implemented in these buildings, a coefficient of performance (COP) was assumed. This issue is non-trivial, as the literature provides a broad range of COP values [19–23], and manufacturer-reported values often serve marketing purposes. In Poland, outdoor temperatures during the heating season frequently hover around 0 °C, which is unfavorable for heat pump performance. High humidity leads to evaporator icing and necessitates periodic defrosting, thereby reducing efficiency and lowering the COP.

For the analysis, two COP values were assumed:

- COP = 3, based on standard values for air-source heat pumps;
- COP = 2, which accounts for reduced performance under high humidity and low ambient temperatures.

At the time of investment decision-making, the actual COP of a given heat pump is unknown. Therefore, when calculating system capacity and ROI, it is safer to consider a wider range of COP values.

Based on the building's heat demand and the assumed COP values, the corresponding electricity demand was calculated. Subsequently, a unit electricity price of EUR 0.35/kWh (1.5 PLN/kWh) was assumed, based on current market prices, and the annual cost of heating was determined. Comparing the annual heating cost before and after modernization allowed for a calculation of the annual savings. The investment payback period was then estimated by dividing the investment cost by the annual savings.

The analysis was based on simplified assumptions. Inflation, financing costs, potential changes in electricity prices, and the self-generation of electricity by prosumers were not considered. Given the numerous uncertain and politically influenced factors, the purpose of the analysis was to obtain a rough estimate of the ROI and to determine the order of magnitude of the involved values.

2.2. Analysis of Incremental vs. Breakthrough Transformation of Polish District Heating

The analysis compared the costs of two district heating transformation pathways in Poland: incremental and breakthrough.

2.2.1. Incremental Transformation Cost Estimation

For the incremental approach, published data were used:

- A 2020 report by the Polish District Heating Chamber of Commerce estimated the cost of transformation between 2020–2030 at EUR 12–24 billion;
- According to a source in the literature [8], the total investment requirement is EUR 92 billion by 2030, and EUR 235 billion by 2050;
- Another source [9] estimated the cost of transforming the centralized heating sector at EUR 70–100 billion by 2050.

Based on data from Poland's Central Statistical Office (GUS), 52.2% of the residential floor area in multi-family buildings was heated by district heating. Given a total of 438.8 million square meters of residential floor area in multi-family buildings, centralized district heating currently serves 229.05 million m^2.

Using published estimates of incremental transformation costs and the serviced area, the cost per square meter of residential floor area was calculated.

An alternative estimate was derived from a case study of the "heating plant of the future" in Lidzbark Warmiński (northeastern Poland) [24], where the total investment amounted to EUR 12 million. The plant is expected to serve 3000 residents of the Astronautów housing estate. Assuming four residents per 50 m^2 apartment (12.5 m^2 per person), the plant is expected to heat approximately 37,500 m^2.

2.2.2. Breakthrough Transformation Cost Estimation

For the breakthrough approach, the cost was estimated based on the implementation of an inductive boiler system with a thermal storage unit. This estimate was based on a prototype system developed by the authors. Market analysis indicates that the cost of implementing heat pumps of an equivalent capacity would be comparable. The investment cost was converted to a per-square-meter basis and the total cost of the transformation for the entire 229.05 million m^2 of residential area currently serviced by district heating was estimated.

Finally, the estimated costs of the incremental and breakthrough transformation approaches were compared.

3. Results

3.1. Analysis of Heat Pump Application in a Multi-Family Building—Implemented Solutions

The analysis concerns a case study of a multi-family building that was disconnected from the district heating system and where heat pumps were implemented for heating [18]. This is an example of a breakthrough transformation in district heating. Based on this example, the authors address key issues related to electroheating. The considered building is located in Urszulin, Lubusz Voivodeship, in the western part of Poland [18] and has the following properties (Table 2):

Table 2. Analysed building properties.

