Navigating the Path to Sustainability: Modeling Romania's Energy Transition with AI and Econometrics

Andrei PISICĂ
Bucharest University of Economic Studies, Bucharest, Romania
pisicaandrei19@stud.ase.ro

Marina-Diana AGAFIȚEI*
Bucharest University of Economic Studies/National Scientific Research Institute for Labour and Social Protection, Bucharest, Romania
**Corresponding author, diana.agafiei@csie.ase.ro*

Eduard-Mihai MANTA
Bucharest University of Economic Studies, Bucharest, Romania
eduard.manta@csie.ase.ro

Abstract. *This paper focuses on Romania and its transition to a sustainable energy model within the framework of global efforts to address climate change and foster economic modernisation. Although Romania has a broad energy mix, which includes hydro, wind, and solar resources with considerable potential for application for renewable energy, there are still challenges, particularly through reliance on fossil fuels and climate vulnerabilities. The research uses Fractional Multinomial Logistic Models (FMNL) and Recurrent Neural Networks (RNNs) to analyse relationships between energy production, GDP per capita, and input coefficients between different economic sectors. The research investigates the impact of energy sources on economic structures, the predictive accuracy of advanced models, and policy strategies for optimising Romania's energy transition. The findings reveal a projected shift toward low-carbon, technology-driven industries by 2031, facilitated by renewable energy integration. The results highlight the importance of investments in green infrastructure, energy network modernisation, and support for emerging industries. This research provides actionable insights for policymakers and stakeholders, emphasising Romania's potential to lead regional sustainability efforts. The research contributes to broader discussions on energy sustainability and economic resilience in the context of global environmental challenges by emphasising the significance of advanced modelling techniques.*

Keywords: sustainable energy transition, renewable energy integration, econometric and AI modelling, energy policy optimisation, Romania energy strategy

Introduction

The planet's health is intricately linked to its biodiversity and biosphere stability. Through industrial activity or energy use, human efforts often upset this balance, creating consequences that can be widespread and even permanent. The biosphere is a complex adaptive system with highly interconnected ecosystem interactions. Climate change, caused by the emission of greenhouse gases, is a clear example of this complexity through feedback loops where the melting of ice caps releases methane and carbon dioxide, which increase global warming. Resolving these issues demands a comprehensive view that takes into consideration the complex interconnections of natural systems.

Transitioning to sustainable energy systems is a critical step in mitigating the impacts of climate change and ensuring environmental resilience. Such a transition is especially important for

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Romania, which is vulnerable to climate change-related phenomena, including altered precipitation patterns, extreme weather, and increasing temperatures. These phenomena affect critical sectors, including agriculture, infrastructure, and public health, necessitating innovative and sustainable solutions. Despite these challenges, Romania's diverse energy resources, including hydro, wind, and solar potential, position it as a candidate for leadership in renewable energy adoption.

This study investigates the dynamics of Romania's energy transition by addressing the following research questions:

1. How do different energy sources interact with economic sectors during the transition to sustainability?
2. Can advanced econometric and artificial intelligence models provide more accurate energy input coefficient predictions than traditional methods?
3. What strategies and policies can optimise Romania's energy transition while minimising socio-economic disruptions?

The study addresses these questions by using fractional multinomial logistic models and recurrent neural networks to analyse interdependencies between energy production and socio-economic factors. This approach offers a novel perspective on optimising Romania's energy policies and identifying pathways toward a low-carbon, sustainable future.

By bridging theoretical frameworks with empirical evidence, this research contributes to global conversations around sustainable energy transitions and provides actionable insights for policymakers and stakeholders hoping to deliver a greener, more resilient economy.

The paper is organised as outlined: The Literature Review synthesises research into studies of sustainable energy transitions to identify gaps and provide context for this research. In what follows, the Data and methodology section provides an overview of the econometric and AI models used (Fractional Multinomial Logistic Models and Recurrent Neural Networks) as well as data sources and framework. Section 4 presents the Results and Discussion, which analyses findings about the impact of the energy mix on economic sectors and discusses some of the policy implications. The Conclusion presents contributions, limitations, and future research directions. These include tables, figures and appendices to simplify complex data and results.

Literature review

The shift towards sustainable energy systems has emerged as an essential research focus as nations globally strive to combat climate change and lessen reliance on fossil fuels. Like numerous other countries, Romania confronts the urgent issue of decreasing greenhouse gas emissions. Pisică et al. (2024) utilised a Vector Autoregressive (VAR) model to investigate Romania's renewable energy potential and the dynamic relationships between energy sources. Their research underscores the significance of solar and hydroelectric energy in decreasing dependence on fossil fuels and stresses the necessity of green infrastructure and innovation for attaining lasting sustainability. This effort entails tackling intricate interrelationships among economic systems, policy structures, technological innovations, and ecological sustainability. Recent studies have provided valuable insights into various aspects of this transition, from analysing historical energy shifts and policy impacts to exploring the potential of advanced modelling techniques and artificial intelligence in shaping energy strategies.

Solomon and Krishna (2011) investigated the transition to sustainable energies, combining a review of previous energy transitions with the analysis of three modern case studies from Brazil, France, and the United States, identifying critical factors influencing the transition process. Sgouridis et al. (2013) integrated techno-economic assessment into an energy model to examine pathways to sustainable energy sources, providing a solid foundation for decision-making processes regarding energy transition.

Ponta et al. (2018) examined the impact of tariff policies on the transition to a sustainable energy system, highlighting how these policies can influence both the course and speed of the transition. Dominković et al. (2018) provided a detailed analysis of available options for fossil fuel systems, also assessing the impact of these options on energy transition. Transition scenarios to renewable energy in South Korea were developed by Hong et al. in 2019, highlighting a variety of opportunities and providing a platform for policy analysis and planning towards sustainable energy transition in the nation.

According to a 2019 study by Nieto et al., achieving ER2050 targets could lead to stagnation in economic growth and job creation in Europe despite significant improvements in energy efficiency. Their MEDEAS model highlighted differences between resource sustainability, climate policy, and economic growth, suggesting that economic policies should focus on redistribution and more energy-efficient industrial policies.

