ENHANCING ELECTRICITY MIX FORECASTING WITH ARTIFICIAL NEURAL NETWORKS
A Case Study of the EU27

by

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Electric power systems are a cornerstone of the European Union's strategy to achieve climate neutrality by 2050. This study introduces a custom-built, transparent, and user-friendly model that leverages artificial neural networks to forecast the electricity mix based on historical generation data. The model accommodates a range of generation technologies, including coal, natural gas, other fossil fuels, nuclear, hydroelectric, wind, solar photovoltaics, bioenergy, and other renewables. In addition to the business-as-usual scenario, three alternative pathways are examined, each aligned with different strategic, technical, and policy objectives. The model estimates plant capacities required to meet projected electricity demand in 2050 while considering direct capital expenditures for new constructions and decommissioning. Results suggest that achieving the EU27's greenhouse gas reduction targets by 2050 will be extremely challenging under the current trajectory. A successful transition demands substantial adjustments in energy strategy at both European Union and member state levels, underpinned by a comprehensive framework that integrates technical, economic, social, and environmental factors.

Keywords: electricity mix, near carbon neutrality by 2050, techno-economic modeling, artificial neural networks, energy strategy.

Introduction

The composition of the electricity mix is shaped by a multitude of technical, economic, social, and environmental factors. Forecasting future developments within this mix is particularly complex due to the rapidly evolving energy landscape and the often slow societal adoption of proposed solutions. Consequently, there is no universal method for accurately predicting the electricity mix.

Numerous forecasting tools have been developed to aid in this process, as referenced in [1-3]. However, many of these tools carry disclaimers stating that results should be interpreted at the user's own risk. Their accuracy depends heavily on the quality of input data, the validity of assumptions, and the configuration of internal parameters.

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Robust forecasting requires a reliable and comprehensive database. This study draws on data from eight reputable sources: the International Energy Agency (IEA) [4], U.S. Energy Information Administration (EIA) [5], World Energy Council (WEC) [6], International Renewable Energy Agency (IRENA) [7], Center for Energy and Environmental Policy Research (CEEPR) [8], Carbon Capture and Storage Association (CCSA) [9], Statista [10], and EMBER [11].

Notably, energy-related data and projections often vary across sources due to differences in methodologies, assumptions about technological advancements, and other variables. For instance, projections by IRENA, IEA, and EMBER indicate a substantial increase in solar PV energy by 2050. In optimistic scenarios, solar PV could account for 50%-70% of electricity generation in the EU27, while more conservative estimates suggest a range of 20%-30%, reflecting uncertainties in regulatory support, public acceptance, and technological feasibility.

This paper presents a custom-built forecasting model designed to predict the future electricity mix based on historical data across various generation technologies. The model incorporates factors such as average capacity factors, operational reliability, lifecycle GHG emissions, and typical specific capital expenditure (CAPEX) values for different technologies.

Artificial neural networks (ANN) are employed as the core analytical tool, supplemented by nonlinear optimization to enhance forecasting accuracy. The model is adaptable for application at multiple scales – from national and regional systems to individual provinces or communities.

Numerous studies have successfully applied ANN to energy forecasting. For instance, [12] provides a comprehensive review of data-driven approaches for solar PV capacity prediction, while [13, 14] propose hybrid neural models for forecasting electricity generation from multiple sources. Further, [15] emphasizes the importance of reproducible methodologies and open data, while [16, 17] apply advanced deep learning techniques, such as long short-term memory (LSTM) networks, for electricity consumption prediction. The reliability of ANN in renewable energy forecasting, especially in the EU context, is also affirmed in [18-21].

Beyond renewables, carbon capture, utilization, and storage (CCUS) technologies offer a critical pathway to achieving near carbon neutrality by 2050. The EU aims to develop the capacity to capture and store at least 50 million tons of CO_2 annually by 2030. This goal will require extensive infrastructure for CO_2 transportation and storage [22-24].

Recently published papers [25-29] are only some of the numerous works dealing with the problems of forecasting energy production and consumption.

Proposed model description

This study presents a custom-built model designed to analyze electricity systems by integrating various electricity generation technologies. The model utilizes historical annual electricity generation data to forecast future energy production, estimate lifecycle GHG emissions, and determine direct capital expenditure (CAPEX) needs for constructing new capacities and decommissioning obsolete facilities. Only direct CAPEX is considered because it is the dominant cost and easier to predict. Forecasts of technology-specific commercial prices are variable but generally more stable than, for example, energy prices (which are part of OPEX).

The emergence of a disruptive technology* that dramatically changes operational parameters is certainly possible. In that case, the entire calculation must be redone, and this simplified model facilitates that.

The initial projections are developed under the business-as-usual (BAU) scenario. Deviations from this baseline inform where strategic interventions are necessary. These adjustments are implemented by modifying relevant parameters within the model.

The ANN are central to the model's analytical framework. They are particularly suitable for systems characterized by incomplete or noisy data [18, 30-32], where conventional deterministic methods are less effective. The ANN serve as powerful non-linear statistical models, capable of identifying hidden patterns in complex datasets and providing reliable forecasting outcomes.

The model is implemented using Microsoft Excel with visual basic for applications (VBA), offering a transparent and fully editable structure. This ensures complete user control over each calculation step - an important advantage over black-box commercial software. It also allows for easy customization and adaptation to specific system requirements.