General Building Data			
Residential Area	Residential Area	1600	m^2
Floors	Number of Floors	5	
Units	Number of Apartments	32	
Average Unit Area	Average Area per Apartment	50	m^2
Occupants	Number of Occupants	80	People
Heating Demand and Performance			
Calculated Heat Demand	Heat Demand at −20 °C	60	kW
Verified Heat Demand	Verified Demand at −15 °C	40	kW
Domestic Hot Water (DHW)			
Average Consumption	Daily Hot Water Consumption	2000	L/day
Peak Consumption	Peak Hourly Consumption	800	L/h
Buffer Tank	Buffer Tank Capacity	700	L
Hot Water Tanks	Number and Size of Hot Water Tanks	3 × 500 L	1500 L total
Heating System			
Radiators	Existing Radiators	Not replaced	
Installed Equipment	Number of Heat Pumps	6	units
Heat Pump Capacity	Capacity per Heat Pump	13	kW
Total Installed Capacity	Total Heating Capacity	78	kW
Commissioning	Date of Commissioning	June 2024	
Heat Pump Model	Assumed Typical Parameters	Not specified	
Energy and Cost			
Previous Heating Cost	Annual Heating Cost	EUR 52,706	
Heating Cost per Area	Annual Heating Cost per m^2	EUR 35.29	$/m^2/year$
Annual Electricity Demand	Total System Consumption	43,971	kWh/year
Per Heat Pump Electricity	Per Unit Consumption	7600	kWh/year per heat pump

Assuming a COP (Coefficient of Performance) of 3, the heat production would amount to approximately 132,000 kWh/year. However, if we assume a COP of 2, the heat production would be approximately 88,000 kWh/year.

Given that at −15 °C, the measured heat demand required is 40 kW, it follows that for an average annual temperature of +0.5 °C, the demand for heat would be around 26 kW (on average, annually). Therefore, the annual heat demand would be 26 kW × 8760 h = 227,760 kWh. This difference suggests bold assumptions (132,000 or 88,000 kWh/year). Therefore, additional cost analysis was performed with assumed higher energy demand.

Costs: In the analyzed building, the annual electricity consumption costs, assuming the energy demand for the heat pumps and a price of EUR 0.35/kWh, would be EUR 15.50/year. Adding the service cost of EUR 1412 /year, the total annual heating cost would be EUR 16,941/year. Previously, the annual heating cost was EUR 52,706/year. The investment cost amounted to EUR 72.94; after deducting the subsidy of EUR 42.35, the cost for residents was EUR 30,588. With annual savings of EUR 35,765, the return on investment (ROI) would occur in less than one year, and without the subsidy, in about two years. This is a very short period and a noteworthy return, which requires a verification of the assumptions and a comparison with results from other implemented solutions for heat savings.

The second calculation is based on a residential building with similar characteristics (1740 m^2 and 45 apartments) [16], after thermal renovation, where heat pumps were installed for hot water production. The annual heating demand was 136,542 kWh, which is comparable to that assumed in [18], where total heat and hot water consumption with COP = 3 (132,000 kWh). The annual hot water demand amounted in [16] to 251,570 kWh. Thus, the total consumption was 388,112 kWh [16]. This is more than the authors' supplementary calculations (227,760 kWh) for the analyzed building [18] with respect to average heat consumption for an average annual temperature. However, since the heating power demand was empirically verified at low temperatures (−15 °C), for this heat demand and an optimistically assumed COP of 3, the electricity demand would amount to EUR 28,207/year. With a COP of 2 (a more realistic value), it would be EUR 41,605 /year. These calculations were made for an electricity price of EUR 0.35+ VAT. Considering additional annual service costs for the heat pumps, the return on investment without subsidies would be achieved in approximately 3 years (optimistic version, COP = 3) or 6.6 years (realistic version, COP = 2). These are very favorable investment return rates, especially for an investment in heating transformation that does not require the involvement of the state budget. Table 3 summarize presented calculations.