Radovanović, Filipović, and Panić (2021) analysed energy transition in Central Asia, finding it at a low level and lacking sustainability, requiring adequate regulatory frameworks and monitoring of natural resources and the region's geopolitical position. Tovar-Facio, Martín, and Ponce-Ortega (2021) highlighted similar issues and proposed solutions for sustainable management of waste generated by new energy technologies.

Additionally, Uhunamure and Shale (2021) emphasised the significant potential of renewable energy sources in South Africa and proposed policies to support their development, such as actions to strengthen political stability and combat corruption.

Finally, Kabeyi and Olanrewaju (2022) presented an approach to sustainable energy transition, emphasising energy savings, increased production efficiency, and the adoption of low-carbon nuclear and renewable energy sources as essential for reducing greenhouse gas emissions and stopping the increase in average global temperatures.

There are also numerous studies addressing the use of artificial intelligence in the realm of sustainable energy. Maithani, Jain, and Arora (2007) proposed developing an artificial neural network-based model for simulating urban growth, using remote sensing and GIS data to simulate urban growth in Saharanpur City, Uttar Pradesh. Stecuła, Wolniak, and Grebski (2023) conducted a literature review to evaluate the role of artificial intelligence in energy-related solutions, categorising publications by their application domains and highlighting AI's extensive uses in residential solutions and urban infrastructure for improving infrastructure for electric vehicles and reducing car emissions, while also emphasising associated challenges such as balancing residential comfort with energy efficiency and managing renewable sources.

In recent years, integrating Input-Output (IO) analysis with Sustainable Energy Transition (SET) has become an increasingly important and relevant research area. By integrating these two fields, researchers explore complex interactions between economy and energy, assessing the impact of energy policies, identifying efficiency opportunities, and promoting renewable energy sources. Among these valuable studies is the one by Guevara, Rodrigues, and Domingos (2015), who introduced the PF-EIO model, providing a detailed description of energy flows in the economy and characterising energy production as a function of eight variables. This new energy input-output model represents a significant advancement over conventional models, enabling the assessment of trends in energy decoupling, energy use, and energy efficiency in the economy.

Zhang et al. (2019) proposed a hybrid static and dynamic Input-Output method (CSDHI/O) for forecasting embodied energy in construction services in China, estimating it would reach 1.79

billion tons of coal equivalent in 2020. Their analysis shows that improving manufacturing levels is crucial for conserving both TPEC and EECS. Vats, Sharma, and Sandu (2021) used Input-Output models to analyse connections between energy, water, and food (EWF) in India, developing an extended Leontief model to evaluate technological and policy interventions related to EWF. Evaluated policy scenarios show that an EWF-oriented approach brings significant long-term benefits in economic, social, and ecological domains.

Finally, Wimmer et al. (2023) used a fractional econometric panel data model to predict the energy mix and input structures of energy sectors in Austria, using data from 26 European countries, indicating that the input percentage from the energy sector itself will remain high, while inputs from the mining sector will decrease, and the increasing share of renewable energy sources will accompany a significant decrease in the input percentage in the workforce.

Data and methodology

The data used in this study was extracted from multiple sources, including websites of several official statistics providers such as Eurostat and the National Institute of Statistics (INS).

Fractional Multinomial Logistic Model (FMNL)

The FMNL model uses input coefficients as dependent variables and the energy mix: Nuclear (nuclear energy), Hydro (hydroelectric energy), Wind (wind energy), Solar (solar energy), Coal (thermoelectric energy), Gas (natural gas-based energy), and Oil (fossil energy); along with GDP per capita (GDPc) as independent variables, also collected from the Eurostat website. The entire modelling process is described in Figure 1. The final dataset comprises 300 observations, representing 25 out of 27 European Union (EU) countries, excluding Cyprus and Malta, due to the unavailability of several data points over 12 years, from 2010 to 2021.

The input coefficients come from the FIGARO tables (Full International and Global Accounts for Research in Input–Output analysis) from Eurostat, which connect EU countries across 64 industries according to NACE Rev. 2. As a first step, we aggregated input coefficients at the sector level for each year, treating all inputs equally. Due to computational limitations, we aggregated the 64 sectors into 7 sectors plus a value-added component (Table 1 appendix). The analysis focuses on the monetary values and value-added of inputs from sector D35, "electricity, gas, steam, and air conditioning supply," simply referred to as the energy sector. Finally, the values were converted into weights that sum up to 1.

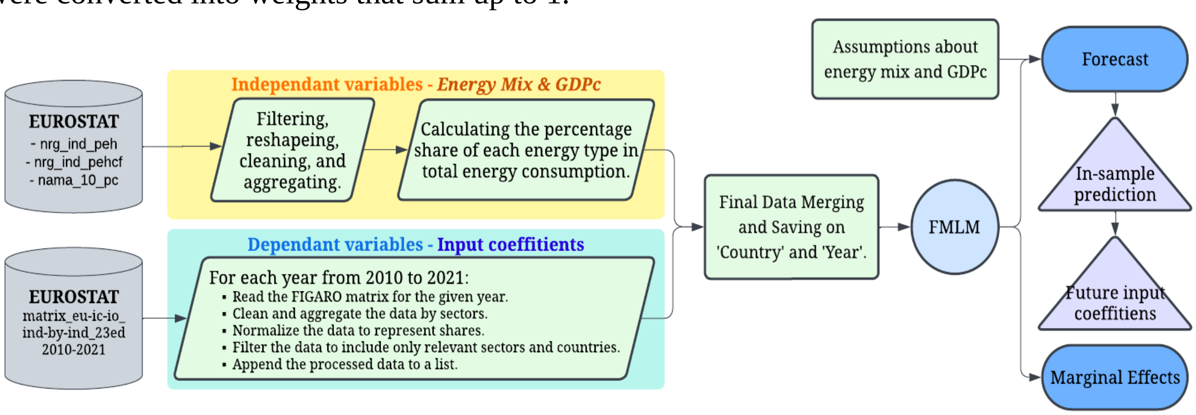

Figure 1. Diagram of Fractional Multinomial Logistic Model

Source: Adaptation in Lucidchart after Wimmer et al. (2023).