While complex deep learning models dominate the literature [30-32] this study's use of two sequential feedforward networks (2-2-1 and 1-2-1 architectures) in a custom-built excel (VBA) environment offers an accessible, adaptable, and user-friendly tool. This fills a significant niche for policymakers and practitioners seeking transparent and interpretable models. This implementation lowers the entry barrier for users without access to advanced programming environments or commercial tools.

The model's outputs depend on the accuracy and temporal stability of historical input data and assumed technology parameters. It considers only direct CAPEX and therefore does not capture operational costs, market dynamics, policy uncertainty, or system-level constraints such as dispatch and grid stability. The simplified ANN structure, while robust to noisy data and transparent, cannot explicitly represent physical causality or sudden structural breaks; disruptive technological changes require model re-parameterization. The Excel/VBA implementation favors accessibility and interpretability over computational scalability.

Step-by-step model workflow

- *Data collection and initial analysis*: The model begins with the analysis of historical electricity generation data across a defined set of technologies, which may include coal, natural gas, other fossil fuels, nuclear, hydro, wind, solar PV, bioenergy, and other renewables. The selection of technologies can be tailored to the specific context being analyzed.
- *Forecasting future generation (BAU scenario)*: Using ANN, the model forecasts electricity generation by technology, based on historical trends. This projection enables assessment of whether the existing strategy aligns with GHG emission reduction goals, forming the BAU baseline.
- *Determining capacity changes*: For each technology, the model calculates the annual percentage change in plant capacity needed to maintain the BAU trajectory. These trends highlight whether existing infrastructure is sufficient to meet future energy and environmental targets.

*Disruptive technology refers to innovations that significantly change how consumers, industries, or businesses operate, often supplanting older processes.

– *Key technology parameters*: The model incorporates the following parameters for each generation technology:
  – Capacity factor (CF) measures the actual electrical energy output of a power generation system over a specified period to the theoretical maximum energy output if the system operated at full capacity for the same period. It is expressed as a percentage and reflects how efficiently a power plant is utilized.
    The CF is crucial for evaluating the performance and viability of power generation systems, helping in project development and financing.
  – Operational reliability (OR) is defined as the ability of a system to perform its intended functions under specified conditions without failure. It generally refers to the system's capability to balance supply and demand in real-time and rapidly respond to unexpected events. High operational reliability indicates a system's consistent performance, safety, and effectiveness in meeting operational demands.
  – Lifecycle GHG emission factor (EF) is a measure that quantifies the total greenhouse gas emissions associated with the entire lifecycle of a product, process, or service. This includes all stages from raw material extraction, production, distribution, use, and disposal or recycling. The EF is typically expressed in units of CO_2 equivalents (CO_2e) per unit of output (*e.g.*, tCO_2e per MWh for electricity generation).

The Lifecycle GHG EF is essential for evaluating the environmental impact of products and services, informing policy decisions and regulatory frameworks, encouraging sustainable practices and reducing overall carbon footprints.

These parameters are drawn from empirical studies and databases but can be replaced with system-specific data when available. Table 1 provides typical values for each parameter, along with direct specific CAPEX and decommissioning cost percentages.

Table 1. Average parameter values for plant capacity calculation and GHG emissions

Technology	CF [%]	OR [%]	Lifecycle EF [tCO_2e/MWh]	Direct specific CAPEX [Million EUR/MWe]	De-commissioning [%]
Coal	55.0	85.0	0.9000	2.75	20.0
Natural gas (NG)	65.0	90.0	0.4500	2.00	10.0
Other fossil fuel	60.0	90.0	0.6750	2.50	15.0
Nuclear	90.0	92.5	0.0150	4.50	22.5
Hydro	50.0	92.5	0.0240	2.00	15.0
Wind	37.5	80.0	0.0175	2.85	20.0
Solar PV	22.5	87.5	0.0450	1.75	20.0
Bioenergy	37.5	80.0	0.0750	2.50	15.0
Other RES	60.0	80.0	0.0200	5.00	15.0

Notes: These values are representative averages derived from a wide body of literature and data sources [21, 33-35].
The statistical data processing used for CF and OR makes sense because it is based on a large population from the databases of relevant institutions. Users are encouraged to substitute these with localized or updated values where available.
CAPEX values include EPC (Engineering, Procurement, and Construction), site development, grid connections, and basic environmental controls.
Decommissioning cost is expressed as a percentage of direct CAPEX.

The model's flexibility allows direct editing of these parameters, enabling dynamic scenario analysis under varying assumptions and constraints. Installed capacity is calculated using:

$$\text{Power [GW]} = \frac{\text{Energy [GWh/y]}}{\text{CF [–]} \cdot \text{OR [–]} \cdot 8760 \text{ [h/y]}} \tag{1}$$

The GHG emissions are computed by multiplying the lifecycle EF by the total electricity generated annually for each technology:

$$\text{GHG emission } [\text{tCO}_{2e}/\text{y}] = \text{Energy } [\text{MWh/y}] \cdot \text{EF } [\text{tCO}_{2e}/\text{MWh}] \tag{2}$$

- *The CAPEX estimation*: The model estimates the direct capital investment needed for infrastructure expansion and decommissioning activities. These projections are derived from the ANN-based forecast trends and unit-specific CAPEX values, tab. 1.
- *Assessment of GHG reduction targets*: If a specific GHG target year is defined (e.g., 2050), the model can assess how well the current or alternative energy strategies align with these goals, using total lifecycle GHG emissions as a benchmark.
- *Scenario development*: By adjusting annual growth rates or generation shares across technologies, alternative scenarios can be developed. Each scenario is evaluated in terms of technical feasibility, economic cost, social acceptability, and environmental performance.
- *Evaluation of CCUS Potential*: Given the importance of CCUS technologies in low-carbon strategies, the model includes a framework for evaluating their deployment potential. This involves estimating CO_2 capture requirements and corresponding infrastructure investments for achieving emissions reduction goals.
- *Evaluation of energy storage potential*: Two main types of storage are considered – battery (Li-ion) and pumped hydro. A large share of variable renewable energy requires their use.

