Journal of
Social and Economic Statistics

Vol. 13, No. 1, Summer 2024
DOI: 10.2478/jses-2024-0004

Transition Trajectory: VAR Projections of Romania's Shift to Renewable Energy

Andrei PISICĂ[a], Adriana AnaMaria DAVIDESCU[b], Marina-Diana AGAFIȚEI[c*], Maria-Bianca BOLBOAȘĂ[d], Mihai GHEORGHE[e]

[a) e)] The Bucharest University of Economic Studies, Bucharest, Romania.

[b) c) d)] The Bucharest University of Economic Studies, Bucharest, Romania/National Scientific Research Institute for Labour and Social Protection, Bucharest, Romania.

Abstract

Romania, along with many other nations, must take urgent action to significantly reduce greenhouse gas emissions to effectively address climate change. Through an examination of Romania's renewable energy potential and strategies for transitioning to a more sustainable energy system, this study employs a Vector Autoregressive (VAR) model to explore the complex dynamic interrelationships between various energy sources within Romania including solar power, hydropower, coal, and natural gas. The results indicate that increased production of renewable resources, particularly solar and hydroelectric energy, serves to diminish reliance on fossil fuels by negatively impacting thermal energy output. Impulse response functions reveal that short-term shocks to thermal energy production lead to temporary decreases in solar and nuclear energy generation, followed by a gradual stabilisation, while variance decomposition analysis underscores solar energy's pivotal role in influencing other energy sources. The findings highlight Romania's ability to replace polluting sources with environmentally friendly alternatives, implying that policies aimed at diversifying the energy mix, investing in green infrastructure development, and fostering innovation across industries are fundamental. Such strategies not only enhance Romania's energy sustainability over the long term but also contribute to broader economic growth and environmental protection objectives.

Keywords: Renewable Energy Transition, Energy Mix Diversification, Vector Autoregressive (VAR) Model, Energy Policy Romania, Sustainable Development

JEL Classification: Q42, Q48, C32, O13, P28

[*] Corresponding author, **Marina-Diana Agafiței** – diana.agafitei@csie.ase.ro

1. Introduction

As global climate change intensifies, primarily driven by increasing greenhouse gas emissions, countries everywhere face mounting pressure to transition from conventional energy resources toward sustainable alternatives. One of humanity's paramount goals in the 21st century is the decarbonization of the worldwide energy infrastructure, according to Kabeyi and Olanrewaju (2022). Numerous governments have positioned the shift to sustainable energy at the core of their policies and have adopted suitable regulations to track and evaluate the consequences, as noted by Radovanović, Filipović and Panić (2021). In this context, policy complementarity has proven crucial, as seen during the COVID-19 pandemic, where well-timed fiscal and monetary policies stabilized economic uncertainties and supported broader macroeconomic goals (Ciocirlan and Nițoi, 2022). Romania, like many nations, is grappling with the dual imperative of fostering economic growth while addressing environmental sustainability. This paper delves into Romania's potential for transitioning to an energy system based on renewables, assessing the role of various energy sources and their economic and environmental impacts.

Romania's diverse energy landscape, incorporating a diverse mix of resources, including fossil fuels, nuclear power, and renewables such as hydropower and wind energy, faces the persistent challenge of transitioning away from fossil fuel reliance. Heavy dependency on coal and other greenhouse gas-emitting resources necessitates a shift toward renewables to limit emissions and fortify climate resilience. Recent climate data underscores Romania's vulnerabilities, with precipitation pattern changes, warmer temperatures and increased extreme weather threatening natural assets, public health and economic stability.

Navigating a renewable transition involves balancing energy security, economic growth and eco-goals. The EU's "Net Zero 2050" roadmap highlights the urgent need to adopt cleaner energy sources. As an EU member, Romania harmonizes national energy policy with these overarching aims, pursuing higher renewable shares. This regulatory integration mirrors Europe's commitment to reducing fossil fuel dependency and cultivating sustainable solutions. The road ahead requires strategic planning to profit from renewables while safeguarding ecosystems, infrastructure and livelihoods in a changing climate.

This examination employs the Vector Autoregressive (VAR) modelling to assess Romania's intricate energy interdependencies, focusing on renewable energy's potential and implications like solar, wind, and hydroelectric power. This original contribution of this paper results from utilizing a Vector Autoregressive approach to capture the complex interdependencies between diverse energy sources - a methodology rarely applied in Romania's energy transition context. By analyzing the impact of renewables on traditional sources such as coal and natural gas, the examination aims to uncover patterns and relationships informing energy policy and strategic planning. Additionally, impulse response functions and variance decomposition analysis are utilized to comprehend how shocks in production influence other sources through time.

The VAR analysis offers critical insight, showing an inverse relationship between thermal energy and renewable resources like solar or nuclear power. An increase in such eco-friendly sources could reduce reliance on fossil fuels. Moreover, the examination highlights solar energy's role in explaining variances among other sources, underscoring its influence on the overall energy mix. The study’s findings provide a foundation for policy recommendations that include diversifying Romania’s energy portfolio, enhancing investments in green energy infrastructure, and fostering technological innovations. By adopting these strategies, Romania can mitigate its environmental impact while stimulating sustainable economic development, ultimately advancing toward a cleaner, more resilient energy future.

The structure of the paper is as follows: the introduction discusses the importance of the study in the context of climate change and Romania's potential for renewable energy. The literature review covers previous research on renewable energy transitions and identifies gaps that this study aims to address. The methodology section explains the VAR model and the data sources used for analysis. The empirical results are presented and analyzed with a focus on their relevance for energy policy. Finally, the paper offers policy recommendations, outlines the study's limitations, and suggests areas for future research.

2. Literature Review

Historically, the narrative of renewable energy has evolved alongside a growing awareness of climate change and the need for energy security. However, some scholars (Harjanne and Korhonen, 2019) argue that the common framing of renewable energy in policy and public discourse has been too simplistic, focusing merely on renewable versus non-renewable sources. A more nuanced approach is needed, one that considers the varying degrees of carbon intensity and true environmental impact of different energy options to more accurately achieve sustainability goals. Moreover, recent critiques suggest that the historical framing of renewable energy, rooted in 1970s environmental movements, may not adequately address the complex challenges of today’s climate imperatives, necessitating a shift toward more integrative, systems-based conceptualizations.

