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Assessment of the decarbonization efficiency in the European Union: machine learning approach

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Abstract

Background The European Union has established a strategic objective to attain carbon neutrality across the continent by the year 2050; however, this complex undertaking is shaped by a variety of influencing factors. It is particularly important to monitor the effects of such a long-term strategy, as it will influence all aspects of the European Union's sustainable energy development as well as the welfare of its citizens. Since no universally accepted methodology exists for tracking the effects of decarbonization, the use of machine learning as a method of artificial intelligence is proposed—not only to generate concrete results but also to evaluate its applicability for this purpose. The main objective of this research is to assess the trends of 13 selected energy indicators that are vital to the decarbonization initiative. The research was conducted on a sample of 27 countries for the period from 2013 to 2030 using a novel predictive model developed in the Python runtime environment.

Results The primary findings of the research indicate that the EU is likely to experience significant fluctuations in the values of specific indicators. The anticipated progressive rise in electricity prices is expected across all EU countries, accompanied by an increase in consumption. In addition, the projected growth in energy imports presents a significant challenge that will affect the competitiveness of the European economy and the social standing of its citizens. Particularly disadvantaged in the implementation of the decarbonization strategy will be landlocked countries that are highly dependent on energy imports and therefore vulnerable to fluctuations in prices and security of supply. Also at risk are countries facing difficulties in the deployment and exploitation of renewable energy sources, as well as those with weaker socioeconomic indicators. The results further indicate a rising risk to energy security, even in the wealthiest EU countries. Overall, the projections suggest an increase in CO_2 levels up to 2030, followed by a gradual decline thereafter. A particular challenge for managing the decarbonization strategy lies in the significant fluctuations of the monitored parameters, which hinder planning in every respect.

Conclusions In light of the geopolitical and supply chain shifts post-2022, it is clear that a comprehensive reassessment of the strategies for managing the decarbonization of the European Union economy is necessary. The research findings demonstrated the effectiveness of the proposed machine learning approach, which has potential for enhancement due to its scalability and adaptability. The study provides governance and methodological recommendations.

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Keywords Decarbonization management, Energy indicators, Assessment and prediction, Machine learning, LSTM recurrent neural networks, European Union

Background

The European Union (EU) demonstrates a strong dedication to enhancing environmental protection, having adopted and implemented regulations focused on this goal for decades. In 2019, the European Commission adopted the Green Deal [1], which serves as a strategic framework outlining the long-term trajectory of the EU's development. The primary objective is to attain the status of a climate-neutral continent by 2050, specifically aiming for the total eradication of carbon dioxide emissions. Decarbonization necessitates significant transformations across all sectors of the economy [2], and also relies on a systematic decrease in the consumption of fossil fuels, particularly coal and oil, as their combustion generates the highest proportion of carbon dioxide emissions [3].

The process of managing decarbonization in EU countries is quite complicated, influenced by multiple factors and marked by substantial differences across countries [4]. Furthermore, the established objectives pertain not solely to the EU but extend to the entirety of the European continent, thereby rendering the governance process increasingly complex [5]. The perspectives of individual member states regarding decarbonization and its various components (such as activities, financing, monitoring, and both economic and social dimensions) can occasionally be inconsistent [6]. Countries seeking EU membership, along with certain member states, particularly in Southeastern Europe, exhibit unique characteristics [7], in their economic and energy structures [8, 9], which necessitates a tailored approach to decarbonization [10]. Given that these countries are economically less advanced compared to the EU and lack access to specific EU funds for decarbonization [11, 12], it is crucial for them to focus on the decarbonization planning process [13]. There are variations in the approach to the decarbonization process, even among EU countries that have access to special funds and mechanisms for financing it [13].

The economy's decarbonization process and the sustainable development goals as a whole are already being influenced by changes in the EU and on the global stage after 2022 [14, 15]. Additionally, there is a likelihood of an increase in geopolitical impacts [16]. Some of them are directly affected by the EU.

Initially, the European Union has implemented sanctions against the import of natural gas from the Russian Federation. It is important to consider that natural gas is an environmentally favorable energy source [17]. An adequate and complete replacement for natural gas does not yet exist. Issues exist regarding the physical security of supply [18], and the reliance on pricier energy sources adversely affects the competitiveness of the EU economy, particularly in certain member states that have depended on gas supplies from the Russian Federation for many years [19]. Moreover, a notable rise in energy prices has significantly impacted the social standing of citizens and led to a discernible shift in the perspectives of EU residents regarding decarbonization [20].