Extrapolation of electricity generation using artificial neural networks

Electricity generation data for each technology is analyzed and projected individually using two sequential ANN. Both networks are of the feedforward type. The first ANN uses a 2-2-1 architecture, while the second employs a 1-2-1 structure.

In the initial network (2-2-1), the input layer consists of two neurons: the year of electricity generation and the corresponding generation value in TWh/year. The hidden layer comprises two neurons with nonlinear activation functions, and the output layer contains a single neuron, also with a non-linear activation function. Notably, one input neuron is directly connected to the output neuron to improve model responsiveness. The model is trained using the complete dataset, and weight and bias parameters are optimized to minimize the root mean squared error (RMSE).

This first ANN generates a mathematical representation of the historical trend in electricity generation for each technology, based on either measured or estimated data. Model training is performed by minimizing the root mean squared error (MSE), which serves as the objective function:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left[y_a(n) - y_p(n)\right]^2} \tag{3}$$

where $y_a(n)$ is the actual electricity generation in year n and $y_p(n)$ – the predicted value for the same year

The sigmoid function is used as the activation function for all neurons. Normalization of both input and output variables is critical for ensuring ANN stability and performance. Autoencoder-style networks, where outputs replicate inputs, are particularly effective for tasks such as data reconstruction, denoising, compression, and extrapolation [30, 32]. Their utility in extrapolation depends on how accurately the latent space reflects the underlying data structure.

To extend projections into future periods, a linear trend derived from the five most recent data points is applied to estimate subsequent values. These estimates serve as input to the network, enhancing its predictive range beyond the training period.

In summary, the first ANN outputs a non-linear approximation of historical electricity generation trends, while the second ANN uses extrapolated future inputs constrained by this learned structure to generate the final projections.

Because annual electricity generation time series are short and smooth, partitioning the data into independent training and testing subsets would substantially reduce the information available for learning long-term trends and may bias extrapolation results. Therefore, the complete historical dataset is used for training in order to maximize information content and ensure stable parameter estimation.

Model performance is evaluated using error metrics computed over the full dataset, which is appropriate for trend-learning and system-representation tasks rather than short-term predictive benchmarking. In addition, internal consistency checks are possible because the model is applied independently to multiple electricity generation technologies as well as to total electricity production. Agreement between the aggregated technology-specific outputs and the independently modeled total generation provides an implicit validation of model robustness.

This approach follows common practice in energy system modeling when data availability is limited and the primary objective is structural trend representation and scenario exploration rather

Normalization considerations for extrapolation

Determining appropriate normalization bounds is a key challenge in extrapolation modeling. These bounds define the expected data range and significantly influence model accuracy and behavior during prediction beyond the known dataset. In this study, the following criteria were considered when establishing normalization limits:

- Statistical distribution and variance of the dataset.
- Expert judgment based on energy system knowledge.
- Physical and technical constraints of each technology.
- Results from prior modeling and validation tests.
- Logical consistency of system behavior over time.

Each technology is extrapolated independently. The goal is to minimize the cumulative extrapolation error across the entire forecast horizon, while maintaining realistic system behavior.

Second-level network filtering

The output from the initial 2-2-1 ANN is passed into a second feedforward neural network with a 1-2-1 architecture. In this model, the input variable is time (year), and the output is the filtered projection of electricity generation values derived from the first ANN. This second network serves to smooth and refine the output, making the data more suitable for subsequent optimization processes and decision support applications.

The ANN-based approach is particularly well suited for long-term forecasting in complex systems, where traditional methods may be less effective due to non-linearity, uncertainty, and data irregularities.

Figure 1 presents the calculation results for one of the technologies. It shows the measured electricity production in coal-fired power plants, along with its mathematical interpretation

and extrapolation using a 2+2+1 ANN, as well as the filtered values of this curve obtained with a 1+2+1 ANN. Similar calculations were performed for each technology and for their respective groups.

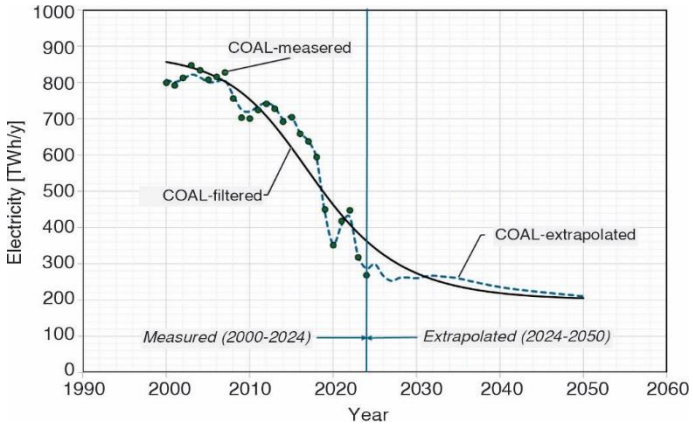

Figure 1. Electricity generation of coal-fired power plants

A case study of the EU27

This section presents the application of the proposed model to the EU27 electricity system. The model forecasts future electricity generation by technology using the BAU scenario and evaluates its implications for GHG emissions, installed capacities, and infrastructure investment. The analysis of the BAU scenario implies the possibility and necessity of changing trajectories in the energy policy.