Germany provides a compelling case study of renewable energy adoption in Europe. In the late 20th century, the nation implemented a feed-in tariff program that catalyzed massive investment in wind and solar power. Within just a few decades, these renewable sources dramatically reshaped Germany's energy landscape (Hinrichs-Rahlwes, 2013). The policy framework also spurred substantial economic growth and job creation, as it established a stable and reliable market for the renewable industry to develop. Notably, the German experience underscores the importance of strong governmental support and a consistent long-term policy structure for encouraging industry growth and gaining public support for renewable transition.

While renewable technologies have improved dramatically in recent decades, fully embracing them continues to face obstacles. Elliott (2000) notes that though wind and solar engineering has progressed well, societal acceptance lags—especially within systems historically reliant on large, carbon-heavy infrastructure. This mismatch between renewable technologies and existing industrial frameworks often creates barriers to implementation, emphasizing the need for adaptive, decentralized infrastructure.

Looking globally, the studies reveal renewable energy's capacity to satisfy future demands while emphasizing location-specific resource potential and prerequisite policies. Resch et al. (2008) conducted a scenario analysis assessing renewables' ability to meet mid- and long-term needs, stressing each region's unique renewable reserves and the necessity of supportive frameworks. Their study, grounded in the International Energy Agency's frameworks, underscores how policy-driven scenarios can drastically alter renewable energy outcomes by 2030 and 2050, highlighting the importance of ambitious yet context-specific strategies.

On a societal level, Qazi et al. (2019) in their systematic review point to public perception's pivotal role in adopting renewable technologies. Their examination uncovers that while renewables are increasingly seen as eco-friendly, there is a gap in public awareness and approval that could hinder take-up. By analyzing social media sentiment, they illustrate how public perception can considerably impact policy and market adoption, suggesting improved engagement and education are pivotal to support renewables as principal energy sources.

Romania's journey towards renewable energy has been marked by potential and strategic efforts aligning with European climate aims. Colesca and Ciocoiu (2013) highlighted Romania's pledge to diversify its energy mix, especially through wind, hydro, biomass and solar integration. EU accession catalyzed reform driving policies fostering a supportive environment for renewable investments focusing on wind energy with substantial untapped opportunity, according to the authors.

Romania's renewable landscape evolved under EU mandates advocating ambitious greenhouse gas cuts and efficiency gains. Dumitrașcu et al. (2019) emphasized the country's favorable geography and climate for renewables noting the prominence of hydro, solar and wind resources. These factors position Romania as a key European renewable player especially as policies encourage a low-carbon shift with significant contribution from renewables. However, harnessing Romania's full renewable potential faces challenges like insufficient infrastructure and regulatory instability. In evaluating European policy effectiveness, Davidescu, Popovici, and Strat (2022) used a Leontief model to assess the impact of European Structural and Investment Funds (ESIF) on transitioning to a low-carbon economy. Their findings highlight that green investments reduced Romania's greenhouse gas emissions by approximately 1.14 million tons during 2014–2020. Moreover, sectoral differences emerged, with agriculture, energy, and public administration identified as the primary beneficiaries of emission reductions. This research underscores the environmental progress achievable through well-structured EU programs while emphasizing the importance of aligning these funds with national development priorities to optimize future outcomes.

Marinescu's (2020) work highlights that while Romania made early progress with green certificates and subsidies attracting foreign money, consistent adjustments to policy generated instability. These changes, meant to optimize subsidy structure, regularly disrupted investor confidence and impacted financial returns especially in wind energy. This underscores the necessity for consistent legislative frameworks to sustain industry development.

Similarly, Mihăilescu (2009) observes Romania's potential in wind energy, emphasizing the nation's substantial wind resources could position it as a regional leader in renewable resources. However, the author also notes achieving such potential demands robust overseas investment and policy stability to foster developing wind infrastructure and market competitiveness.

In strategic evaluation, Răboacă et al. (2020) conducted a SWOT analysis of renewable sources, identifying strengths in Romania’s geographic advantages and its noteworthy solar capacity. The investigation underscores the pivotal role of predictable legislative support in leveraging Romania’s renewable capabilities and notes the high levels of solar radiation as an underutilized opportunity. This analysis calls for targeted policies to address barriers and maximize the sector’s contributions to national energy independence.

Overall, Romania’s renewable energy landscape exemplifies both the potential and challenges faced by emerging markets in integrating renewables. Future growth in this sector will depend on consistent policy frameworks, technological advancements, and a strategic alignment with both EU goals and Romania's unique energy profile.

In the broader context of renewable energy forecasting, recent advancements illustrate the integration of complex statistical and machine learning methodologies to enhance prediction accuracy, as seen in studies by Cavalcante et al. (2016, 2017). For instance, Cavalcante et al. (2016) explore the use of LASSO vector autoregression (VAR) models tailored for very short-term wind power forecasting, emphasizing the scalability and computational efficiency gained through sparse modelling techniques, especially relevant for large-scale renewable deployments. This study underscores the critical role of real-time data from wind power plants in optimizing forecasts and managing variability in wind generation. By employing distributed sensors and parallel computing, the study showcases the potential for enhanced reliability in energy grid management.

Similarly, Cavalcante and Bessa (2017) apply a comparable VAR-LASSO framework to solar forecasting. This approach, involving 15-minute and hourly forecasts across microgeneration units, demonstrated marked improvements over traditional autoregressive models. Such spatial-temporal methods allow for high-frequency updates in solar generation forecasts, which are particularly advantageous for integrating photovoltaic (PV) energy into regional grids.

While predictive improvements and coupling sustainable power with economic development have been researched regarding their environmental and monetary impacts, the interdependence between renewables, growth, and emissions merits continued analysis. Charfeddine and Kahia (2019) probe this interconnection within the MENA region, where financial sector expansion has facilitated increasing renewable adoption as a strategy to lessen CO2 emissions. Through utilizing a panel VAR model, they unveil how investments can promote ecological benefits alongside economic gains.

For solar energy specifically, Jung et al. (2022) utilize a VAR model for regional PV forecasting across South Korea. The study highlights the importance of clustering power plants for enhanced accuracy, proposing that regional forecasts for clustered plants yield better predictability and grid efficiency. This clustering-based forecasting method reflects a trend toward region-specific strategies that can manage renewable variability and optimize grid integration.

Together, these studies demonstrate a cohesive movement towards renewable energy systems that are not only more accurate in forecasting but also integrative of financial and environmental metrics, supporting a sustainable and resilient energy transition.