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Since the analysis targets sector D35 as a whole, the energy mix must include the energy used for producing electricity and steam (heat). The data for the energy mix come from the Eurostat energy statistics database: nrg_ind_peh and nrg_ind_pehcf, concerning the gross production of electricity and heat from major producers for each energy product. We aggregated the data published according to the Standard International Energy Product Classification into the most important 7 energy products. The rest includes energy from geothermal sources, tides, waves, ocean, heat pumps, heat from chemical sources, etc.

To predict Romania's input coefficients for 2031, we forecasted an energy mix for 2031 based on classic linear regression models (Figure 2). We used these assumptions in the fractional multinomial logistic model, with the final goal of predicting the input coefficients.
Regarding GDP per capita (GDPc), based on data provided by the OECD, we calculated a GDP per capita growth of 38% in 2031 compared to 2021. In the FMNL model, GDPc was standardised $\left(\frac{x_i-\bar{x}}{s_x}\right)$. After applying the previously calculated growth coefficient, we standardised the prediction using the same mean and standard deviation calculated across all 300 observations.

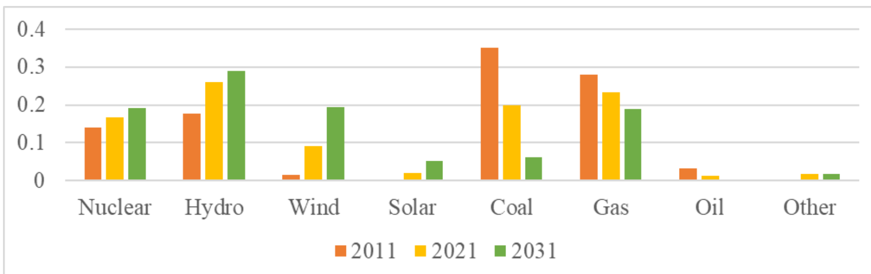

Figure 2. Transition of Energy Mix

Source: Processing done using R 4.1.1. and Excel.

The fractional model is used to model the j-th input coefficient from the energy sector for a specific country and a specific year, Y_i, based on the energy mix and GDPc X_i from the same year and country, taking into account all other input coefficients $y_{i,-j}$, excluding the one being modelled. This problem can be formalised as follows:

$$y_{ij} = f\left(X_i, y_{i,-j}\right) \tag{1}$$

where $f(\cdot)$ is an unspecified function. The model must ensure that $0 \leq y_{ij} \leq 1$ and that the sum of all input coefficients is equal to 1. To estimate this relationship, we use the FMNL model, which extends the approach of Papke and Wooldridge (1996) for binary fractional response variables to a multinomial context.

Given I observations, we assume:

$$E\left(y_{ij} \middle| x_i\right) = G\left(X_i \beta_j\right) \tag{2}$$

where y_{ij} is the fraction j for the observation i, X_i is a vector of K independent variables, and β_j is a vector of K regression coefficients.

The function $G(\cdot)$ must lie between 0 and 1 (equation 3). The binomial logistic function is used for binary responses, and the multinomial logistic function is used for multinomial responses:

$$G\left(X_i \beta_j\right) = \frac{e^{X_i \beta_j}}{1 + \sum_{m=2}^{M} e^{X_i \beta_m}} \tag{3}$$

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The multinomial likelihood function is:

$$\ln(L_i) = \sum_{m}^{M} y_{im} \ln G(X_i \beta_m) \quad (4)$$

The parameters are estimated using:

$$\hat{\beta}_m = argmax_{\beta_m} \sum_{i=1}^{I} \ln(L_i) \quad (5)$$

The interpretation of the coefficients in the FMNL model requires calculating marginal effects (ME), similar to coefficients in classic linear models. Estimations were conducted in R using the fmlogit package.

Key references for this model include the works of Papke and Wooldridge (1996), Ramalho et al. (2011), Wulff et al. (2015), and Wimmer et al. (2023).

To improve results, errors from FMNL were extracted and used as dependent variables in a classic Artificial Neural Network (ANN). This approach helped capture nonlinear relationships that the initial model did not capture. Predictions from the FMNL model were combined with ANN predictions to obtain the final predictions of the FMNL+NN model, resulting in the best outcomes.

Classic Artificial Neural Networks (ANNs) are machine learning models inspired by the structure and function of the human brain, consisting of layers of artificial neurons. Each neuron receives weighted inputs, applies an activation function, and transmits its output to neurons in the next layer. ANNs are typically organised into three types of layers: the input layer, where raw data is introduced; one or more hidden layers, where computations and significant transformations occur; and the output layer, where the final result of the network is obtained. Training an ANN involves adjusting weights through an iterative learning process using techniques like backpropagation and stochastic optimisers to minimise the error between the network's predictions and actual values. Thus, ANNs learn to recognise and model complex relationships in input data, enabling precise predictions or efficient classifications. A key reference for these networks is the work of Batres-Estrada (2015).

Recurrent Neural Network Multi-Output (RNN)

The use of a Multi-Output Recurrent Neural Network (RNN) is an additional method for modelling input coefficients for a specific country and year. The model begins with two layers of Long Short-Term Memory (LSTM) neural networks with a specified number of units, ending with two Time Distributed layers (Figure 3). LSTMs, an RNN architecture, can capture and utilise long-term information, which is important in time series. For each time unit, the first LSTM layer receives the input data and returns a sequence of outputs. The second LSTM layer processes these outputs to extract more complex features from the series.