Extrapolation of electricity generation using artificial neural networks

The analysis is based on historical data from 2000 to 2024 [11], with extrapolations extending to 2050. Table 2 summarizes the annual electricity generation by technology, and the ANN-based model is applied to derive projections for each source.

Using the filtered extrapolated generation values from 2025 to 2050, the model calculates the corresponding required installed capacities and lifecycle GHG emissions. These results form the core of the BAU scenario, which assumes no substantial change in current policies, regulations, or energy strategies through the forecast period.

To simplify the analysis, nine energy technologies are grouped into three main categories:

- Fossil fuels (Fossil): coal, NG, and other fossil fuels.
- Nuclear energy (Nuc).
- The RES: hydro, wind, solar PV, bioenergy, and other RES

Figure 2 shows the normalized electricity generation values from 2000 to 2024 across these categories. The values are scaled using the minimum and maximum for each dataset to facilitate comparative analysis.

Electricity generation in the EU27 peaked in 2008 and has since experienced a slight overall decline. Fossil fuel-based generation reached its highest output in 2007, while nuclear energy peaked earlier in 2004. In contrast, renewable sources have shown consistent and significant growth, aligning with the EU's long-term decarbonization strategy.

Table 2. Annual Electricity Generation in EU27 [TWh/y]

Year	TECHNOLOGY									TOTAL
	Coal	NG	Other fossil	Nuc	Hydro	Wind	Solar PV	Bioenergy	Other RES	
2000	800.33	328.19	226.81	859.95	350.17	21.27	0.05	30.11	5.29	2,622.2
2001	792.92	351.41	229.35	888.90	373.43	25.74	0.17	31.90	5.09	2,698.9
2002	814.34	374.60	240.85	902.34	312.60	35.06	0.28	36.80	5.25	2,722.1
2003	849.04	418.90	227.38	907.18	304.64	43.30	0.40	43.16	5.92	2,799.9
2004	835.42	458.48	205.03	928.46	323.19	57.52	0.68	52.76	5.99	2,867.5
2005	808.89	512.54	203.41	916.08	307.02	68.08	1.48	61.00	5.87	2,884.4
2006	816.50	540.05	194.13	914.44	309.98	78.72	2.52	69.86	6.08	2,932.3
2007	828.74	571.96	178.60	872.24	307.72	99.92	3.83	78.43	6.24	2,947.7
2008	757.01	611.65	165.74	884.73	325.59	113.22	7.51	88.09	6.20	2,959.7
2009	703.55	564.03	144.78	824.92	329.00	124.57	14.22	97.24	5.99	2,808.3
2010	701.20	587.36	149.76	854.47	371.82	139.82	23.49	111.47	6.09	2,945.5
2011	724.81	556.85	143.30	837.77	307.43	165.33	47.71	118.98	6.42	2,908.6
2012	742.68	482.70	137.26	811.95	331.67	187.48	70.50	132.87	6.28	2,903.4
2013	728.90	413.43	128.23	806.23	368.02	209.47	83.76	139.13	6.44	2,883.6
2014	692.78	355.41	125.99	812.57	370.06	222.38	93.60	144.25	6.79	2,823.8
2015	705.03	394.84	127.86	786.69	336.00	263.17	100.20	149.37	7.09	2,870.3
2016	659.16	464.77	128.20	767.95	345.60	266.81	100.49	151.09	7.23	2,891.3
2017	638.86	523.62	126.88	759.40	294.34	312.30	107.30	153.64	7.23	2,923.6
2018	595.54	488.95	120.86	761.94	343.84	320.62	113.79	155.46	7.14	2,908.1
2019	450.79	568.62	110.91	765.34	320.29	367.13	124.53	159.65	7.23	2,874.5
2020	352.33	559.70	97.77	683.51	347.16	397.97	144.82	162.59	7.23	2,753.1
2021	419.00	547.04	100.41	731.71	348.47	386.69	163.12	171.54	7.03	2,875.0
2022	448.43	533.97	105.63	609.26	276.15	421.30	209.86	165.51	6.93	2,777.0
2023	319.15	455.57	93.15	619.60	329.86	472.39	249.78	151.65	6.72	2,697.9
2024	268.77	430.08	94.38	648.33	361.69	480.41	303.07	150.45	6.90	2,744.1

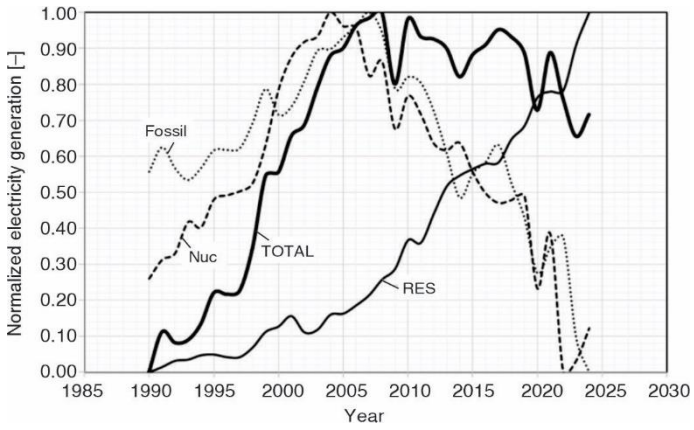

Figure 2. Normalized values of electricity generation in EU27

Between 1990 and 2005, both fossil fuel and nuclear generation increased steadily. However, since 2005, these sources have declined while renewable generation has expanded rapidly – reflecting the EU's evolving policy framework.