3. Data and Methodology

The VAR model utilizes net energy generation quantities from various fuel types in Romania, measured in GWh, spanning from January 2017 to February 2024, on a monthly basis, without seasonal adjustment. The analyzed variables include thermal energy (Coal), natural gas energy (Natural Gases), nuclear energy (NF), wind energy (Wind), solar energy (Solar), and hydroelectric energy (Hydro). The data used in this study was extracted from Eurostat.

The steps followed within the VAR model, as showed in Figure no. 1, are as follows:

Step 1: Since the analysis is conducted on monthly data, the presence of seasonality in the data is examined. If confirmed, seasonal adjustment is applied using the Tramo Seats method.

Step 2: An analysis is conducted to determine the stationarity of the data series using tests such as ADF (Augmented Dickey-Fuller), KPSS (Kwiatkowski-Phillips-Schmidt-Shin), and PP (Phillips-Perron) to identify the order of integration of the series. A series is considered integrated of order d if it becomes stationary after differencing of order d. If the computed value of the ADF or PP test does not exceed the critical value associated with a certain significance level (1%, 5%, or 10%), then the series is considered non-stationary and requires differencing to achieve stationarity. In the case of the KPSS test, the hypotheses are reversed.

There are several possible scenarios:

i) The series may be stationary, (I(0)).

ii) The series may be non-stationary and integrated of the same order (typically order 1, (I(1))).

iii) The series may be mixed, integrated at different orders (usually, some variables are (I(1)), while others are (I(0))).

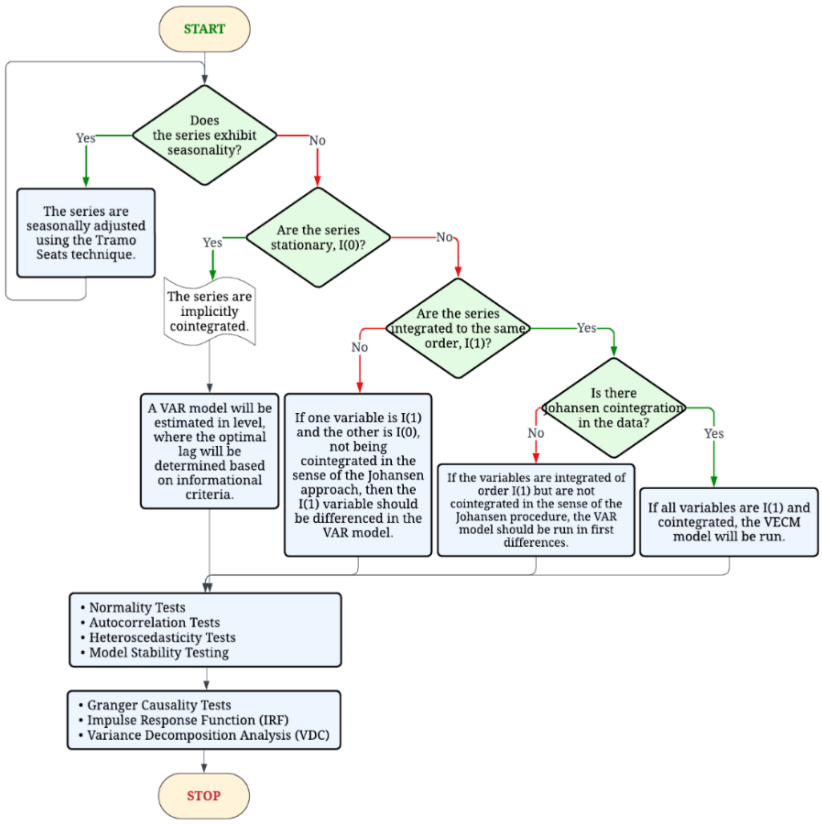

Figure no. 1: Diagram of Multivariate Models

Source: Own processing in Lucidchart

Step 3: In light of the three previous situations, the next step involves estimating a VAR model or VECM (Vector Error Correction Model) as follows:

i) If the series are stationary ((I(0))), they are implicitly cointegrated, and thus a VAR model is implemented in levels (on the original variables). The first step in estimating this VAR model is to determine the optimal lag based on information criteria such as AIC (Akaike Information Criterion), SC (Schwarz Criterion), HQ (Hannan-Quinn Criterion), and FPE (Final Prediction Error Criterion), to test the hypothesis of no autocorrelation of the VAR model residuals. The VAR model is estimated using Ordinary Least Squares (OLS), aiming to verify the model's performance (significance of model parameters, validity, and goodness of fit), as well as checking the regression model assumptions.

$$X_t = A_1 X_{t-1} + \ldots + A_p X_{t-p} + \mu + \varepsilon_t \quad (1)$$

ii) If the series are not integrated at the same order, with one being (I(1)) and the other (I(0)), then the (I(1)) variable needs to be differenced. In this case, a VAR model is estimated (which will contain only short-term results), and its performance is analyzed.

iii) If both variables are integrated at order (I(1)), proceed to step 4 to verify the existence of cointegration in the data using the Johansen multivariate cointegration test.

Step 4: Confirming/Rejecting Cointegration in the Data

iii.1) If the variables are integrated at order (I(1)) but are not cointegrated in the Johansen procedure sense, the VAR model should be estimated in first differences (short-term results), and its performance is analyzed.

The performance of the VAR model involves assessing the significance of model parameters, its validity, goodness of fit, and testing the regression model hypotheses. Additionally, in this case, a Granger causality test for the short term is performed.

Granger causality assumes that variables X with lags significantly influence variable Y in equation (2), and variables Y with lags significantly influence variable X in equation (3). In other words, the hypothesis that the coefficients are significantly different from zero according to the Fisher (F) test is tested. If this hypothesis is rejected, then the causal relationship between X and Y is confirmed.

$$Y_t = a_1 + \sum_{i=1}^{n} \lambda_i X_{t-i} + \sum_{j=1}^{m} \delta_j Y_{t-j} + u_{1t} \tag{2}$$

$$X_t = a_2 + \sum_{i=1}^{n} \alpha_i X_{t-i} + \sum_{j=1}^{m} \beta_j Y_{t-j} + u_{2t} \tag{3}$$

iii.2) If both variables are (I(1)) and cointegrated, a Vector Error Correction Model (VECM) like equation (4) is estimated for the level data, where the t-test of the ECM coefficient and the F-test of the model must be statistically significant. Within this model, Granger causality tests are conducted for both short-term and long-term relationships, and impulse response function (IRF) and variance decomposition analysis (VDA) can also be applied.