The operation of an LSTM neuron (Figure 4) is based on three main components: the memory cell, the forget gates, and the input and output gates. Relevant information is retained in the memory cell throughout the time sequences. At each time step, the forget gate uses a sigmoid function that takes the current input and the previous state as input to decide what information from the previous state should be erased. The input gate is influenced by a linear combination of the previous state and the current input, followed by a sigmoid function, to decide what new information should be added to the memory cell. A hyperbolic tangent (tanh) function generates new information. The proposed values to be added to the memory cell state are created through this process. Finally, the output gate determines which parts of the cell state should be used for the current output by applying a sigmoid function to scale the cell state, thus generating the current output of the LSTM neuron. This structure allows the LSTM neuron to maintain and manipulate information across time sequences, ensuring that long-term dependencies are efficiently captured.

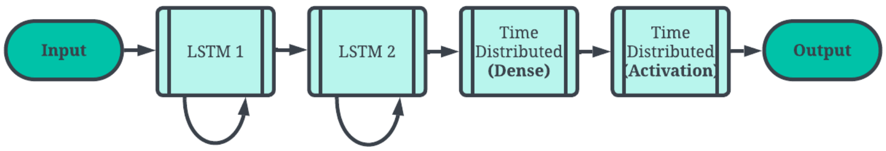

Figure 3. Layers of Recurrent Neural Network Multi-Output

Source: Own processing in Lucidchart.

The next step involves applying a `TimeDistributed` layer, where each output of the LSTM layer is transformed through a fully connected (Dense) layer with a specified number of outputs for each time unit. This allows the model to learn and capture the complex relationships between different input and output features for each time unit.

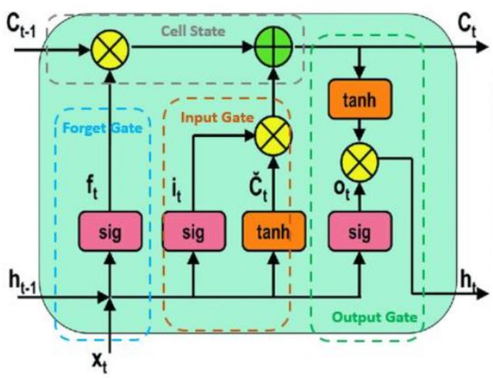

Figure 4. LSTM Cell

Source: https://www.pluralsight.com/resources/blog/guides/introduction-to-lstm-units-in-rnn.

The completion of the model architecture involves adding a final `TimeDistributed` activation layer, which applies the softmax activation function to each output of the previous layer. This ensures that the model outputs are normalised and interpreted as probabilities, making them suitable for the research problem.

The model's hyperparameter tuning was performed using a Randomized Search Cross Validation (RandomizedSearchCV) method, which explores a wide range of hyperparameters to find optimal combinations. Among the hyperparameters searched for were the number of LSTM units in the two layers, the learning rate of the Adam optimiser, the number of training epochs, and the batch size. This hyperparameter tuning approach allowed the model to be adjusted to achieve optimal performance in predicting the time series data.

The Adam optimiser (Adaptive Moment Estimation) was chosen for model training due to its robustness and efficiency. Adam can adaptively adjust the learning rate for each model parameter, ensuring fast and stable convergence by combining the advantages of AdaGrad and RMSProp optimisers. Due to its high computational efficiency, it is well-suited for complex models and large datasets.

Compared with a classic neural network, using a Recurrent Neural Network (RNN) presents distinct advantages and disadvantages. The main advantage of RNNs lies in their ability to work with time series data, such as the dataset in this study spanning 12 years across 25 countries. RNNs can capture complex temporal dependencies in data through recurrent connections between neurons. Moreover, when making predictions, they can consider historical context, making them ideal for problems where there is a dependency between past, present, and future data.

On the other hand, issues with storing and transferring data over long periods can pose a disadvantage for RNNs. The vanishing gradient problem can cause issues in training RNNs for long data sequences, potentially impacting model performance and generalisation. Due to their recurrent nature and the need to process entire data sequences, training RNNs can also be more computationally expensive than training conventional neural networks. Key references underpinning this model include the works of Peñaloza et al. (2023), Sherstinsky (2020), and Zhang et al. (2018).

Results and discussions

Estimating Models on Structural Changes in the Energy Sector

The attempt to investigate how the energy mix and GDP per capita influence input coefficients is possible by combining the fractional multinomial logistic model and neural networks (FMNL+NN). These models provide a detailed picture of how economic elements and energy policies can aid in adopting and utilising renewable energy sources. This helps in creating effective strategies for sustainable energy transition in Romania.

The results from FMNL+NN provide valuable insights into how different energy sources impact various economic sectors in Romania. Table 1 presents the FMNL model, which can be interpreted economically. The coefficients for each energy type indicate the direction and magnitude of influence on the economic industry, along with a measure of the statistical significance of these effects.

Table 1. Fractional Logistic Model Results

	Agriculture, forestry and fishing	Construction	Electricity, gas, steam and air conditioning supply	Manufacturing	Mining and quarrying	Services	Transport-ation
Nuclear	-3.641*** (0.539)	-1.898*** (0.361)	1.944*** (0.394)	0.354* (0.212)	-1.709*** (0.283)	0.048 (0.139)	-0.557 (0.41)
Hydro	-3.839*** (0.641)	-2.124*** (0.362)	4.166*** (0.474)	1.025*** (0.375)	-2.379*** (0.409)	-0.145 (0.149)	-1.888*** (0.5)
Wind	-7.933*** (1.182)	-4.477*** (0.742)	1.753** (0.743)	-1.111** (0.447)	-3.147*** (0.611)	-1.381*** (0.236)	-4.115*** (0.719)
Solar	-2.103 (4.029)	-16.049*** (2.652)	11.389*** (1.439)	2.929*** (1.067)	-0.773 (1.854)	4.633*** (0.71)	9.379*** (2.063)
Coal	-3.078*** (0.522)	-0.574** (0.262)	-0.327 (0.4)	-0.003 (0.207)	-0.691** (0.277)	-0.435*** (0.107)	-1.041** (0.407)
Gas	-4.329*** (0.573)	-1.954*** (0.301)	2.27*** (0.383)	0.106 (0.23)	-1.795*** (0.386)	0.094 (0.12)	-0.721 (0.48)
Oil	-7.116*** (0.932)	-5.215*** (0.493)	1.858*** (0.453)	0.337 (0.279)	-1.241*** (0.365)	-0.627*** (0.172)	-3.05*** (0.611)
GDP_pC	0.071 (0.062)	0.247*** (0.032)	-0.117*** (0.04)	-0.21*** (0.033)	-0.403*** (0.107)	0.103*** (0.017)	-0.644*** (0.08)

	Agriculture, forestry and fishing	Construction	Electricity, gas, steam and air conditioning supply	Manufacturing	Mining and quarrying	Services	Transport-ation
constant	-0.841* (0.459)	-0.71*** (0.227)	-2.474*** (0.327)	-1.561*** (0.197)	-0.302 (0.237)	-0.704*** (0.083)	-1.795*** (0.365)
Note: *p<0.1 **p<0.05 ***p<0.01							

Source: Own processing in R 4.1.1.