Table 3. Analysis of heat pump application in a multi-family building.

		Calculations for Design Assumptions	**Calculations for Corrected Energy Demand**	
			COP = 3	**COP = 2**
Residential area	m^2		1600	
Heat demand	kWh/year	132,000	227,760	
Electricity demand	kWh/year	43,971	75,920	113,880
Heating cost EUR 0.35/kWh + EUR 1412/year service	EUR/year	16,931	28,207	41,605
Previous annual heating cost	EUR/year		52,706	
Heating Cost Difference	EUR/year	35,775	24,499	11,101
Investment cost	EUR		72,941	
Return On Investment (ROI)	Years	~2	~3	~6.6

Conclusions from the analysis and general practical conclusions regarding electroheating with heat pumps:

- Dual benefit for investors: The residents of the analyzed multi-family building, investing their own financial resources, achieved a dual benefit: the first is material—reduced heating costs after the amortization period; the second is environmental—contributing to air-quality protection. Such actions should be incentivized through partially for-

givable investment loans (e.g., energy loans similar to technology loans). The transformation of district heating into electroheating must be rational; the choice of an electric heat source, such as a heat pump, must consider its operational specifics. In the case of air-to-water heat pumps, the COP coefficient must account for the temperature difference between the lower source (heat extraction) and the required heating fluid temperature under real operating conditions, rather than relying solely on laboratory-based performance characteristics. Local weather conditions during the heating season, which significantly affect the COP (fog, humidity), should also be considered. In high humidity conditions (November, December) and temperatures of around 0–5 °C, frost on the evaporator and defrosting requirements can significantly lower the COP. This important dependency is often not acknowledged or concealed from investors. In practice, it is safe to assume an average annual COP of 2 [19–23];
- Electroheating must be integrated with energy efficiency measures: Electroheating must be linked to minimizing heat losses in the building and should only be implemented when there are no further reserves for reducing energy losses, i.e., alongside thermal renovation. Only then does it make sense. Energy prosumerism inherently promotes energy-saving thinking; thus, optimal management of energy use, including heating, is required. Maximum COP values are achieved when there is a minimal temperature difference between the lower heat source (external source) and the upper source (required heating temperature). The lower-source temperature is weather-dependent (evaporator outside the building); however, the upper-source temperature can be controlled. Limiting the upper temperature to 35–40 °C and using underfloor heating or larger radiator surfaces ensures optimal performance. This investment pays off through the savings on electricity consumption;
- Heat storage: It is important to store the heat produced by the heat pump or electric boiler when energy from renewable sources (RES) is at the cheapest price. Distributed heat storage, near the heating nodes of the building, is the cheapest and simplest form of energy storage from a technical implementation perspective. The cost analysis shows how significant the electricity price is in determining the cost of heat. For electroheating, it is beneficial when electricity comes from local renewable sources, i.e., prosumer sources, making distributed electricity generation crucial. It is usually not optimal to transmit energy through the transmission network to convert it into heat. Transmission costs significantly increase the fixed costs of heating. Distributed RES sources owned by investors in local government units (LGUs) or industrial zones are better solution. Investors, who often do not receive permission to connect photovoltaic or wind farms to the electricity grid, as well as bio-power plants, can create local "direct networks" or green prosumer electricity networks (MV/LV), along with prosumer billing platforms, relieving the national electricity grid (KSE). Importantly, local RES investments do not burden the state budget.

3.2. Analysis of Published Costs of Transforming District Heating

After the completion of the incremental transformation, the cost of heat will primarily depend on:

- the price of electricity, which will be influenced by the amortization costs of large-scale renewable energy sources (RES), particularly the amortization of nuclear power plants and investments in the transmission and distribution infrastructure for electric power;
- the amortization costs of investments in centralized district heating networks, associated with the energy transition.