Secondly, the decarbonization process faces significant challenges due to issues in the supply chains of essential minerals [21], a situation that originated during the Covid-19 pandemic and was exacerbated by the European Commission's 2024 decision to halt imports of rare earth minerals from specific countries [22]. These minerals are vital for producing environmentally friendly goods, making their availability crucial for the decarbonization effort [23]. The world's largest supplier is the People's Republic of China, which provided most of the EU's needs for rare earth minerals. The EU is actively seeking alternative sources for rare earth minerals from various countries. However, the development of new supply chains is a lengthy endeavor fraught with unpredictability and considerable resistance from potential exporting countries, primarily due to the environmental and social challenges associated with the extraction of these minerals within their borders [24].

The process of decarbonization primarily depends on a continuous increase in energy production from renewable sources. However, the energy generated through these means is insufficient to fully replace fossil fuels. Additionally, the cost of energy derived from renewable sources is higher, making it less favorable for both economic stability and public acceptance [25].

Decarbonization imposes the need for major changes in the economy (especially in the energy sector). The EU has been implementing a comprehensive strategy aimed at systematically phasing out coal extraction, a major source of environmental pollution. However, this approach has led to an increase in electricity imports, and post-2022, there has been a notable rise in prices.

The social challenges associated with decarbonization are significant, as altering the economic structure raises concerns about generating employment opportunities for workers [26] whose jobs have been or could be displaced [27]. The rise in energy prices significantly affects citizens' quality of life, highlighting the issue of energy poverty within the EU. This phenomenon refers to a specific segment of the population's inability to secure sufficient energy for their household requirements [28].

Given the numerous uncertainties associated with Europe's decarbonization process by 2050, it is critical to continuously analyze all its aspects (economic, social, technological, and environmental) in order to develop appropriate policies and make decisions that can then guide the modeling and refinement of the management process.

Methods of artificial intelligence present opportunities for application in specific areas of managing the decarbonization process, particularly in controlling the efficiency of its implementation, which is accomplished by considering the values of selected indicators. This study examines the current values and forecasts the trends of energy-related indicators, offering a comprehensive understanding of the effectiveness of the EU's decarbonization efforts to date, with projections extending to 2030.

The initial section of the study outlines related works and is followed by a detailed description of the methodology and a comprehensive overview of the application of machine learning modeling. The Results section of the study presents a comprehensive overview of the past and future trends of selected energy-related indicators, followed by the Discussion and Conclusions sections.

One of the primary challenges associated with artificial intelligence (AI) lies in its application for predicting trends, events, and behaviors, whether concerning individual entities [29] or components of intricate systems [30]. This extends to the analysis of entire systems across various domains within contemporary society [31]. The modeling of decarbonization in the EU, as outlined in the introduction, is a complex process shaped by various factors that exhibit diverse trends and behaviors across different countries and time periods [32]. Artificial neural networks are commonly referred to as the most appropriate AI technology for this purpose [33, 34]. The complexity of the problem, which encompasses numerous interrelated variables and extensive historical data from various countries, can be effectively addressed through the application of artificial neuron networks (ANN) models. Moreover, these models can be methodologically evaluated and fine-tuned [35] for specific purposes before their practical usage.

The recurrent neural networks (RNN) represent a subtype of ANN specialized for the processing of sequential data (e.g., time-series) [36–38]. Machine learning models are different from ones used in ANN. The same concept is divided into different neuron models and network architectures. ANN typically consists of three or more layers—an input layer, one or more hidden layers, and an output layer—where neurons sum the inputs and forward them, with or without modification [39]. RNN can consist of just one layer of neurons, each containing at least one loopback connection. Therefore, these neurons are commonly referred to as recurrent units.

For instance, RNNs, used in the prediction of air quality [40], overcome the limitations of existing models when processing numerous influential factors over long periods of time. Another example is the use of RNNs in hydrological predictions [41] to improve water resources management under climate change conditions. Frequent anomalies in water streamflow and rainfall (complex, non-linear relationships among data series) make it difficult to implement commonly adopted regression and ANN models. RNNs are also used in business. For instance, they are applied to predicting stock market trends under uncertain investment conditions [42]. Further, RNNs are used to predict financial time series influenced by various political and economic factors [43]. The specific type of RNN called Long Short-Term Memory (LSTM) is used in most of the applications mentioned [44]. LSTM brings an improvement to RNNs, as it is designed to uncover and learn the long-term mutual dependencies among a large number of features presented in sequential data [45]. Based on published research and results, LSTM has been found to be appropriate for this study.