We observe that renewable energy sources such as hydroelectric, wind, and solar energy have significant negative coefficients for traditional sectors like agriculture, construction, and mining. This indicates that an increase in the use of these energy sources is associated with a reduction in activity in traditional sectors, possibly due to changes in labour demand or infrastructure.

On the other hand, conventional energy sources such as coal, oil, and natural gas have significant negative coefficients for some sectors but also significant positive coefficients for others. This suggests that these energy sources may have different effects on economic sectors, likely depending on how they are utilised and integrated into the economy.

Evaluation of Estimated Model Performance

Figure 5 illustrates the performance of the FMNL+NN model, used as a reference for predictions as it has proven to be the best (Table 2), while Figure 1 from the Appendix shows the performance of the FMNL model, which is similar to that of the RNN Multi-Output.

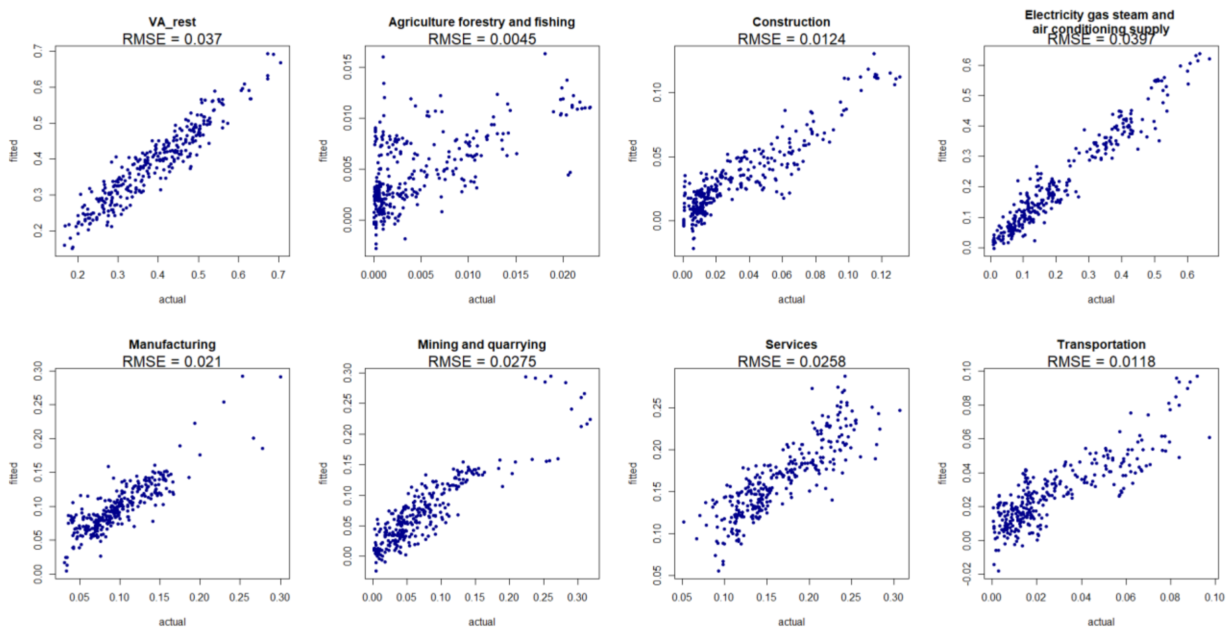

Figure 5. Performance of FMNL+NN Model

Source: Own processing in R 4.1.1.

Table 2. RMSE Metric Values for Estimated Models

	FMNL	FMNL+NN	RNN
VA_rest	0.0938	0.0370	0.0961
Agriculture..forestry.and.fishing	0.0051	0.0045	0.0123
Construction	0.0214	0.0124	0.0311
Electricity.gas.steam.and.air.conditioning.supply	0.1198	0.0397	0.1205
Manufacturing	0.0373	0.0210	0.0371
Mining.and.quarrying	0.0481	0.0275	0.0449
Services	0.0407	0.0258	0.0425
Transportation	0.0170	0.0118	0.0197

Source: Own processing in R 4.1.1.

Forecasting Romania's Input Coefficients for the Year 2031

The input coefficients, calculated as weights for various industries, have undergone changes during the period 2011-2031, as illustrated in Figure 6. The results indicate a significant shift in Romania's economic structure towards more sustainable energy sources and economic diversification. In 2011, adjustments and value-added had the highest share (44.91%), suggesting a heavily concentrated economy in unspecified sectors. The next largest sector was mining (18.96%), followed by electricity (11.52%). These figures highlight a strong dependence on electricity and mining.

Reflecting a transition towards electric power potentially derived from renewable sources, there was a decrease in the share of value-added, which remained at 32.76% in 2021, and a notable increase in the electricity sector, which was 20.91%. Additionally, manufacturing (12.58%) and services (12.88%) sectors grew, indicating both industrial and service sector expansion. For 2031, projections indicate a continued increase in the share of electricity to 35.39% and a nearly complete disappearance of mining. Moreover, the agricultural sector's contribution has increased by 0.46%, demonstrating growth potential through sustainable practices.