Prosumer-based district heating systems powered by local renewable energy sources (RES) free the heat price from the aforementioned burdens—there is no or limited need for transmission of electricity through the national grid (KSE), and no investment in the systemic heating network.

Let us analyze the amortization costs of investments in centralized district heating infrastructure under incremental transformation.

In the 2020 report on district heating by the Polish District Heating Chamber of Commerce (in Polish: Izba Gospodarcza Ciepłownictwo Polskie), the cost of the transformation in the decade to 2030 is estimated at EUR 12 to 24 billion. This includes the modernization of 6500 km of the network (approximately 36%), in which:

- EUR 10 to 17 billion relates to heat generation;
- EUR 3 to 7 billion relates to heat distribution.

According to one study in the literature [8], the total investment in the transformation is estimated at:

- EUR 92 billion by 2030;
- EUR 235 billion by 2050.

This implies an annual expenditure of EUR 9,5 billion over 25 years. The percentage of the centralized network to be modernized by 2030 for EUR 92 billion is not explicitly stated; however, a comparison of the figures suggests 39% coverage.

From another source [9], the estimated cost of transforming the centralized heating sector is EUR 70–100 billion by 2050. The discrepancy between the estimates is significant: EUR 118–235 billion. The conclusion of the author [9] is as follows:

> *"It will be necessary to spread these costs over time in order to minimize their impact on tariffs and heat prices for end users."*

Question 1: Will such high investment expenditures in centralized district heating ensure a heat price that is socially acceptable?
Question 2: What does EUR 118 or 235 billion mean in relation to the residential floor area?

According to data from Poland's Central Statistical Office (GUS) on energy consumption in 2021:

- In 2021, 52.2% (compared to 40.4% in 2018) of the residential floor area in multi-family buildings was heated by district heating;
- 78.2% of district heating consumers used network-supplied hot water;
- The total residential floor area in multi-family buildings in Poland amounted to 438.8 million square meters.

Thus, centralized district heating currently supplies 229.05 million m^2 of the residential floor area (438.8 million $m^2 \times 0.522 = 229.0536$ million m^2).

Assuming that, based on the previously mentioned data, a total investment of EUR 235 billion is needed to fully modernize the district heating network by 2050, this translates to EUR 1027 per square meter. If the cost were EUR 118 billion, the figure would be halved.

This means that a 50 m^2 apartment would carry a cost burden of EUR 51,362 for the modernization of the district heating network.

An alternative calculation is based on a case study from the construction of the "heating plant of the future" in Lidzbark Warmiński (north-east part of Poland) [24], where the investment amounted to EUR 12 million. It is reported that this source of heat will primarily serve 3 000 residents of the Astronaut housing estate. Assuming four persons per 50 m^2 apartment, which amounts to 12.5 m^2 per person, the plant is expected to heat approximately 37 500 m^2.

This results in a cost of EUR 307 per square meter.

With these projected costs—of both the estimates [8,9] and the realized case (Lidzbark Warmiński)—a key question arises:

Will the heat price remain "socially acceptable"?

Another major issue is the source of financing. As noted in one study [9]:

> "...*Given the enormous costs, the state will have to play a crucial role as a guarantor of long-term investment financing. Funding may come from emissions trading revenues, EU funds, or financing from banks and other institutions.*"

"The state" means the citizens. With the national budget deficit growing, this implies higher taxes and greater debt for future generations.

What, then, is the alternative? What is the rationale behind the logic of a breakthrough transformation in centralized district heating?

The investment cost for an induction boiler, including a thermal storage unit and installation work in the heating substation, is estimated at EUR 38–47/m^2 (at current market prices), for systems with 100 kW capacity serving 2500 m^2, depending on the size of the on-site thermal storage unit. This estimate is based on a prototype implementation [17].

The total cost of full electrification of the heating sector—transforming it into electroprosumer-based heating—would be as follows:

- 438.8 million m^2 $\times$ EUR 38/m^2 = EUR 17 billion;
- or EUR 21 billion, if the cost is EUR 47/m^2.