Additionally, using the results of a VAR model, impulse response functions (IRF) and variance decomposition analysis (VDA) can be determined, serving as tools to evaluate dynamic interactions and the strength of causal relationships between system variables. Variance decomposition analysis shows the percentage of forecast error variance of a variable attributable to its own innovations and the innovations of other variables. The impulse response function highlights the response of a variable to a one-standard-deviation shock in another variable, quantifying the direction, magnitude, and persistence of the dependent variable's response to variations in the independent variable.

$$\Delta X_t = \mu + \Gamma_1 \cdot \Delta X_{t-1} + \ldots + \Gamma_{p-1} \Delta X_{t-p+1} + \Pi \cdot X_{t-1} + \varepsilon_t \tag{4}$$

where Δ is the differencing operator, X is the vector of n variables (I(1)), μ is the intercept, ,$\varepsilon_t \approx niid(0, \Sigma)$ is the model residuals, $\Pi = -(I - A_1 - \ldots - A_p)$ is the coefficient matrix of size $(n \times n)$ containing information about the long-run relationships between variables, it decomposes into $\Pi = \gamma \cdot \beta'$, where γ represents the adjustment coefficients (error correction terms - ECT) that indicate how quickly ΔX_t adjusts to imbalances in the cointegrating relationship, and β are the cointegration vectors, while $\Gamma_i = -(I - \sum_{j=1}^{i} A_j)$ represents the coefficient matrix of size $(n \times n)$ containing information about short-term relationships between variables (short-term adjustment).

In a VECM model, the long-term and short-term parameters are separated. According to the representation of the Granger theorem, the cointegration results imply that X and Y have the following specifications:

$$\Delta Y_t = C_1 + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{i=1}^{p} \alpha_i X_{t-i} + \rho ECT_{t-1} + u_t \tag{5}$$

$$\Delta X_t = C_2 + \sum_{i=1}^{p} \gamma_i X_{t-i} + \sum_{i=1}^{p} \zeta_i Y_{t-i} + \eta ECT_{t-1} + \varepsilon_t \tag{6}$$

where X and Y are (I(1)) variables, ρ, η are adjustment coefficients, ECT_{t-1} represents the error correction term derived from the residuals of the cointegration relationship.

In equation (5), X Granger-causes Y if α_i, ρ are significantly different from zero. In equation (6), Y Granger-causes X if ζ_i, η are significantly different from zero.

4. Empirical Results and Discussions

4.1. Exploratory and Stationarity Analysis of Time Series Used in Research

Figure no. 2 depicts monthly net electricity production measured in gigawatt-hours (GWH) by energy sources, covering an extended period of 7 years. We observe significant variability in electricity production from month to month and across different energy sources.

Fortunately, coal is increasingly less utilized in electricity production, with generation decreasing from 1200 GWH in 2017 to just over 400 GWH in 2024, while natural gas usage has slightly increased over these 7 years, averaging close to 700 GWH. Regarding renewable energy sources, wind and hydroelectric power have seen slight increases, whereas nuclear and solar energy have fluctuated around 0.2 GWH monthly decreases.

Detailed analysis of these data can provide a solid foundation for developing and implementing energy policies, as well as making strategic decisions regarding the energy mix, aimed at more sustainable and resource-efficient energy solutions.

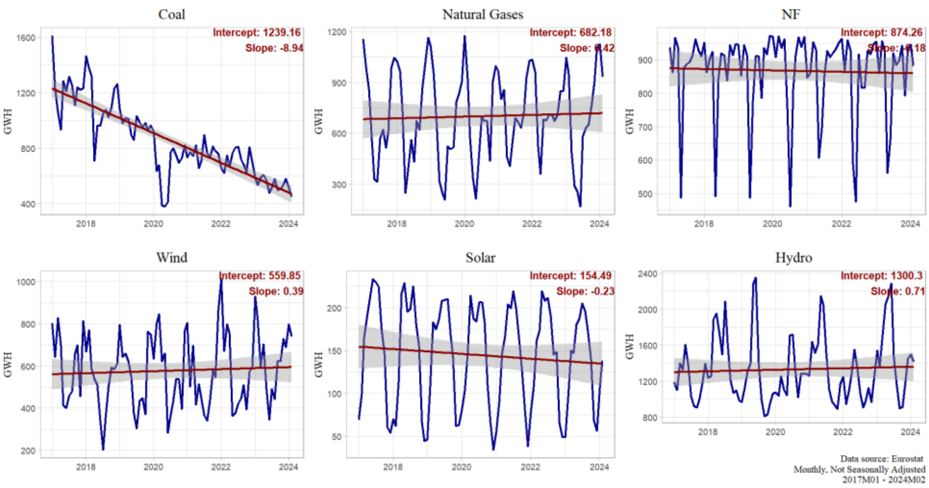

Figure no. 2: Monthly Net Electricity Production

Source: Own processing in R

Energy derived from coal combustion exhibits minor variations from month to month, similar to nuclear energy, which typically remains unaffected by seasonal fluctuations, except for special cases such as maintenance work. The lowest amount of nuclear energy is generated in the months of May and June. Natural gas-based energy is produced in smaller quantities in the second quarter of each year due to the depletion of stocks during winter, with the highest amounts produced during December and January (Figure no. 3).

Throughout the year, electricity production from renewable sources such as wind, solar, and hydroelectric power experiences significant variations. In the months of May to August, wind and solar energy reach high levels due to strong winds and long sunny days, while hydroelectric power benefits from snowmelt and spring and summer rains. However, during the periods of November to February and September to December, wind and solar energy production decreases due to shorter days and less favorable weather conditions, while hydroelectric power may be affected by reduced precipitation and less snowmelt. These seasonal variations in electricity production are essential for planning and managing energy systems, ensuring balance between energy supply and demand throughout the year (Figure no. 3). Therefore, the seasonal component was removed using the Tramo Seats method.