Methods

The research methodology was chosen to analyze and predict the movement of energy-related indicators crucial for the decarbonization process in the EU by 2030. For this purpose, 13 indicators were used, selected in accordance with the specific challenges faced by decarbonization after 2022—changes in energy supply. The values of these indicators differ significantly from country to country and from year to year; the variations are almost stochastic, which makes it difficult to model the decarbonization process with mathematical functions. On the other hand, with the historical data collected, it is possible not only to examine the state of this process through 2030 but also to predict its future trajectory. The implementation of the objective of this study involved the utilization of recurrent artificial neural networks.

To achieve the primary objective of the study, RNNs were employed, as they represent a type of ANN adept at handling sequential data, including time series [44]. In addition to "forward" data propagation, RNNs also support "backward" data flow. Loopback connections enable the processing of data inputs sequentially, combining the memorized outcomes of previous inputs with actual input values. This feature allows RNNs to predict new data based on the sequence of previous ones.

Figure 1 illustrates a simple RNN model comprising four acceptors (*A1-4*) in the input layer and three recurrent units (*RUs*) in the hidden layer.

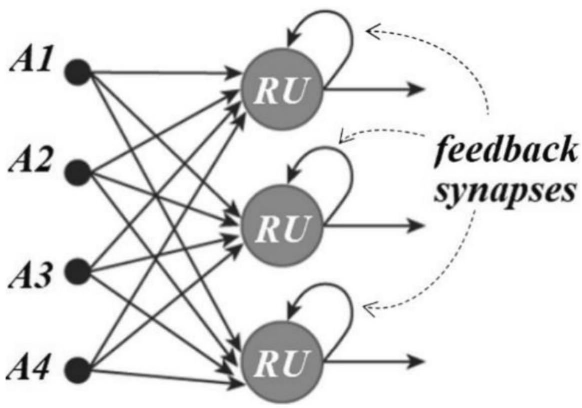


Fig. 1 Example of RNN

Each recurrent unit receives data from all input units and produces outputs based on a specified function. The output data is fed back into the network, enabling predictions based on previous inputs. The most common activation functions in RNNs are the Rectified Linear Unit (ReLU) and the Tangent Hyperbolic function (tan-h). ReLU is a piecewise linear function that outputs the input directly if it is greater than zero; otherwise, it outputs zero. Unlike ReLU, tan-h is a nonlinear function that maps real numbers to the range [-1,1]. The function's values are located in the first and fourth quadrants of the coordinate plane, with the function's zero positioned at the origin of the coordinate system.

The operation of a single RU from the previous example can be represented by the following mathematical expression (Eq. 1).

$$h_j^t = f_a(\sum_{i=1}^{4} w_i \cdot x_i^t + w_j \cdot h_j^{t-1} + bias) \quad (1)$$

Simultaneously, h_j^t it represents the output RU_j at step *t*. In other words, it represents the output of the activation function f_a. Given that the RU has four data inputs, the aggregated input is computed as the sum of the products of the corresponding weights w_i and input values x_i^t at step *t.* The effect of the previous state on the current state Ru_{di} is determined by the feedback synapse function, which calculates the product of the weight factor w_j and the previous state RU_j: h_j^{t-1}. By adding a *bias* factor to the expression, the RU can be adjusted to better match the input data and RNN model structure.

Building upon the previously presented equation, the overall function of the network can be derived, as shown in Eq. 2.

$$H_t = f_a(W_x \cdot X_t + W_h \cdot H_{t-1} + B_h) \quad (2)$$

At step *t*, the RNN produces an output H_t, which is determined by the activation function f_a configured for the entire RNN model. The function's argument comprises the input weight vector W_x, the input data vector X_t, the feedback weight vector W_h for the hidden layer *h*, the previous step's hidden state vector H_{t-1}, and the hidden layer's bias vector B_h.

In the application of RNNs, the method used to adjust the network synaptic weights can lead to learning gradient-related issues. If the weight values exceed one, an exponential increase in the learning gradient may occur for extended time series. Conversely, when weight values are within the [0,1] range, long time series can lead to gradients diminishing to near zero or vanishing entirely. In order to overcome this problem, a special type of RNN, i.e., Long Short-Term Memory (LSTM) (Fig. 2), was used in the research. Commonly, RU in LSTM is called a cell since it is modified to contain 2 components: Long Term Memory (LTM) and Short-Term Memory (STM). The LTM is responsible for maintaining the cell state and does not involve weighting factors, relying instead on adders and multipliers for its operations. Conversely, the STM functions similarly to traditional RUs by utilizing weighting factors for both the input data (*x*) and the cell's feedback synapse. The STM is tasked with storing the hidden state, which is combined with the input value across all elements of the LSTM structure. In the structure of LSTM, the units— *forget gate, input gate*, and *output gate*—are distinguished by having the same structure but serving different purposes. The *Forget gate* determines, based on the input data, whether the cell's current state (LTM) should be ignored (cancelled) or will affect the cell's training process in the current step (*point A*). The *input gate* multiplies its activation by the candidate cell state (generated by *Evaluator 1*) and adds this product to update the cell state at *point B*. The *output gate* is intended to form a product with the output value of the evaluator's new cell state (*Evaluator 2*). This resulting value represents the new hidden state and contributes to the formation of the cost function. The new cell state value and the new hidden state value are used, along with the input value, in the next training iteration. The cost function plays a crucial role in determining whether the LSTM is properly trained. It is also used to adjust the weight factors applied to the input data (including the hidden state and input data) across all gates.