The above figures assumed that electrification is based solely on induction boilers for the entire residential floor area in multi-family buildings.

For the 229.5 million m^2 currently covered by centralized district heating (52.2% of total), the cost would be as follows:

- EUR 9 billion at EUR 38/m^2;
- or EUR 11 billion at EUR 47/m^2.

This is a staggering difference, when compared to the EUR 118 or 235 billion investment estimates cited in the literature [8,9].

Spread over 25 years, the annual investment cost would be only EUR 0.43 billion, not EUR 9.5 billion (or EUR 4.7 billion depending on the estimate). Translated into investment per PEC company (with approx. 400 companies in Poland), this equals just EUR 1 million per year per company. Table 4 summarize presented calculations.

Table 4. Analysis of costs for transforming district heating.

		Estimates from [8]	**Estimates from [9]**	**Theoretical Implementation of Induction Boilers (Cost Similar to Heat Pumps)**
Estimated cost	EUR	235×10^9	118×10^9	11×10^9
Estimated cost per year	EUR/year	9.5×10^9	4.7×10^9	0.43×10^9
Estimated cost per m^2	EUR/ m^2	1027	51,362	47
Cost per 1 m^2 per year (assumed 25 years until 2050)	EUR/ m^2/year	41	21	2

For comparison, the electrification of a heating system in a residential block with 32 apartments in Urszulin cost EUR 72,941. Thus, with a EUR 1 million budget, it is possible to modernize 13 residential buildings. Even without government subsidies, the investment achieves payback within five years. Therefore, by 2050, it would be feasible to electrify 65 residential buildings (within the area served by a single district heating company, PEC) by taking out only a EUR 1 million loan over 5 years—i.e., EUR 200,000 annually. This level of financing does not place a significant burden on the PEC. Moreover, an "ecological loan", partially forgiven due to the social and environmental benefits, could further facilitate the breakthrough transformation.

The calculated cost of a breakthrough transformation does not include the cost of electric RES (renewable energy sources); however, the incremental transformation estimates also do not include such costs.

The operating costs of the district heating system under the TEE (Transformation of Energy to Electroprosumerism) concept [5,11,12] are not included in this analysis, but are likely to represent only a fraction of a percent of the total transformation cost. Energy consumption of the induction boiler is recorded remotely and can be transmitted to a centralized management and billing system. Likewise, the operation of each heat exchange station can be remotely monitored from a control center.

The price of electricity must reflect market rates, comparable to EU prices—this is a critical condition for the societal acceptance of electroheating in general. Specifically, "energy at 50 EUR/MWh" [25], i.e., 0.215 PLN/kWh. A low electricity price, and thus low heat price, can be ensured by local investments in RES and local "green grids" that enable peer-to-peer energy trading and balancing (e.g., internal electricity distribution systems, WSDEs).

Demonopolization of the energy market is a core feature of electroprosumerism and a driver of rapid innovation.

An Electro-PEC (electroprosumer district heating company) can operate within the existing energy law. It can invest in its own RES assets, purchase additional green electricity, and sell heat to consumers.

4. Discussion

4.1. Industrial Electroheating

According to the Theory of Energy Transformation to Electroprosumerism (TEE) [5,11,12], the optimization of industrial heating systems should be implemented within the framework of crisis shields. An industrial electroprosumer crisis shield—a physically defined area in which an electroprosumer manages the full balance of their energy needs —serves as an effective model for minimizing energy costs, particularly when renewable energy generation is aligned with energy demand, thereby maximizing self-consumption.

Renewable energy sources (RES) should be dimensioned to cover not only electricity demand but also the thermal energy requirements (process and space heating) of the enterprise. On-site RES installations, combined with electricity and thermal energy storage systems, enable energy supply at minimal cost, unburdened by grid transmission and distribution charges.