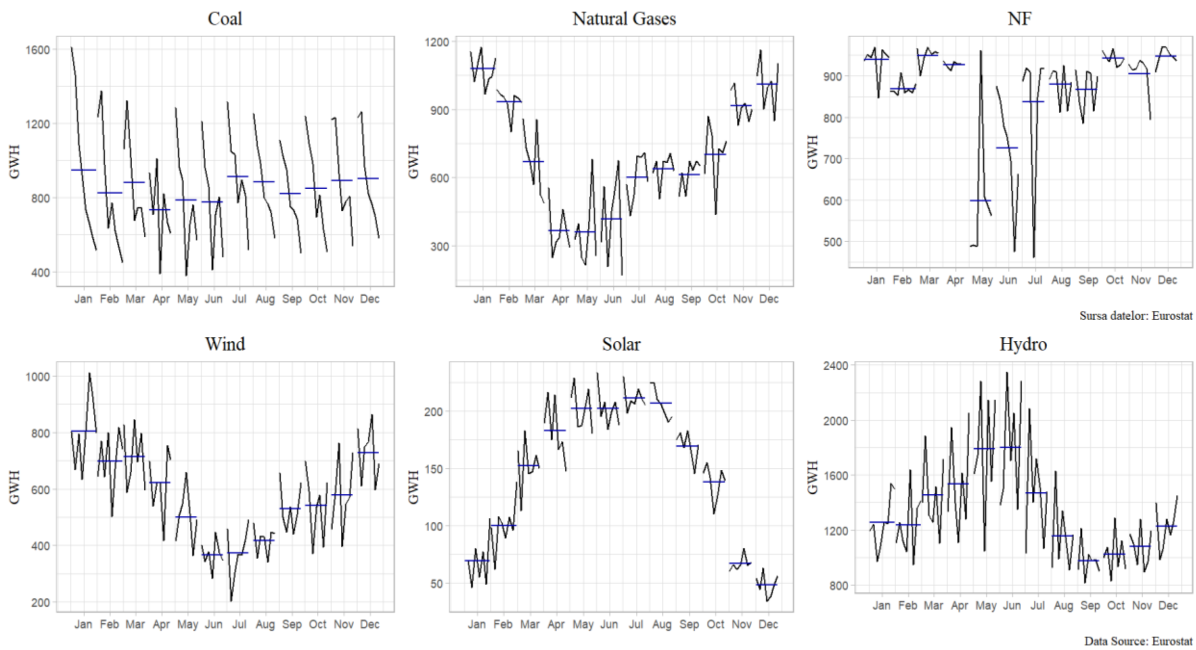

Figure no. 3: Seasonality of Energy Production

Source: Own processing in R

Table no. 1 presents the results of Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron (PP) stationarity tests for the 6 energy sources (coal, natural gas, nuclear, wind, solar, and hydroelectric). These tests are used to assess whether a time series is stationary or not. For each energy source, the table shows the test statistics values (ADF and KPSS) and their associated p-values (PP). Additionally, critical values for α=0.01 are included. According to PP, all series are stationary, while ADF and KPSS tests indicate that only the Coal series is non-stationary at a significance level of α=0.01. Therefore, the Coal series was differenced at lag 1, making all series stationary according to ADF (t-statistic=-8.09; 21.91; 32.85), KPSS (t-statistic=0.07), and PP (p-value=0.01).

Table no. 1: Stationarity Tests

	ADF			KPSS	PP
	t-statistic (tau; phi2; phi3)			t-statistic (tau; phi2; phi3)	p-value
Coal	-3.62	4.79	6.56	1.8951	0.01
NG	-5.26	9.25	13.87	0.0654	0.01
NF	-9.15	27.93	41.89	0.1574	0.01
Wind	-6.52	14.16	21.24	0.1803	0.01
Solar	-4.43	6.85	10.20	0.2865	0.01
Hydro	-4.64	7.19	10.77	0.1139	0.01
	t-critic (α=0.01)			t-critic (α=0.01)	
	-4.04	6.5	8.73	0.739	
Total Observations (N:) 86					

Source: Own processing in R

Since the series are not integrated at the same order, i.e., Coal is I(1) and the rest are I(0), a VAR model will be applied, as the series are not cointegrated in the Johansen sense. In the VAR model, the Coal variable is differenced at the first lag. Lag selection for the VAR model was conducted using specific tests. AIC, HQ, and FPE indicate that lag 2 is optimal, while SC suggests lag 1. Therefore, lag 2 was chosen for the model.

4.2. Estimating VAR Models

Detailed Analysis of the VAR Model Equations (Table no. 2) reveals complex interactions among different energy sources. Initially, a model incorporating all six variables (thermal, natural gas, nuclear, wind, solar, and hydroelectric energy) was estimated. However, the hypotheses for this model were invalidated. Consequently, through a recursive and iterative approach, multiple models were estimated to improve validity. The optimal model that will be presented was selected based on the goodness of fit and the validity of its underlying assumptions.

For the Hydro variable, we observe that the coefficient for hydroelectric power production at lag 1 is positive (0.705, $p < 0.01$), indicating a strong correlation between current and previous month's production. This suggests persistence in hydroelectric production, crucial for forecasting and resource management planning. Additionally, the significant negative coefficient for solar energy at lag 1 (-5.494, $p < 0.01$) suggests an inverse relationship between hydroelectric and solar energy production, indicating a compensatory effect between these two energy sources.

Regarding the Solar variable, the coefficient associated with solar energy production at lag 1 is positive and significant (0.367, $p < 0.01$), indicating a strong correlation between current and previous month's production. This finding underscores persistence in solar energy production, highlighting that past trends significantly influence current production. This is particularly relevant for short-term planning of solar resource utilization, anticipating both demand and supply of solar energy. Furthermore, the negative coefficient associated with thermal energy production at lag 2 (-0.036, $p < 0.05$) suggests an inverse relationship, indicating that an increase in thermal energy production in one month is associated with a corresponding decrease in solar energy production in the following month. Thus, it appears that these two energy sources operate in tandem, an important consideration in energy planning strategies and assessing environmental impact.

In the equation for the NF variable (nuclear fuels), the negative coefficient for nuclear energy production at lag 2 suggests a strong correlation between current production and that from two months prior. Additionally, an increase in thermal energy production in one month leads to a decrease in nuclear energy the following month.

For the Coal variable, we observe that the coefficient for nuclear energy production at lag 2 is significantly positive (0.283, $p < 0.05$), indicating a significant influence of nuclear energy production from two months prior on thermal energy production.

The intercepts in the VAR model provide information about the production level of each energy source in the absence of influences from other variables in the system. In this model, the constants for Hydro, Solar, NF (nuclear fuels), and Coal indicate the estimated production of hydroelectric, solar, nuclear, and coal energy when other variables are zero or have no influence on them. For instance, the intercept for solar energy suggests that, in the absence of other influences, the estimated production of solar energy would be around 95,020 GWH. These values can serve as a baseline to understand each source's contribution to total electricity production and aid in assessing the impact of changes in explanatory variables on energy production.