To achieve the described functionality, the LSTM alternately uses two activation functions: the sigmoid and tan-h functions (Fig. 3). Both are non-linear, but they differ in range. As previously mentioned, the tan-h function outputs values in the range [-1,1], while the sigmoid function outputs values in the range [0,1].

The purpose of these functions is corrective, as they help prevent abrupt changes in the output data in

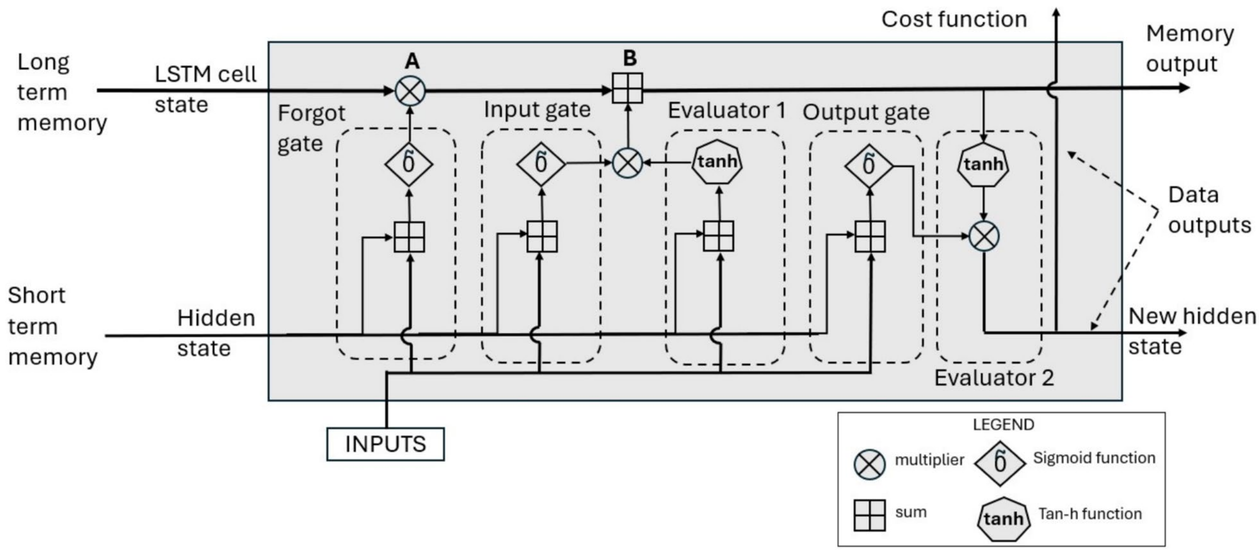


Fig. 2 LSTM cell (RU) structure

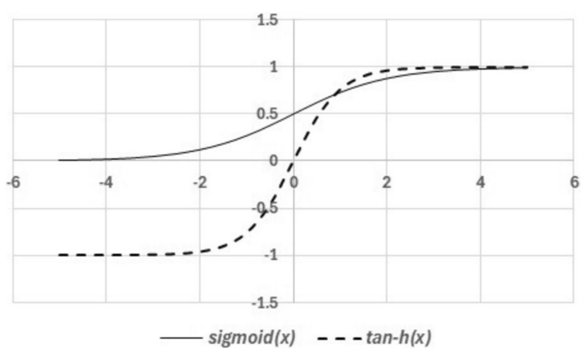


Fig. 3 Sigmoid and tan-h functions diagram

response to large variations in the input data. Specifically, the tan-h function in the LSTM takes the input and the state from the feedback synapse to compute the cell's output (i.e., the current state). Regardless of the input values—whether negative or extremely large—the tan-h function produces an output constrained between -1 and 1. At the same time, the nonlinearity of the function ensures that only small input values are passed to the cell's output. For larger input values, the function weakens the input, with attenuation increasing as it moves further from the origin along the x-axis. The sigmoid function in the cell controls the percentage of information that is retained in the LTM. The sigmoid function enables smaller changes to be remembered at a higher percentage than larger ones in the LTM. In other words, the sigmoid function smooths out variations that could destabilize the prediction model, thereby indirectly preventing undesirable changes in the learning gradient—such as vanishing gradients or overfitting.