Policy context and strategic framework

Since 1990, the EU has introduced a wide range of policies to reduce GHG emissions and accelerate the transition to sustainable energy. Key directives and strategies include:

- *Renewable Energy Directives* (RED I and RED II): Mandate an increased share of renewables in energy consumption and set binding targets for GHG reductions.
- *Emissions Trading System* (ETS): Introduced in 2005 as the EU's flagship carbon pricing mechanism, covering electricity generation, industry, and aviation sectors.
- *Energy Efficiency Directive* (EED): Establishes binding targets and policies for improving energy efficiency across sectors.
- *European Green Deal* (2019): Aims for climate neutrality by 2050 and outlines intermediate targets for 2030, including a 55% reduction in GHG emissions from 1990 levels.

Additional policies, such as the Energy Labeling Directive, the Energy Performance of Buildings Directive (EPBD), and the Ecodesign Directive, have also contributed significantly to shaping the EU27 electricity landscape.

The 2015 Paris Agreement [36] further catalyzed climate action by establishing a global consensus on limiting temperature rise and implementing systemic decarbonization.

In July 2009, EU and G8 leaders committed to reducing GHG emissions by 80% by 2050, relative to 1990 levels. The European Council later endorsed an even more ambitious range of 80%-95%. This laid the foundation for the Energy Roadmap 2050 [37], which has become a cornerstone of the EU's long-term energy planning framework [38].

The ANN-based forecasting results

Each technology was modeled independently using ANN to extrapolate future electricity generation to 2050. The projections were then aggregated to estimate the EU27's total electricity output under the BAU scenario.

The forecasts suggest that, under the BAU scenario:

- Total electricity generation will remain relatively stable.
- Fossil and nuclear generation will decline significantly.
- Renewable generation - particularly wind and solar PV - will continue to grow robustly.

Figure 3 illustrates the historical and forecasted generation by category, along with the total output.

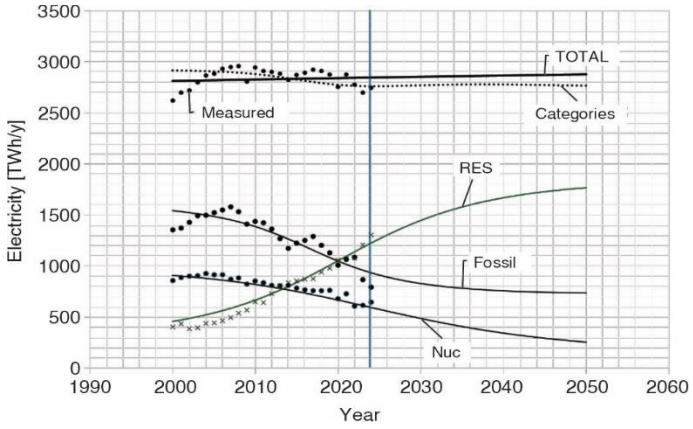

Figure 3. Filtered electricity generation from 2000-2050 by category and total (BAU)

Validation of model consistency was achieved by comparing the sum of individual forecasts with the direct ANN extrapolation of total electricity generation. The relative error was 3.9% in 2050, indicating strong agreement between independent and aggregate forecasts.

The IEA [4] projects that by 2050 electricity demand in the EU27 will rise substantially, driven by the electrification of transport, heating and industry. Electricity production is expected to shift strongly from fossil fuels to renewables, with wind and solar expanding the most. In near carbon neutrality by 2050 scenarios the electricity sector becomes the largest final energy carrier; supply is dominated by variable renewables supplemented by flexibility measures (storage, hydrogen, demand response) and some low-carbon firm capacity (nuclear and CCUS where deployed). These trends informed the definitions of S1, S2 and S3. The current (BAU) scenario does not capture these changes sufficiently, which led to stagnant electricity production as identified by the ANN. For comparability, S1, S2, and S3 were constructed under the assumption of constant electricity supply; however, an alternative set of scenarios allowing for growth in electricity production and consumption is also possible.

Lifecycle GHG emissions analysis

Table 3 presents lifecycle GHG emissions for fossil, nuclear, and renewable energy categories under the BAU scenario.

Table 3. Lifecycle GHG emissions ($MtCO_2e/y$) (BAU scenario)

Year	FossiL	Nuc	RES	TOTAL
2000	1129.54	13.61	13.07	1156.22
2005	1084.09	13.07	16.47	1113.63
2010	1000.74	12.30	21.29	1034.34
2015	863.77	11.28	27.49	902.53
2020	706.76	10.03	34.69	751.48
2025	586.99	8.66	41.79	637.45
2030	515.47	7.33	47.64	570.44
2035	476.16	6.16	51.85	534.17
2040	454.70	5.19	54.66	514.55
2045	442.78	4.44	56.47	503.69
2050	436.00	3.88	57.62	497.50

Table 4 compares BAU scenario results with targets from the EU Roadmap. While progress toward the 2030 target is promising, achieving full neutrality by 2050 will require substantial policy adjustments.