The VAR model is evaluated based on its coefficients of determination (R-squared and Adjusted R-squared), residual standard error, and F-statistics. The coefficients of determination range from 0.186 to 0.540, indicating moderate to good coverage of data variance by the model. The residual standard error is low, ranging between 13.383 and 174.429, suggesting a good fit of the model to the observed data. The F-statistics are significant for all equations, indicating overall model significance. In conclusion, these results suggest that the VAR model performs well.

Table no. 2: VAR Model Results (p=2)

	Hydro	Solar	NF	Coal
Hydro.l1	0.705*** (0.117)	0.022** (0.009)	-0.046 (0.047)	0.038 (0.06)
Solar.l1	-5.494*** (1.513)	0.367*** (0.116)	1.188* (0.602)	1.426* (0.768)
NF.l1	0.166 (0.287)	-0.02 (0.022)	-0.03 (0.114)	-0.086 (0.146)
Coal.l1	-0.077 (0.229)	0.011 (0.018)	-0.327*** (0.091)	-0.135 (0.116)
Hydro.l2	-0.078 (0.109)	-0.019** (0.008)	0.064 (0.043)	-0.009 (0.055)
Solar.l2	3.216* (1.85)	0.157 (0.142)	0.385 (0.736)	-1.302 (0.94)
NF.l2	0.322 (0.251)	-0.014 (0.019)	-0.368*** (0.1)	0.283** (0.128)
Coal.l2	0.555** (0.227)	-0.036** (0.017)	-0.115 (0.09)	-0.152 (0.115)
const	415.849 (516.33)	95.020** (39.614)	953.776*** (205.4)	-239.09 (262.294)
R2	0.54	0.221	0.347	0.186
Adjusted R2	0.491	0.137	0.276	0.098
Resid. Std. Error (df=74)	174.429	13.383	69.389	88.61
F Statistic (df=8; 74)	10.872***	2.631**	4.905***	2.119**
Total Observations (N)	86	86	86	86
Note:		*p<0.1	**p<0.05	***p<0.01

Source: Own processing in R

4.3. Testing hypotheses on residuals of the identified optimal model

Residual diagnostics were based on autocorrelation analysis using the Portmanteau test, which yielded a calculated chi-squared of 135.62 (p-value=0.9194), indicating that errors are not autocorrelated. The ARCH test for homoscedasticity calculated a chi-squared of 710 (p-value=0.99), accepting the null hypothesis that errors are homoscedastic. Finally, the normality hypothesis was tested using the Jarque Bera test, resulting in a chi-squared of 240.98 ($p<0.05$), indicating that errors are not normally distributed.

Furthermore, an empirical fluctuation process based on a generalized framework for testing fluctuations was used to assess model stability (Figure no. 4). While significant structural changes could have indicated the need for model adjustments or revisions, the results show no significant structural changes, indicating model stability.

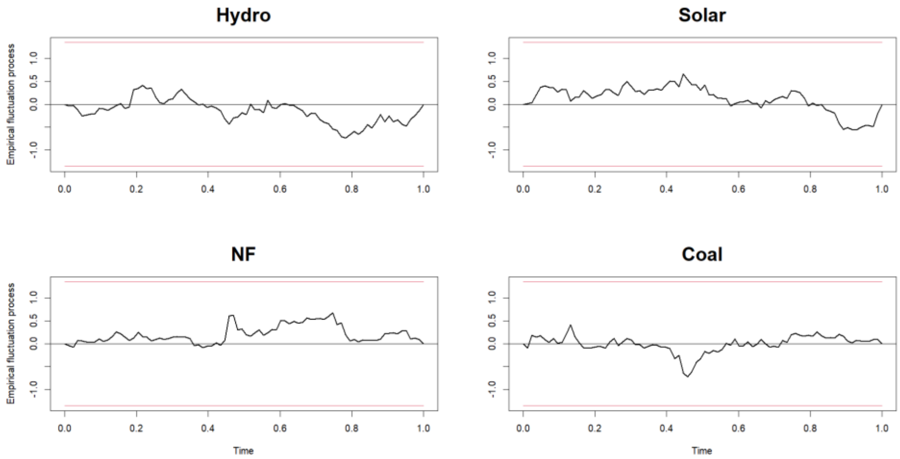

Figure no. 4: Model Stability

Source: Own processing in R

4.4. Causality analysis among different energy sources

Causality Granger analysis indicates the influence relationships among the variables in the VAR model. For the Hydro variable, the test suggests that there is no significant influence on the Coal, NF, and Solar variables, as the p-value (0.122) is greater than the significance level of 0.1. However, for the Solar variable, the results show a significant influence on the Coal, Hydro, and NF variables, with a p-value of 0.0002356, which is lower than the significance level. Additionally, for the Coal variable, the test indicates significant influence on the NF, Hydro, and Solar variables, whereas for the NF variable, there is no significant influence on the other variables. Thus, the Solar variable, followed by Coal, appears to be the most influential in the model, while the other variables do not significantly influence each other.

Impulse response functions (Figure no. 5) analyze the dynamic impact of changes on the input variables. In the current analysis context, these functions are crucial for understanding how the system reacts to exogenous changes. They allow us to strategize and evaluate the consequences of specific energy policies.

There is a rapid decline in solar and nuclear energy production in response to thermal energy production shocks, which is short-lived. In the immediate subsequent periods, both energy sources experience increases, and over the following periods up to one year, the impulse response functions stabilize. As for hydroelectric energy response, it shows an initial positive shock in the first few months, gradually decreasing until the fifth month. The response of thermal energy production initially shows no change but is followed by an increase and then a decline, ultimately stabilizing after approximately 10 months.