The original data used in this research are organized by country, with the primary source being the official EU database: Eurostat. The dataset covers a 10-year period, from 2013 to 2022. Following this, a forecast was generated for an additional eight-year period, extending to 2030.

The names of the indicators, their corresponding abbreviations, and units of measurement are presented in the following table (Table 1):

Indicator values are grouped by countries and years. The structure and original data for one of the EU countries considered are given below (Table 2).

Table 1 Indicators used in the research

	Indicator name	Abbrev	Unit of measurement
1	CO_2 emissions per capita	CO_2	10^6metric tones
2	Electricity prices for household consumers	EPHH	€ per kWh
3	Electricity prices for non-household consumers	EPNHH	€ per kWh
4	Energy efficiency	EE	10^6 tons of oil equivalent
5	Energy import dependency by product	ENIMP	%
6	Energy intensity	ENINT	kJ per $
7	Population unable to keep homes adequately warm by poverty status	POWP	%
8	Imports of electricity and heat derived by partner country	IMPEL	GWh
9	Imports of natural gas by partner country	IMPGAS	10^6 m^3
10	Imports of oil and petroleum products by partner country	IMPOIL	10^3 tones
11	Net greenhouse gas emissions	NETEM	%
12	Primary energy consumption	ENCONS	%
13	Share of energy from renewable sources	RENEN	%

Table 2 Structure of data for one of the 27 EU countries considered

Year	CO_2	EPHH	EPNHH	EE	ENIMP	ENINT	POWP	IMPEL	IMPGAS	IMPOIL	NETEM	ENCONS	RENEN
2013	8	0.1361	0.0865	32.07	61.26	111.3	2.7	24,959.57	6421.02	13,981.49	111.9	32.1	9.695
2014	7.5	0.1294	0.0786	30.8	65.625	106.69	3.2	26,711.72	7709.12	13,672.74	104.6	30.8	10.983
2015	7.7	0.1239	0.0729	31.66	60.379	108.2	2.6	29,389.16	6072.55	14,185.07	109.6	31.7	11.409
2016	7.7	0.1222	0.0685	32.04	62.102	107.56	2.7	26,366.16	7498.89	14,130.47	110.6	32	10.583
2017	7.9	0.1218	0.0688	32.82	63.93	107.07	2.4	29,362.43	8464.45	14,205.57	119.4	32.8	9.703
2018	7.5	0.1265	0.072	31.83	64.223	102.15	1.6	28,076.14	7830.96	15,006.07	126.9	31.8	9.931
2019	7.7	0.1349	0.0814	32.27	71.601	102.92	1.8	26,046.85	11,377.63	15,326.21	125.1	32.3	10.051
2020	7	0.1384	0.0871	29.85	58.42	102.53	1.5	24,522.49	6462.23	13,844.08	101.4	29.9	10.283
2021	7.4	0.1448	0.0961	31.61	51.841	104.06	1.7	26,436.19	4754.66	13,701.53	98.9	31.6	9.471
2022	6.9	0.209	0.1717	30.16	74.454	94.07	2.7	28,595.17	12,190.07	12,634.77	103	30.2	10.139

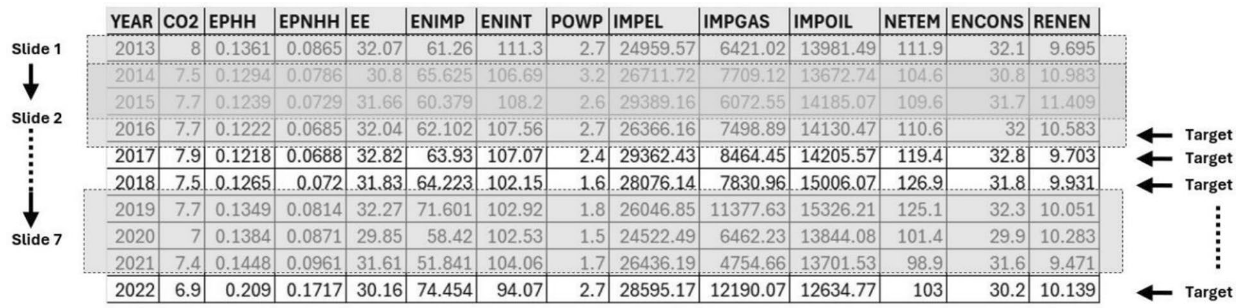
To make the data suitable for processing with an LSTM RNN, it first needed to be adapted to the required input format. Given the significant differences in the magnitudes of individual indicators (ranging from 10^{-2} to 10^{5}), data preprocessing was essential. The first step involved normalization using the *MinMax* method, which scales input values to a new range [0,1]. This transformation was performed using the following equation (Eq. 3).