Table 4. Comparison of planned (EU roadmap) and BAU calculated GHG emission reductions

	1990	2000	2030	2050
Reduction (EU Roadmap)	–	–	from –54 to –68%	from –93 to –99%
BAU reduction predicted	–	–	–61%	–66%
BAU scenario (calculated) ($MtCO_2e/y$)	1474	1156.22	570.44	497.50

Key findings:

- The GHG emissions are forecasted by BAU to decline from 1156 $MtCO_2e$ in 2000 to 497.5 $MtCO_2e$ by 2050.
- This represents a 66% reduction relative to 1990 levels (1474 $MtCO_2e$), but still falls short of the 93%-99% reduction required by the EU Energy Roadmap 2050 [37].

– Achieving a carbon-neutral power sector in the EU27 by 2050 is a core objective of the European Green Deal as well [39]. However, various analyses suggest that significant challenges may delay this goal beyond 2050 [40, 41]. This study explores those challenges and identifies key areas that require focused attention.

Capacity adjustments and infrastructure requirements

Table 5 shows the changes in installed capacity by technology between 2000-2024 (historical) and 2025-2050 (forecast). Negative values represent capacity decommissioning; positive values indicate new installations.

Table 5. Addition of new capacities or reduction of existing ones for BAU scenario [GWe]

Period	COAL	NG	OF	Nuc	Hydro	Wind	Solar PV	Bioenergy	Other RES
2000-2004	–5.50	0.06	–4.36	–3.80	0.97	11.01	4.95	8.22	0.10
2005-2009	–12.93	0.06	–4.69	–5.44	0.93	17.69	11.30	9.93	0.10
2010-2014	–24.90	0.06	–4.49	–7.33	0.89	25.67	22.97	9.12	0.10
2015-2019	–31.20	0.06	–3.88	–9.02	0.84	31.73	36.53	6.80	0.10
2020-2024	–24.48	0.06	–3.10	–9.95	0.79	32.37	42.51	4.50	0.10
2025-2029	–14.37	0.06	–2.36	–9.82	0.73	27.69	37.43	2.82	0.10
2030-2034	–7.54	0.06	–1.75	–8.75	0.68	20.84	27.30	1.73	0.10
2035-2039	–3.85	0.06	–1.28	–7.21	0.62	14.57	17.94	1.06	0.10
2040-2044	–1.96	0.06	–0.93	–5.63	0.57	9.84	11.19	0.65	0.10
2045-2049	–1.35	0.07	–0.87	–5.48	0.65	8.57	8.98	0.52	0.10
TOTAL	–128.06	0.58	–27.71	–72.43	7.66	199.98	221.09	45.35	1.01

Highlights:

– The most significant reductions are in coal and nuclear plants.
– Wind and solar PV show the largest capacity expansions, reflecting strong policy support and cost declines.
– Total net capacity addition from 2025 to 2050 is 122.05 GW, indicating an infrastructure expansion under the BAU scenario.

Direct capital expenditure (CAPEX) estimates

Table 6 provides a rough estimate of direct CAPEX for capacity changes. These costs include only basic construction and equipment costs (EPC, grid connection). These are investments that follow the trajectory of capacity changes (construction or decommissioning).

Table 6. Rough estimate of direct costs* for the BAU scenario [€ Billion]

PERIOD	Coal	NG	Other fossil	Nuclear	Hydro	Wind	Solar PV	Bioenergy	Other RES
2000-2004	4.18	0.19	3.03	2.72	3.31	39.90	18.70	29.08	0.25
2005-2009	9.67	0.19	3.22	3.87	3.18	63.55	42.33	34.09	0.26
2010-2014	17.82	0.19	3.05	5.16	3.03	90.75	83.87	30.61	0.27
2015-2019	21.19	0.19	2.61	6.28	2.86	109.93	128.83	22.53	0.27
2020-2024	16.09	0.19	2.08	6.86	2.68	110.08	145.32	14.82	0.27
2025-2029	9.33	0.19	1.58	6.69	2.50	92.88	125.31	9.27	0.26
2030-2034	4.88	0.19	1.17	5.91	2.31	69.35	90.38	5.70	0.25
2035-2039	2.49	0.19	0.85	4.85	2.12	48.28	59.06	3.49	0.23
2040-2044	1.27	0.19	0.62	3.77	1.93	32.56	36.74	2.13	0.22
2045-2049	0.65	0.19	0.45	2.85	1.76	21.74	22.32	1.31	0.20

*Based on current average prices, tab. 1

Key observations:

- The highest investment is required for wind and solar PV.
- Total CAPEX from 2025 to 2050 under BAU is substantial (€625.84 billion), but not sufficient to achieve full decarbonization.

Alternative scenarios

In addition to the BAU scenario, three alternative transition pathways are evaluated. All scenarios assume that total annual electricity generation between 2025 and 2050 remains the same as in the BAU scenario, ensuring a consistent basis for comparison.

Scenario 1: Full decarbonization with phase-out of fossil and nuclear power

Scenario 1 (S1) envisions a complete transition to RES by 2050, with the full phase-out of both fossil fuel and nuclear power plants.

Key Assumptions:

- All fossil fuel-based power plants are decommissioned by 2050.
- Nuclear power plants are also fully phased out by 2050.
- Wind and solar PV technologies are designated as the primary RES contributors.
- Hydro, bioenergy, and other RES technologies grow at the same rate as in the BAU scenario.
- Capacity expansion for wind and solar PV is optimized to meet total generation demand.

Storage Requirements:

Due to the intermittent nature of wind and solar generation, the scenario includes energy storage infrastructure to ensure grid stability. The model assumes:

- 25% of daily electricity demand must be covered by storage [42, 43].
- Two types of storage are used: Li-ion batteries (short-duration) and pumped hydro storage (long-duration), each covering 50% of the required capacity.