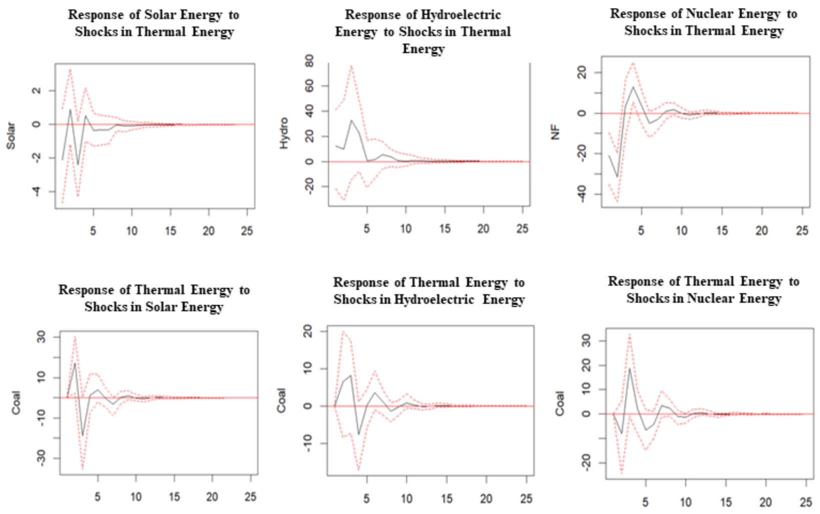

Figure no. 5: Impulse Response Functions

Source: Own processing in R

Figure no. 6 illustrates the decomposition of forecast variance errors. Thus, in the initial period, over 95% of the variance in hydroelectric, solar, and nuclear energy production comes from their own shocks. In the second period, 10% of the variance in hydroelectric energy comes from solar energy, 10% of solar energy variance comes from its own shocks, and 5% from thermal energy. Approximately 25% of nuclear energy variance, starting from the second period, comes from shocks in other energy sources.

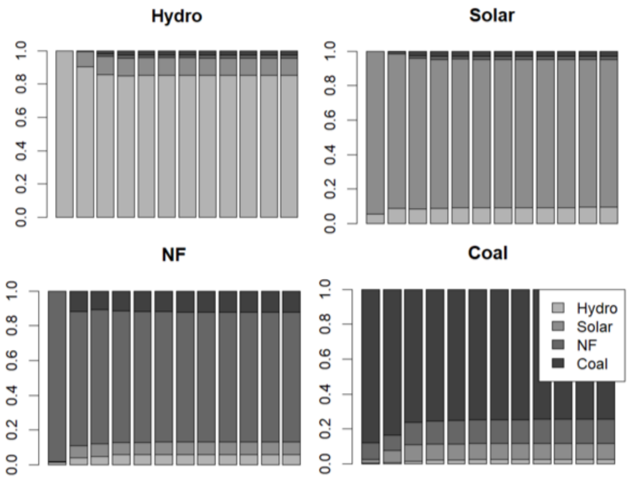

Figure no. 6: Forecast Error Variance Decomposition (FEVD)

Source: Own processing in R

4.5. Forecasting Energy from Different Types of Sources

Figure no. 7 shows the final forecasts of the 4 variables used. It can be observed that the production of thermal and nuclear energy remains approximately constant, while the production of hydroelectric and solar energy decreases in the following months.

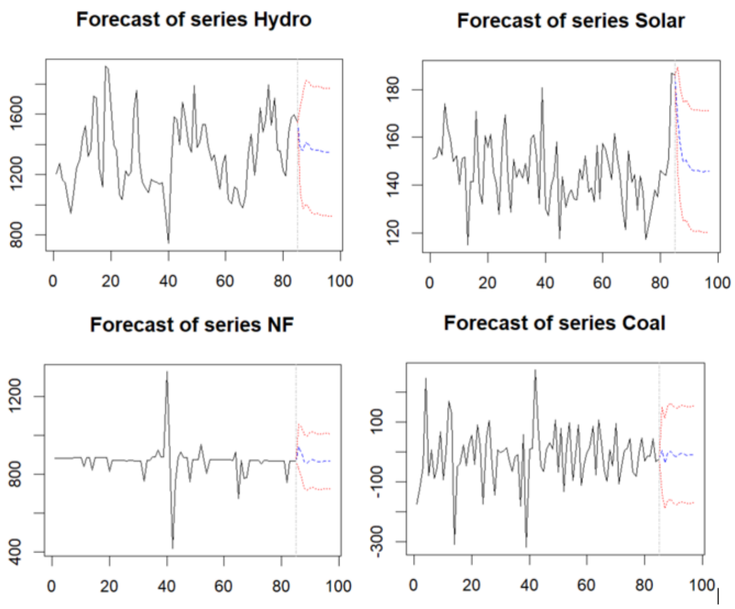

Figure no. 7: VAR Forecast

Source: Own processing in R

In conclusion, the developed VAR model provides a detailed perspective on the dynamics of electricity production from various sources. The time series analysis over the 7-year period reveals significant variations in monthly net electricity production, highlighting trends and changes in the use of different energy sources. Particularly, coal usage in electricity production has decreased significantly, while energy from renewable sources has experienced minor fluctuations.

Regression coefficients indicate nearly constant hydroelectric and solar energy production, as well as inverse relationships between thermal energy and solar or nuclear energy production. Granger causality tests highlight the significant impact of solar and thermal energy. A thorough diagnostic was conducted to confirm the model's ability to detect data variations. Additionally, heteroscedasticity and autocorrelation in residuals are absent.

The decomposition of forecast variance errors, final predictions, and impulse response functions provide a comprehensive view of how different variables in the energy system interact with each other.

The results of this research are consistent with and build upon previous studies in Romania's energy sector. In particular, there was a decrease in the energy produced from coal and a slow but steady increase of renewable energy sources over the 7 year period, which is in line with Romania’s commitments on EU energy targets. For instance, studies highlight Romania's achievement as the first European country to meet its renewable energy target by 2015, five years ahead of the 2020 deadline (Cîrstea et al., 2018).

Several studies have noted Romania’s dependence on natural gas, oil, and nuclear energy, and how they were important for the energy mix used for electricity generation. This is consistent with our findings where natural gas has a constant level of production while renewable wind and hydropower sources fluctuate. The previous literature (Cîrstea et al., 2018) also pointed out that hydropower accounts for about 30% of total electricity output, which correlates rather closely with the persistence of electric energy provided by hydropower that we estimated using the VAR model.

Our causality analysis reveals the influential role of solar energy, which resonates with Romania's emerging focus on photovoltaic development noted in earlier research (Cîrstea et al., 2018). Despite the significant drop in solar installations after the phase-out of incentives, our study shows that solar energy remains a critical component of Romania's energy future.

The findings of this study provide a comprehensive understanding of the dynamics and interdependencies among various energy sources in Romania. The results highlight significant trends, such as the decreasing reliance on coal and the growing contribution of renewable energy sources like wind and solar. These trends align with Romania's commitment to transitioning toward a more sustainable energy system. Importantly, Dumitraşcu et al. (2019) suggest that Romania is on track to meet its 2030 renewable energy targets, with an increasing focus on wind and solar power.