$$I_{j,k,l}^{norm} = \frac{I_{j,k,l}^{real} - I_{j}^{min}}{I_{j}^{max} - I_{j}^{min}} \tag{3}$$

The normalized values of the j^{th} indicator for the k^{th} country in year l are denoted by the symbol $I_{j,k,l}^{norm}$. The symbol $I_{j,k,l}^{real}$ represents the actual (real) value of the j^{th} indicator for the k^{th} country in year l. The symbols I_{j}^{max} i I_{j}^{min} denote the maximum and minimum values, respectively, of the j^{th} indicator across all 27 observed countries.

In the next stage of data preparation, time series were generated based on a defined time window size. Three-year sliding windows (samples) were selected, meaning that the lookback period in the network's learning process is three years. Given that the data series spans ten years and that neural network training requires the data to be divided into at least two subsets (one for training and one for testing), a three-year lookback window was chosen for generating the samples. The nature of the indicator changes suggests that a two-year lookback period is too short, while using a window longer than three years results in too few training samples. The three-year sequence was chosen as the optimal solution. This approach resulted in seven sliding windows and an equal number of target samples for network training (Fig. 4).

For the prediction model, designed as an LSTM RNN, the *Keras* library (*Python*) was used to construct the necessary model components. The model is developed as a sequential artificial neural network using the *keras.models.Sequential* class consisting??? of two layers (Fig. 5). The first layer (input layer) is an RNN. It is composed of 500 LSTM cells (recurrent units), with the *keras.layers.LSTM* class used for this purpose. The number of cells varies based on the nature of the data for each country, with the goal of obtaining the training targets at the LSTM RNN level. For each unit, *tan-h* is specified as a function for evaluating cell state (LTM) and hidden state (STM). On the other hand, the *sigmoid* function is used for activation in the *forget, input,* and *output* gates of the LSTM cells. The second (output) layer consists of 13 neurons, each corresponding to one of the 13 indicators (features). These neurons are fully connected to the LSTM cells from the previous layer. This layer is constructed using the *keras.layers.Dense* class.



YEAR	CO2	EPHH	EPNHH	EE	ENIMP	ENINT	POWP	IMPEL	IMPGAS	IMPOIL	NETEM	ENCONS	RENEN
2013	8	0.1361	0.0865	32.07	61.26	111.3	2.7	24959.57	6421.02	13981.49	111.9	32.1	9.695
2014	7.5	0.1294	0.0786	30.8	65.625	106.69	3.2	26711.72	7709.12	13672.74	104.6	30.8	10.983
2015	7.7	0.1239	0.0729	31.66	60.379	108.2	2.6	29389.16	6072.55	14185.07	109.6	31.7	11.409
2016	7.7	0.1222	0.0685	32.04	62.102	107.56	2.7	26366.16	7498.89	14130.47	110.6	32	10.583
2017	7.9	0.1218	0.0688	32.82	63.93	107.07	2.4	29362.43	8464.45	14205.57	119.4	32.8	9.703
2018	7.5	0.1265	0.072	31.83	64.223	102.15	1.6	28076.14	7830.96	15006.07	126.9	31.8	9.931
2019	7.7	0.1349	0.0814	32.27	71.601	102.92	1.8	26046.85	11377.63	15326.21	125.1	32.3	10.051
2020	7	0.1384	0.0871	29.85	58.42	102.53	1.5	24522.49	6462.23	13844.08	101.4	29.9	10.283
2021	7.4	0.1448	0.0961	31.61	51.841	104.06	1.7	26436.19	4754.66	13701.53	98.9	31.6	9.471
2022	6.9	0.209	0.1717	30.16	74.454	94.07	2.7	28595.17	12190.07	12634.77	103	30.2	10.139