Investment Implications:

- The estimated direct CAPEX for energy storage is €393.1 billion.
- This results in an average annual storage investment of approximately €15.1 billion over 26 years.

Environmental Impact:

- The GHG emissions reach a minimum by 2050.
- Electricity generation is fully derived from RES technologies.

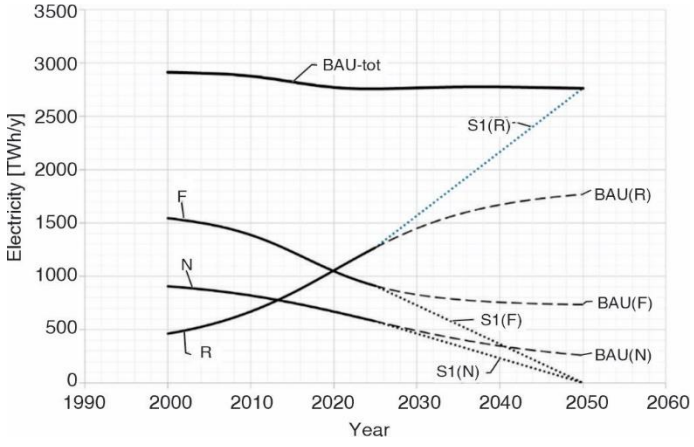

Figure 4. Generated electricity according to BAU and Scenario 1

Figure 4 illustrates the projected generation under Scenario 1, compared to the BAU trajectory.

Scenario 2: Fossil fuel phase-out with nuclear retention and expansion

Scenario 2 (S2) assumes a complete phase-out of fossil fuels by 2050 but retains and expands nuclear capacity to reduce reliance on storage and manage system stability.

Key Assumptions:

- All fossil fuel plants are decommissioned by 2050.
- Starting in 2026, 0.5 GW of new nuclear capacity is added annually.
- Renewable generation mirrors Scenario 1, but with reduced growth in wind and solar PV.

Storage Requirements:

- Owing to the constant presence of nuclear baseload generation, required storage capacity is reduced to 15% of daily electricity demand.

Environmental Impact:

- Lifecycle GHG emissions are significantly reduced.
- The system relies on a mix of nuclear and RES to achieve near-zero emissions.

Scenario 3: Enhanced BAU with CCUS and nuclear power plants

Scenario 3 (S3) modifies the BAU scenario by incorporating Carbon Capture, Utilization, and Storage (CCUS) for fossil fuel plants and expanding nuclear capacity.

Key Assumptions:

- Fossil fuel-based power plants continue to operate but are equipped with CCUS technologies by 2050.
- Nuclear capacity increases by 0.5 GW per year from 2026.
- Wind and solar PV capacities grow more slowly than in the BAU scenario.
- RES contributions are complemented by low-carbon fossil generation.

The CCUS Considerations:

- Capture efficiency is assumed at 90% [23, 24] for retrofitted fossil fuel plants.
- CAPEX for CCUS retrofits is estimated as a percentage increase over base plant costs [4]:
  - +40% for coal
  - +30% for natural gas and other fossil sources

Investment Implications:

- The use of CCUS reduces the need for electricity storage infrastructure.
- Total CAPEX is substantially lower compared to S1 and S2.

Environmental Impact:

- The GHG emissions are reduced to approximately 121.5 $MtCO_2e$ by 2050.
- This scenario offers a transitional pathway with lower investment barriers but depends on rapid deployment of CCUS infrastructure.

Summary results and discussion

This section presents a comparative analysis of the BAU scenario and three alternative pathways (S1, S2, and S3), focusing on their implications for installed capacity, electricity generation, lifecycle GHG emissions, tab. 7, and capital expenditures (CAPEX), tab. 8.

These CAPEX estimates are based on average current technology-specific costs (from tab. 1), adjusted for decommissioning, storage, and CCUS upgrades. While indicative, they help illustrate the economic trade-offs between different transition strategies only.

Table 9 shows the Capacity Change Overview. Scenario 1 requires the highest capacity increase, particularly in variable renewable technologies with lower capacity factors. In

contrast, Scenario 3 results in the lowest capacity expansion due to the continued use of dispatchable fossil and nuclear generation, supported by CCUS.

Table 7. Summary of key indicators for BAU and alternative scenarios

	Category	Capacity			Energy			Lifecycle GHG emissions		
		2020	2024	2050	2020	2024	2050	2020	2024	2050
		GW	GW	GW	TWh/y	TWh/y	TWh/y	million tCO_2e/y	million tCO_2e/y	million tCO_2e/y
BAU	F	347.1	196.6	154.7	1545.5	936.2	736.6	1129.5	606.8	436.0
	N	124.5	79.2	35.4	907.7	595.9	258.5	13.6	8.9	3.9
	R	134.2	490.8	720.8	461.4	1228.5	1770.4	13.1	40.4	57.6
	TOTAL	605.7	766.7	910.9	2914.6	2760.6	2765.4	1156.2	656.1	497.5
S1	F	347.1	196.6	0.0	1545.5	936.2	0.0	1129.5	606.8	0.0
	N	124.5	79.2	0.0	907.7	595.9	0.0	13.6	8.9	0.0
	R	134.2	490.8	1164.7	461.4	1228.5	2765.4	13.1	40.4	84.1
	TOTAL	605.7	766.7	1164.7	2914.6	2760.6	2765.4	1156.2	656.1	84.1
S2	F	347.1	196.6	0.0	1545.5	936.2	0.0	1129.5	606.8	0.0
	N	124.5	79.2	91.7	907.7	595.9	668.8	13.6	8.9	10.0
	R	134.2	490.8	861.1	461.4	1228.5	2096.7	13.1	40.4	65.6
	TOTAL	605.7	766.7	952.8	2914.6	2760.6	2765.4	1156.2	656.1	75.6
S3	F	347.1	196.6	154.7	1545.5	936.2	736.6	1129.5	606.8	66.3
	N	124.5	79.2	91.7	907.7	595.9	668.8	13.6	8.9	10.0
	R	134.2	490.8	526.7	461.4	1228.5	1360.1	13.1	40.4	45.2
	TOTAL	605.7	766.7	773.1	2914.6	2760.6	2765.4	1156.2	656.1	121.5