From the perspective of thermal supply and within the framework of the electricity monism paradigm, the establishment of industrial electroprosumer crisis shields is a strategic approach. A prototypical solution developed for research, training, and dissemination purposes is the "OK-P Energo-Complex" shield, as described in references [17].

An example is the 100 kW induction boiler, illustrated in Figure 3, installed in the heat substation of a company's boiler plant and currently undergoing performance testing. The system is powered by renewable energy sources and integrated with waste heat recovery from a generator set. Air conditioners, operating as heat pumps during the heating season, are also incorporated into the company's energy management system.

Experimental results confirm the full suitability of the induction boiler for both industrial and municipal applications. Although the electricity cost associated with induction heating is estimated to be at least twice as high as that of heat pump operation, the induction boiler is proposed for applications where heat pumps are not technically or economically viable.

4.2. Advantages of Electroheating and Tasks for Innovators of the Breakthrough Transformation of Heating

Summary of the previously described advantages:

- Elimination of operational disruptions caused by failures in district heating networks;
- Crisis resilience in energy supply, enabled by on-site renewable energy sources (RES);
- Minimal failure rate of the induction boiler as a thermal energy source;
- High responsiveness and flexibility of the heating system for the facility;
- Thermal energy storage, with charging during periods of peak RES production and local, small-scale thermal storage units;
- Lowest investment cost for the energy transition toward electrothermal systems;
- Energy transformation independent of state budget financing.

In light of the aforementioned advantages, innovators of the breakthrough energy transformation can engage in the following tasks:

- In small- and medium-sized enterprises (SMEs), building crisis-resilient industrial control shields with renewable energy sources (RES). Optimizing energy costs produced by RES for production and heating purposes. Striving for self-consumption of generated energy;
- In high-temperature technological processes that are thermally stabilized with thermal oil, replacing gas or oil boilers with electric boilers, e.g., induction boilers;
- Building public energy awareness;
- Constructing bio-power plants as backup energy sources and for the production of green hydrogen.

Socially, it is unacceptable to present a hype-driven optimism in the promotion of heating system transformations, such as that which accompanied the promotion of heat pumps, without raising awareness of the technical limitations of the product, the thermal requirements of the building, and without protecting against potential manipulations by installation companies. It is also unacceptable to promise so-called thermal security at the expense of excessively costly investments and the indebting of society.

4.3. Opportunities for Breakthrough Energy Transformation to Electroheating

Opportunities for Electroprosumer Heating in the District Heating System—Slim to None—Why?

The breakthrough transformation is not of interest to heat producers and distributors, i.e., heating corporations and district heating companies (PEC). They want to sell as much heat as possible and maintain the existing heat supply system. The more deregulated the heating network at the consumer's end, the higher the sales. The flat-rate fee for heating per square meter is the most advantageous form of billing for PECs. Propaganda is often used to promote the concept of energy security. Decentralized heating systems and electroprosumerism are seen as a threat.

For well-managed, innovative housing cooperatives and PECs, electroprosumerism offers a chance for development through investments in new heating technologies, renewable energy sources (RES), including bio-power plants, energy storage, and a new heat distribution system. The opportunity lies in the transformation of a PEC into an Electro-PEC.

Even if housing cooperatives are interested in the breakthrough transformation, they are often incapacitated by PECs. Not every management board is willing to risk disconnecting from the district heating network and invest in their own solutions. With a guaranteed supply of heat from PECs, there is no risk.

Suggestions:

- The launching by, for example, the NCBR (The National Centre for Research and Development), of a pilot program called "Electro-PEC of the Future," similar to the "Future Heat Plant" program, which would include RES sources and the electrification of buildings, where electricity is converted into heat using heat pumps and induction boilers, depending on the results of a technical–economic analysis. The goal would be maximizing self-consumption of energy from RES, including from biogas plants and cogeneration, as well as energy storage;
- Creation of a Research and Development Center for Electroprosumers, with a structure of research facilities as shown in Figure 2, as an NCBR program, aimed at the practical implementation of electroprosumer heating and training in the implementation of the Electro-PEC and Housing Cooperative of the Future structures in district heating systems.