Analysing the structural changes in input coefficients in Romania's economy in the context of transitioning to sustainable energy, there is a trend towards reducing the share of traditional sectors and a significant increase in electricity, gas, steam, and air conditioning supply sectors. This evolution signifies a gradual shift towards a service- and low-carbon technology-oriented economy, reflecting concerns for sustainability and reducing dependence on traditional resources. However, agriculture, forestry, and fishing continue to be an important part of the economic structure, requiring an integrated approach to balance economic development needs with natural resource preservation and rural community sustainability.

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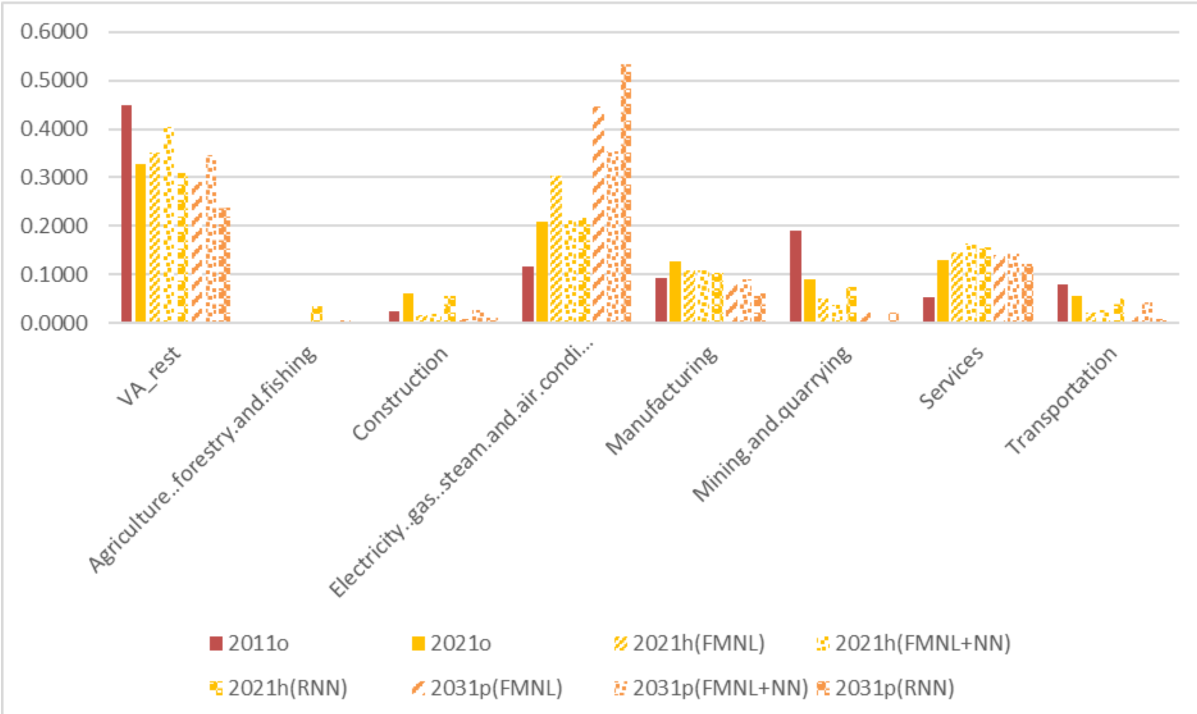

Figure 6. Structural Changes in Input Coefficients

Source: Own processing in R 4.1.1.

Investing in green energy infrastructure, modernising distribution networks, and supporting emerging industries is essential. Professional retraining policies and economic incentives are also needed to promote sustainable agriculture and gradually phase out mining. Therefore, Romania has the capacity to achieve its energy sustainability goals while reducing its environmental impact and stimulating sustainable economic growth.

In Romania, adopting strategies that maximise economic impact and encourage AI-driven innovation is crucial for managing the transition to sustainable energy. Investment in smart infrastructure and energy networks is essential to optimise consumption and integrate renewable energy sources. Additionally, implementing fiscal policies and innovation incentives in the green energy sector could create a conducive environment for technology development and sustainable energy growth.

Rehabilitating and retraining traditional industries affected by the transition to sustainable energy should receive special attention. It is also important to ensure that the workforce involved in this transition does so in a fair manner. This could include funding for creating new industries and jobs in growing green economy sectors, as well as training and professional requalification programs.

Analysis of Potential Scenarios for Transitioning to Sustainable Energy in Romania

Further, various scenarios for transitioning to sustainable energy sources in Romania will be analysed. Figure 7 illustrates a comprehensive overview of the input coefficient structure in different sectors of the Romanian economy in 2031, derived exclusively from nuclear, hydroelectric, wind, and solar energy sources.

For instance, in the scenario where energy is entirely sourced from nuclear power in 2031, over 37% of the total output of sector D35 is used as input in the electricity sector, significantly impacting its dependency on nuclear energy. However, nuclear energy also covers a substantial proportion of consumption in other sectors, such as construction and services, indicating diversification in the use of this energy source across the economy.

On the other hand, in the scenario where all energy comes from solar sources, over 81% of the energy used in the electricity sector originates from solar sources. This radical shift in the energy mix could have significant economic implications, necessitating substantial investments in solar energy infrastructure. Additionally, the agricultural and service sectors may be less affected by the transition to solar energy, requiring alternative energy sources for operation.