Fig. 4 Method of data preparation

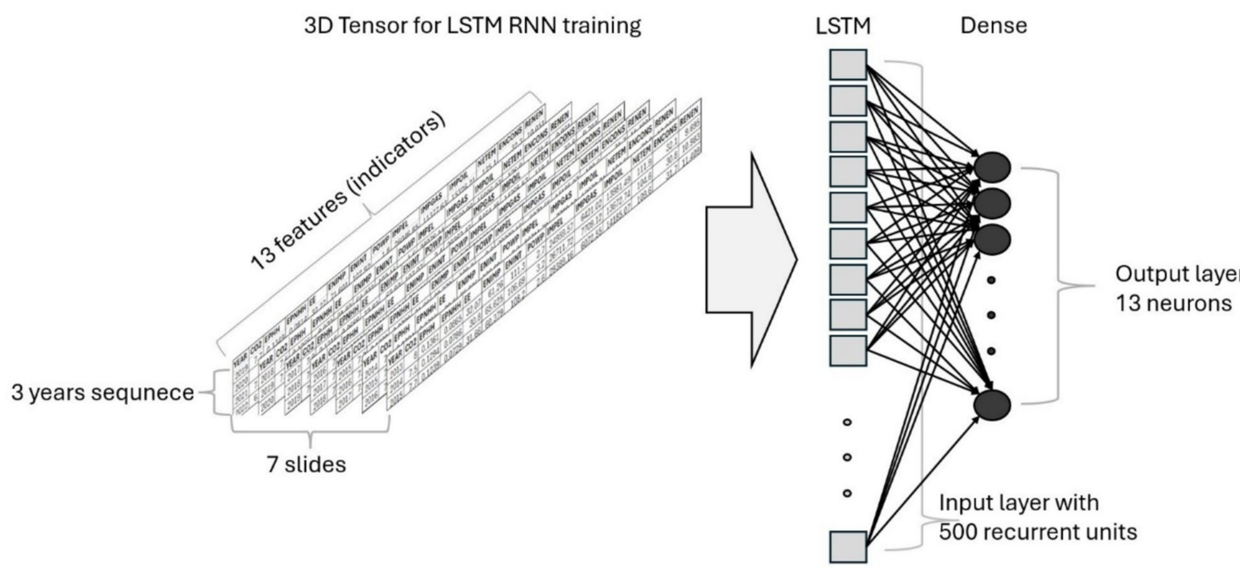


Fig. 5 Overview of the data model and LSTM RNN

The data model for training is presented on the left-hand side of the figure above. It is constructed as a 3D tensor with 7 slides (batch size) of 13 features (indicators), with years used as indices and organized in sequences of 3 years (rows). Training was performed in 100 epochs, using the minimum squared error as the metric to monitor the process. To minimize the training loss, experiments were conducted with models having different numbers of units in the LSTM layer. Finally, acceptable results were obtained with models containing 250, 275, 400, 500, 600, and 700 units in the LSTM layer, depending on the specific country. As a result of the training process, the average loss of the models is approximately $\sim 10^{-4}$, and for most countries, it is around $\sim 10^{-5}$. For each country, the optimal model is created and saved for further use. Consequently, the model of application (Fig. 6) consists of three main resources: prediction models and datasets for 27 countries and the prediction logic implemented in the Python programming language, stored as separate files.

When the prediction logic is loaded into the system (Python runtime environment), it loads the model and dataset for the selected country based on user input, makes predictions, visualizes the results, and saves them to a specified location.

Results

The presented data visualization offers a clearer understanding of the variations in indicator values and their fluctuations across the 27 observed EU countries. To enhance understanding, and given the extensive range of indicators, four diagrams were created for each country. These diagrams illustrate the recorded decade-long changes in indicators (represented by a solid line) and the forecasts generated by the proposed model (depicted by a dashed line). To enhance understanding, each figure includes four diagrams that illustrate a specific set of interconnected indicators. The configuration of the indicators within the diagrams is based on their respective values, despite variations in the measurement units for each indicator. Consequently, the diagrams, marked with an *a*, encompass the following parameters: *CO_2 emissions per capita*, *Population unable to keep home adequately warm by poverty status* and *Share of energy*