Examples of Implemented Solutions:

- Housing Cooperative "Sienkiewicza Estate" in Wieliczka: The cooperative decided to abandon its own coal boiler and district heating network and instead use distributed heat sources. Each building has its own gas boiler. The cost of heating decreased significantly, by about 25%. In the future, after 2050, gas boilers may be replaced in the heating network by heat pumps or induction boilers. This is an example of the first stage on the trajectory of energy transformation to electroprosumerism (TEE)—a breakthrough transformation;
- In Rybnik, as a result of the shutdown of the heat and power plant in Chwałowice, two gas-fired heating plants were built, supplying the existing district heating network. The cost of heating almost doubled, and this is not the final price. Issues with heat distribution (transmission losses, failures) persisted. This is an example of the first stage of incremental transformation.

Opportunities for Electroprosumer Heating in Industry

Significant opportunities exist for the optimization of energy within the industrial sector. A particularly promising area where electroprosumerism and electroprosumer heating can be implemented is within special economic zones (SEZs). Within these zones, industrial control shields (OK-P1) can be established by specific companies through individual investments in photovoltaic power plants, wind farms, energy storage systems, bioelectric plants, and backup generators.

There is ample roof space above production halls and large maneuvering and parking areas that can be utilized for the installation of photovoltaic power plants. OK-P2 control shields could be created by companies located within the zone, enabling mutual balancing and settlements through internal energy distribution systems (WSDE). An example of this could be settlements between entities located in shopping malls.

Energy generated from renewable sources (RES) during weekends, holidays, and non-production hours could be stored, converted into heat, or used for hydrogen production, instead of being fed back into the National Power Grid (KSE). Such an electroprosumer network would significantly reduce the load on the KSE network, lowering required modernization costs. More importantly, it would reduce fixed energy costs by eliminating distribution costs.

This solution also enables companies to obtain a "green certificate" for "green heating", which can be realized through the use of the company's own RES.

Suggestion:

- Extension of the Law on Energy Cooperatives: The possibility of establishing energy cooperatives should be expanded to include urban municipalities where economic zones are located. The current law is unconstitutional. Why are rural and urban–rural municipalities allowed to establish such cooperatives, while urban municipalities are excluded from this opportunity?

5. Conclusions

- The breakthrough transformation of district heating, involving the distribution of electricity through the electrical grid and its conversion into heat at the point of use, is the only logical and economically justified path toward an ecological, emission-free economy that should be adopted, assuming that electrical monism is achieved by 2050. The economic justification is presented in the article. The costs of this breakthrough transformation to electroheating are 26 times lower than the costs of incremental transformation presented in [8] and 13 times lower than the costs of incremental transformation defined in [9]. These costs can be financed without involving the state budget;
- Electricity in Electroheating: Electricity in electroheating should come from local renewable energy sources (RES), electroconsumer sources, as well as industrial and consumer energy storage, including energy storage in the distribution system and storage at wind farms and on-site (distributed) heat storage. Distributed power generation has its justifications. It is expensive to transmit energy over long distances through the KSE transmission network, e.g., from the north to the south, only to convert it into heat. The transmission costs and investment in the transmission network significantly increase the fixed costs of heat generated from electricity. Local investments in RES should not burden the state budget. These should come from the business policies of energy producers. Heat sources generated from electricity can be distributed sources and this heat should come from local renewable energy sources. Locally generated heat will ensure thermal crisis resilience;
- Heat Price after Transformation: The price of heat after the transformation of district heating into electroheating will depend on the price of electricity, which must be a market commodity at the price levels occurring in the European Union, ensuring the minimization of heat costs, specifically, "energy at 50 euros/MWh" [25]. Electroprosumerism in heating is the only solution to minimize the price of heat. "Energy from RES is and will be cheaper, and there is no turning back," quote from [25];
- Rational Transformation: The transformation of district heating into electroheating must be rational and the selection of an electric heat source, such as a heat pump, must take into account its operating specifications. The heat pump is a desirable heat source in electrical monism, emission-free and economically justified, as demonstrated in the article and supported by publications [19–23]. Negative experiences of investors in unsuitable buildings do not indicate the ineffectiveness of heat pumps. The induction boiler is an electric heat source taking over the role of the primary heat source in a high-parameter system, which was previously delivered to the building's heat exchange station through the district heating network. It should be applied in cases where the installation of heat pumps is technically and economically unjustified, as was discussed in this article. It is an alternative heat source providing optimal regulation of the heat exchange station and is purposeful in the breakthrough transformation of district heating to electroheating;
- Opportunities for District Heating Companies (PECs) and Housing Cooperatives: For well-managed, innovative district heating companies (PECs) and housing cooperatives, electroprosumerism is an opportunity for growth through investments in new