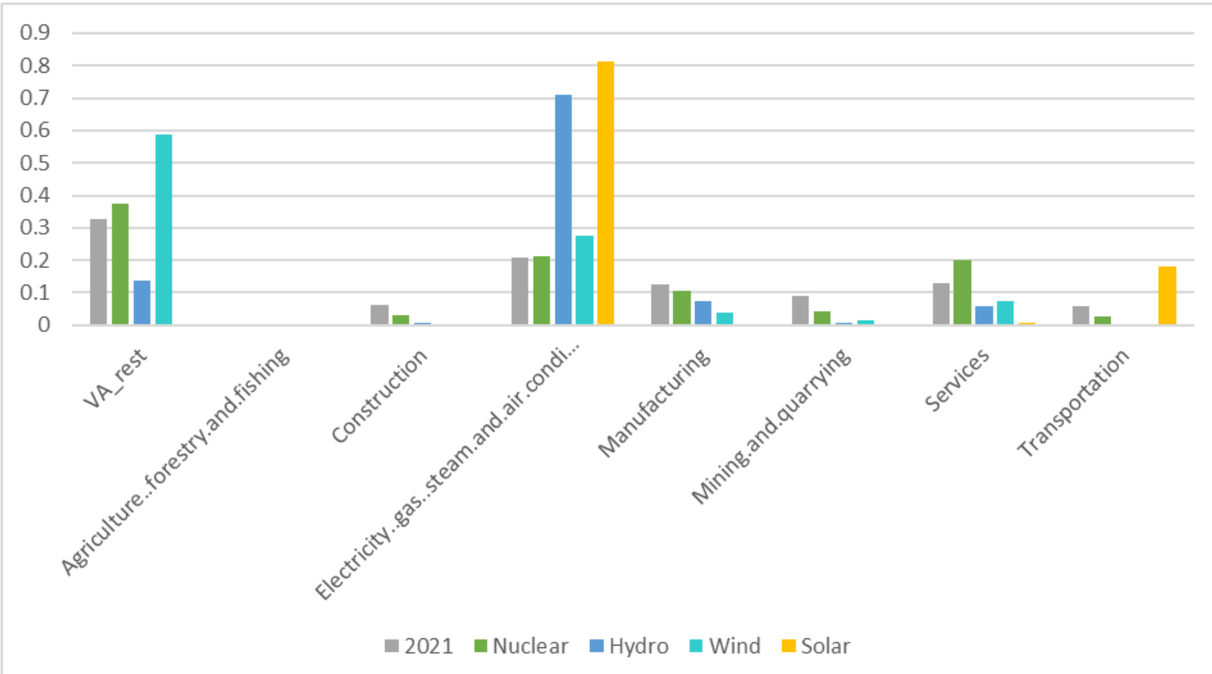

Figure 7. Input Coefficients – 4 Possible Scenarios of Exclusive Use of Renewable Sources

Source: Own processing in R 4.1.1.

Diversification of the energy mix is a key strategy. To rely less on non-renewable energy resources, Romania has a real potential based on renewable natural resources: solar, wind and hydroelectric energy. This is how these resources must be optimally exploited. Combining these energy sources in a coherent and efficient manner could create energy security and reduce vulnerabilities to economics driven by fossil dependency.

Moreover, artificial intelligence-based solutions and technologies are vital in managing smart energy networks and improving energy efficiency. One major AI application for managing energy is AI-based energy management systems, which can track energy consumption, predict energy demand, allocate energy accordingly, and locate areas for rational energy consumption across industries.

Another method is to offer innovation promotion for sustainable energy and ensure investments in research and development in sustainable energy. As this technology continues to improve, it is possible for sustainable energy sources to become cost-competitive compared with traditional fossil fuel sources. Moreover, spending on green energy infrastructure can boost growth and create jobs in industries related to renewable energy.

Conclusion

This study highlights the great importance of requiring a transition to a sustainable energy system in Romania to meet the challenge of climate change and economic modernisation. By leveraging advanced econometric techniques, such as the Fractional Multinomial Logistic Model (FMNL), combined with Artificial Neural Networks (ANNs) and Recurrent Neural Networks (RNNs), this research provides a detailed analysis of how the energy mix and GDP per capita influence input coefficients across various economic sectors. The study showcases a clear trend toward a carbon-light economy with a gradual transition from primary sectors, such as mining and agriculture, to tertiary sectors that rely on a sustainable and low-carbon model through technology.

Forecasts for 2031 highlight Romania's capability to greatly diversify its energy mix, with rising inputs from renewable sources like wind, solar, and hydropower. This shift is marked by a significant decrease in dependence on fossil fuels, mirroring the wider European goal of reaching net-zero emissions by 2050. Achieving this vision necessitates significant investments in green energy infrastructure, updating energy networks, and fostering new industries that enhance innovation in sustainability.

The study shows that energy strategies and economic elements can serve as significant tools in enabling this transition. Policymakers should focus on approaches that improve energy efficiency while also guaranteeing fair and inclusive economic growth. This involves re-educating employees to adjust to changes in industry needs, encouraging the advancement of renewable energy technologies, and promoting public-private collaborations to boost green investments. Future research directions could enhance the analytical framework by incorporating Generative Adversarial Networks (GANs). These models offer promising applications for simulating complex energy scenarios, optimising energy mixes, testing policy impacts, and anticipating market dynamics. GANs can also improve the management of renewable energy transitions by detecting anomalies in distribution networks, planning infrastructure development, and generating hypothetical scenarios for energy demand and supply.

Shifting to a sustainable energy system in Romania is both an achievable objective and a crucial measure for guaranteeing enduring environmental health, economic stability, and social welfare. The findings from this research enhance our comprehension of the methods and approaches essential for attaining energy sustainability, highlighting the importance of collaborative actions among stakeholders at local, national, and global levels. By adopting these strategies, Romania can establish itself as a regional leader in renewable energy utilisation, serving as a model for other nations undergoing similar transformations.

In summary, the results of this study highlight the transformative capacity of sustainable energy transitions in promoting economic development while reducing environmental effects. The combination of sophisticated modelling methods and creative policy initiatives will play a crucial role in crafting a sustainable future for Romania and securing a lasting heritage for the coming generations.