Table 8. Estimated CAPEX for BAU and alternative scenarios (2025–2050)

Category	CAPEX for Basic Plant [€B]	Energy Storage CAPEX [€B]	CCUS Investment [€Billion]	Total CAPEX [€Billion]
BAU	625.84	0.00	0.00	625.84
S1	1773.27	393.09	0.00	2166.36
S2	1041.28	192.95	0.00	1234.23
S3	211.72	0.00	149.19	360.91

Table 9. Percentage change in installed capacity by 2050 (relative to BAU in 2025)

Technology	BAU	S1	S2	S3
Coal	–40.4%	–100.0%	–100.0%	–40.4%
Natural Gas	+0.4%	–100.0%	–100.0%	+0.4%
Other Fossil Fuels	–42.0%	–100.0%	–100.0%	–42.0%
Nuclear	–55.3%	–100.0%	+15.8%	+15.8%
Hydro	+4.5%	+4.5%	+4.5%	+4.5%
Wind	+53.6%	+194.9%	+105.5%	+7.0%
Solar PV	+76.0%	+194.9%	+105.5%	+7.0%
Bioenergy	+12.4%	+12.4%	+12.4%	+12.4%
Other RES	+23.6%	+23.7%	+23.6%	+23.6%
Total	+18.8%	+27.9%	+4.6%	−15.1%

A summary of the important parameters of the BAU scenario and three alternative pathways is given in tab. 10.

Table 10. Scenario comparison by 2050

Scenario	Capacity share of fossil plants [%]	Capacity share of nuclear plants [%]	Capacity chare of renewable energy plants [%]	CCUS	Battery storage	Total CAPEX [€B]	Notes
BAU	26.6%	9.3%	64.0%	No	No	626	Mixed portfolio without CCUS
S1	0.00%	0.00%	100.00%	No	Yes	2166	Full RES transition, highest investment
S2	0.00%	9.62%	90.38%	No	Yes	1234	Fossil phased out, expanded nuclear
S3	20.01%	11.86%	68.13%	Yes	No	361	CCUS-enabled fossil plants and expanded nuclear

Finaly, main takeaways are:

- Achieving near-total decarbonization by 2050 under the BAU scenario is highly unlikely without further strategic intervention.
- Scenario 1 delivers the lowest GHG emissions (zero from fossil and nuclear) but demands the highest CAPEX, especially for renewable deployment and storage infrastructure.
- Scenario 2 achieves deep decarbonization at moderate cost, leveraging nuclear generation to reduce storage needs.
- Scenario 3 presents the most cost-effective path, relying on continued fossil fuel use with CCUS and expanded nuclear, but it assumes rapid deployment of CCUS infrastructure, which remains uncertain.

Conclusion and Policy Implications

The transition of the EU27 electricity sector toward climate neutrality by 2050 presents significant technical, economic, and policy challenges. This study introduced a transparent and adaptable forecasting model that combines ANN with scenario-based analysis to project electricity generation, installed capacity, lifecycle GHG emissions, and capital expenditure (CAPEX) across multiple energy pathways.

The BAU scenario indicates that, without additional interventions, the EU27 will fall short of the emission reductions targeted by the EU Energy Roadmap 2050. Three alternative scenarios were explored to evaluate different strategic approaches: full reliance on renewables (Scenario 1), combined renewables and nuclear with fossil fuel phase-out (Scenario 2), and continued use of fossil fuels with CCUS alongside nuclear (Scenario 3).

Key findings include:

- Scenario 1 achieves nearly-zero carbon emissions but requires the highest investment and poses operational risks related to storage and variability of supply.
- Scenario 2 balances emissions reductions and cost by leveraging nuclear power to stabilize the grid and reduce the need for energy storage.
- Scenario 3 presents a cost-effective transitional pathway, but its success relies on rapid deployment and acceptance of CCUS technologies, which are still maturing.

From a policy perspective, the results underline the necessity for:

- Clear and consistent regulatory frameworks to support long-term investment in low-carbon technologies.
- Accelerated permitting and grid integration for renewables and storage.
- Strategic planning for nuclear capacity expansion or decommissioning, based on national preferences.

- Financial mechanisms and public-private partnerships to scale up CCUS deployment.
- Greater harmonization of EU-wide data collection and modeling efforts to improve forecasting reliability.

Ultimately, no single scenario can meet all technical, economic, and societal criteria simultaneously. Policymakers must therefore evaluate trade-offs and prioritize actions based on national contexts, existing infrastructure, and political feasibility. The proposed model provides a flexible decision-support tool to assist in these complex evaluations.

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