heating technologies and RES, including bio-power plants and energy storage. The opportunity lies in transforming local PECs into Electro-PECs. Energy storage in heat is the cheap and technically simple method of stabilizing heat and utilizing excess electricity produced by weather-dependent RES sources;
- The breakthrough transformation of district heating systems is achievable, without involving the state budget, at the local level through local district heating companies;
- Involvement of Government: Engaging the government to solve local heating problems, burdening central authorities with local issues, and demanding billions in support from corporations and district heating companies for inefficient incremental transformation, the financing of which will burden future generations, is a sign of the irresponsibility and incapacity of local authorities. In the case of PEC management and heating corporations, it reflects their inability to move beyond existing habits. The breakthrough transformation requires a mental shift in management;
- Promises of "Heat Security": heating corporations promise "thermal security" at the cost of overpriced investments and indebting society.

Although this paper focuses on Poland, the core concept—the breakthrough transformation of district heating through decentralized electroheating—is broadly relevant across Europe, especially in Eastern EU countries. Countries with legacy district heating infrastructure face similar challenges: the need to decarbonize heating, rising modernization costs, and increasing pressure to integrate renewable energy sources (RES) at scale. The Polish case exemplifies the tension between incremental and systemic change.

For example, Germany has committed to climate neutrality by 2045 and faces substantial challenges in modernizing district heating systems while phasing out natural gas and coal. Although it has a less centralized heating structure than Poland, Germany is also grappling with how to decentralize heating via heat pumps, local RES, and thermal storage, especially in dense urban areas and older housing stock [26,27].

Similarly, Denmark faces limitations in flexibility and rapid decarbonization due to the scale and rigidity of its existing centralized networks. Recent Danish energy plans have acknowledged the need to integrate decentralized heat pumps and smart grid systems, particularly in small towns and rural areas [28].

Generally, thermal storage at the building or neighborhood level is an increasingly discussed solution in EU decarbonization roadmaps [29].

Countries with a high share of RES and grid congestion, such as Spain and parts of Italy, may particularly benefit from decentralized heat models that avoid stressing national power grids and maximize local self-consumption.

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Abbreviations

The following abbreviations are used in this manuscript:

PEC	Thermal Power Company, District Heating Company (Przedsiębiorstwo Energetyki Cieplnej)
RES	Renewable Energy Sources
KSE	National Power System (Krajowy System Elektroenergetyczny)
COP	Coefficient Of Performance
LGU	Local Government Units
TEE	Transformation of Energy to Electroprosumerism (Transformacja Energetyczna do Elektroprosumeryzmu)
PLN	Polish złoty-official currency of Poland
MV	Medium voltage network
LV	Low voltage network
NCBR	The National Centre for Research and Development (Narodowe Centrum Badań i Rozwoju)

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