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Appendix

Table 1. Industries in an Economy (NACE Rev.2)

Code	Label	Sector
A01	Crop and animal production, hunting and related service activities	Agriculture, forestry and fishing
A02	Forestry and logging	Agriculture, forestry and fishing
A03	Fishing and aquaculture	Agriculture, forestry and fishing
B	Mining and quarrying	Mining and quarrying
C10T12	Manufacture of food products; beverages and tobacco products	Manufacturing
C13T15	Manufacture of textiles, wearing apparel, leather and related products	Manufacturing
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	Manufacturing
C17	Manufacture of paper and paper products	Manufacturing
C18	Printing and reproduction of recorded media	Manufacturing
C19	Manufacture of coke and refined petroleum products	Manufacturing
C20	Manufacture of chemicals and chemical products	Manufacturing
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	Manufacturing
C22	Manufacture of rubber and plastic products	Manufacturing
C23	Manufacture of other non-metallic mineral products	Manufacturing
C24	Manufacture of basic metals	Manufacturing
C25	Manufacture of fabricated metal products, except machinery and equipment	Manufacturing
C26	Manufacture of computer, electronic and optical products	Manufacturing
C27	Manufacture of electrical equipment	Manufacturing
C28	Manufacture of machinery and equipment n.e.c.	Manufacturing
C29	Manufacture of motor vehicles, trailers and semi-trailers	Manufacturing
C30	Manufacture of other transport equipment	Manufacturing
C31_32	Manufacture of furniture; other manufacturing	Manufacturing
C33	Repair and installation of machinery and equipment	Manufacturing
D35	Electricity, gas, steam and air conditioning supply	Electricity, gas, steam and air conditioning supply
E36	Water collection, treatment and supply	Services
E37T39	Sewerage, waste management, remediation activities	Services
F	Construction	Construction
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles	Services
G46	Wholesale trade, except of motor vehicles and motorcycles	Services
G47	Retail trade, except of motor vehicles and motorcycles	Services
H49	Land transport and transport via pipelines	Transportation
H50	Water transport	Transportation
H51	Air transport	Transportation

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Code	Label	Sector
H52	Warehousing and support activities for transportation	Services
H53	Postal and courier activities	Services
I	Accommodation and food service activities	Services
J58	Publishing activities	Services
J59_60	Motion picture, video, television programme production; programming and broadcasting activities	Services
J61	Telecommunications	Services
J62_63	Computer programming, consultancy, and information service activities	Services
K64	Financial service activities, except insurance and pension funding	Services
K65	Insurance, reinsurance and pension funding, except compulsory social security	Services
K66	Activities auxiliary to financial services and insurance activities	Services
L	Real estate activities	Services
M69_70	Legal and accounting activities; activities of head offices; management consultancy activities	Services
M71	Architectural and engineering activities; technical testing and analysis	Services
M72	Scientific research and development	Services
M73	Advertising and market research	Services
M74_75	Other professional, scientific and technical activities; veterinary activities	Services
N77	Rental and leasing activities	Services
N78	Employment activities	Services
N79	Travel agency, tour operator and other reservation service and related activities	Services
N80T82	Security and investigation, service and landscape, office administrative and support activities	Services
O84	Public administration and defence; compulsory social security	Services
P85	Education	Services
Q86	Human health activities	Services
Q87_88	Residential care activities and social work activities without accommodation	Services
R90T92	Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities	Services
R93	Sports activities and amusement and recreation activities	Services
S94	Activities of membership organisations	Services
S95	Repair of computers and personal and household goods	Services
S96	Other personal service activities	Services
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	Services
U	Activities of extraterritorial organisations and bodies	Services
D21X31	Taxes less subsidies on products	VA_rest
OP_NRES	Purchases of non-residents in the domestic territory	VA_rest
OP_RES	Direct purchase abroad by residents	VA_rest
D1	Compensation of employees	VA_rest

Code	Label	Sector
D29X39	Other net taxes on production	VA_rest
B2A3G	Gross operating surplus	VA_rest

Source: Own processing in Excel.

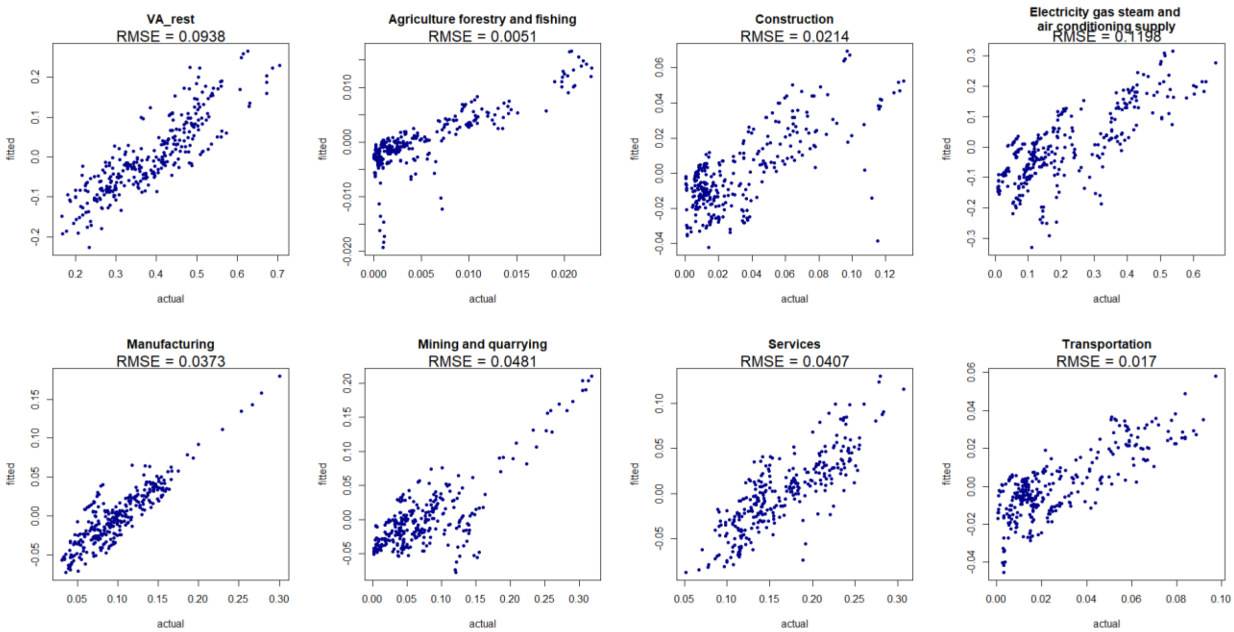

Figure 1. Prediction Quality of FMNL Model

Source: Own processing in R 4.1.1.