5. Conclusions

This study provides a comprehensive analysis of Romania's progression towards renewable resources, highlighting interdependences between energy sources using a Vector Autoregressive model. Findings revealed a notable decrease in coal usage, offset by a gradual rise in renewable alternatives such as solar and wind power, which positively impact the energy portfolio through reliance reduction on fossil fuels. Key insights comprise the persistence of hydroelectric and photovoltaic energy generation and inverse relationships between thermal and solar or nuclear energy, underscoring renewables' potential to diminish fossil fuel dependency.

The study's results indicate important policy directions for boosting Romania's energy sustainability. Policymakers are encouraged to prioritize investments in renewable infrastructure, with special focus on solar and wind energy, considering their substantial influence within the energy mix. Policies should also promote technological innovations to improve efficiency and stability in renewable production. Additionally, establishing a stable regulatory environment could attract further investment in green energy, ensuring the transition aligns with EU climate goals. Romania could consider adopting incentives for renewable adoption, such as subsidies for solar installations or tax benefits for renewable investments.

While the study provides valuable insights, some limitations must be noted. First, the examination relies on data that may not capture recent shifts in energy policies or technological advancements. The study also does not include specific regional variations within Romania, which could influence renewable adoption rates and outcomes.

Future research could build upon these findings by incorporating recent data and considering alternative modelling approaches, such as machine learning techniques, to enhance predictive precision. Expanding the study to include a regional analysis within Romania may reveal more targeted policy needs and opportunities. Finally, examining the socioeconomic impacts of energy transitions could provide a holistic view of the benefits and challenges associated with the shift to renewable energy, helping to align energy policies with broader social and economic goals.

Acknowledgements

The research study was elaborated within the Business Economics Data Science Lab of the Bucharest University of Economic Studies, within the project "Analysis of the economic recovery and resilience process in Romania in the context of sustainable development - REDER," contract no. 1353/10.06.2024.

References

Cavalcante, L. and Bessa, R. (2017). Solar power forecasting with sparse vector autoregression structures, 2017 IEEE Manchester PowerTech, pp.1-6. doi: 10.1109/PTC.2017.7981201.

Cavalcante, L., Bessa, R.J., Reis, M. and Browell, J. (2016). 'LASSO vector autoregression structures for very short-term wind power forecasting', Wind Energy, 20, pp.657–675. doi: 10.1002/we.2029.

Charfeddine, L. and Kahia, M. (2019). Impact of renewable energy consumption and financial development on CO2 emissions and economic growth in the MENA region: A panel vector autoregressive (PVAR) analysis, Renewable Energy, 139, pp.198-213. doi: 10.1016/j.renene.2019.01.010.

Ciocirlan, C., & Nițoi, M. (2022). Policy complementarity: major fiscal and monetary announcements during the pandemic. Applied Economics Letters, 31(6), 530–534. https://doi.org/10.1080/13504851.2022.2140102.

Cîrstea, Ş. D., Martiş, C. S., Cîrstea, A., Constantinescu-Dobra, A., & Fülöp, M. T. (2018). Current Situation and Future Perspectives of the Romanian Renewable Energy. Energies, 11(12), 3289. https://doi.org/10.3390/en11123289

Colesca, S. and Ciocoiu, C. (2013). An overview of the Romanian renewable energy sector, Renewable & Sustainable Energy Reviews, 24, pp.149-158. doi: 10.1016/j.rser.2013.03.042.

Davidescu, A., Popovici, O., and Strat, V. (2022). Estimating the impact of green ESIF in Romania using input-output model, International Review of Financial Analysis, 84, p.102336. doi: 10.1016/j.irfa.2022.102336.

Dumitraşcu, M., Grigorescu, I., Micu, D., Mocanu, I., Vrînceanu, A., Mitrică, B., Havriş, L., Şerban, P., Dumitrică, C. and Kucsicsa, G., (2019). Renewable energy, climate change and environmental challenges in Romania, 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), Bucharest, Romania, pp.1-5. doi: 10.1109/ISGTEurope.2019.8905552.

Elliott, D. (2000). Renewable energy and sustainable futures, Futures, 32, pp.261-274. doi: 10.1016/S0016-3287(99)00096-8.

Harjanne, A. and Korhonen, J. (2019). Abandoning the concept of renewable energy, Energy Policy. doi: 10.1016/j.enpol.2018.12.029.

Hinrichs-Rahlwes, R. (2013). Renewable energy: Paving the way towards sustainable energy security, Renewable Energy, 49, pp.10-14. doi: 10.1016/j.renene.2012.01.076.

Jung, A., Lee, D., Kim, J., Kim, C., Kim, H., & Lee, Y. (2022). Regional Photovoltaic Power Forecasting Using Vector Autoregression Model in South Korea, Energies. doi: 10.3390/en15217853.

Kabeyi, M.J.B. and Olanrewaju, O.A. (2022). Sustainable energy transition for renewable and low carbon grid electricity generation and supply, Frontiers in Energy Research, 9, p.743114. doi: 10.3389/fenrg.2021.743114.

Marinescu, N. (2020). Changes in renewable energy policy and their implications: The case of Romanian producers, Energies. doi: 10.3390/en13246493.

Mihăilescu, L. (2009). 'Wind power in Romania', Renewable Energy Focus, 10, pp.44-46. doi: 10.1016/S1755-0084(09)70153-X.

Qazi, A., Hussain, F., Rahim, N., Hardaker, G., Alghazzawi, D., Shaban, K., & Haruna, K. (2019). Towards Sustainable Energy: A Systematic Review of Renewable Energy Sources, Technologies, and Public Opinions, IEEE Access, 7, pp.63837-63851. doi: 10.1109/ACCESS.2019.2906402.

Răboacă, M.S., Năsture, A. and Corbu, A. (2020). SWOT of renewable energy sources in Romania, 2020 12th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), pp.1-4.

Radovanović, M., Filipović, S. and Andrejević Panić, A. (2021). Sustainable energy transition in Central Asia: status and challenges, Energy, Sustainability and Society, 11, p.49. doi: 10.1186/s13705-021-00324-2.

Resch, G., Held, A., Faber, T., Panzer, C., Toro, F. and Haas, R. (2008). Potentials and prospects for renewable energies at global scale, Energy Policy, 36, pp.4048-4056. doi: 10.1016/j.enpol.2008.06.029.