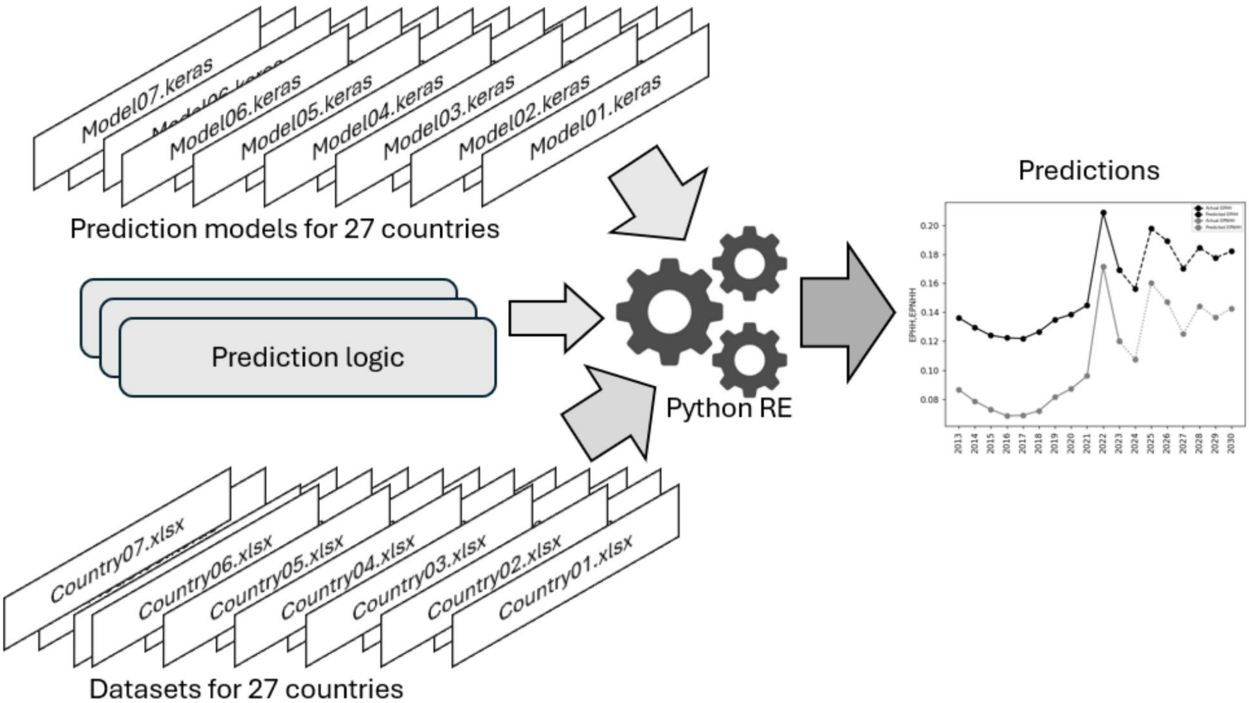


Fig. 6 Prediction model overview

from renewable sources. Diagrams marked with a *b* include parameters that characterize the energy-economy-environment nexus: *Energy import dependency by product*, *Energy intensity*, *Net greenhouse gas emissions*, *Primary energy consumption*. Diagrams marked with a *c* include parameters of electricity prices: *Electricity prices for household consumers* and *Electricity prices for non-household consumers*. Diagrams marked with a *d* include energy import parameters: *Imports of electricity and derived heat by partner country*, *Imports of natural gas by partner country,* and *Imports of oil and petroleum products by partner country*.

For each EU country, the following are provided: predictions, analysis, and an assessment of the impact on decarbonization.

Austria

Figure 7 displays the indicator prediction diagrams for Austria.

The first diagram (diagram a) indicates that no significant changes are expected in the CO_2, POWP, and RENEN indicators in the future. A similar trend is observed for the indicators ENIMP, ENINT, NETEM, and ENCONS (diagram b). On the other hand, the electricity prices (diagram c, indicators EPHH and EPNHH) show a sharp increase, particularly during the period from 2019 to 2022. The predictions suggest that variations in electricity prices are expected to persist; however, a gradual decline is anticipated, with prices unlikely to return to the peaks observed in 2022. The diagram presents indicators related to the import of energy products (specifically diagram d, which includes the IMPOIL, IMPEL, and IMGAS indicators). Consistent oil imports are anticipated, while fluctuations in electricity and gas imports are expected to stabilize beginning in 2026.

The analysis indicates that the values of the chosen energy-related indicators are likely to stay stable, which will create favorable conditions for the country's decarbonization efforts up to 2030. The prediction indicates that there is neither significant progress nor any setbacks in this regard.

Belgium

Figure 8 illustrates the progression of selected indicators for Belgium. The first diagram (diagram *a*) indicates that, except for *CO_2 emissions,* no major changes in the indicator values, particularly *POWP* and *RENEN*, are expected by 2030. The values of the *CO_2* indicator are expected to remain relatively stable. The second diagram (diagram *b*) indicates that the *ENIMP* indicator, despite the downward trend from 2013 to 2022, will experience moderate growth in the coming years, with fluctuations from year to year.

Other indicators (*ENINT, NETEM,* and *ENCONS*) are anticipated to remain stable, showing no substantial fluctuations in their values. On the other hand, although electricity prices saw a slight uptick until (as illustrated in diagram *c,* indicators *EPHH* and *EPNHH*), a substantial increase is expected in the coming years, continuing through 2030. Regarding the imports of energy products

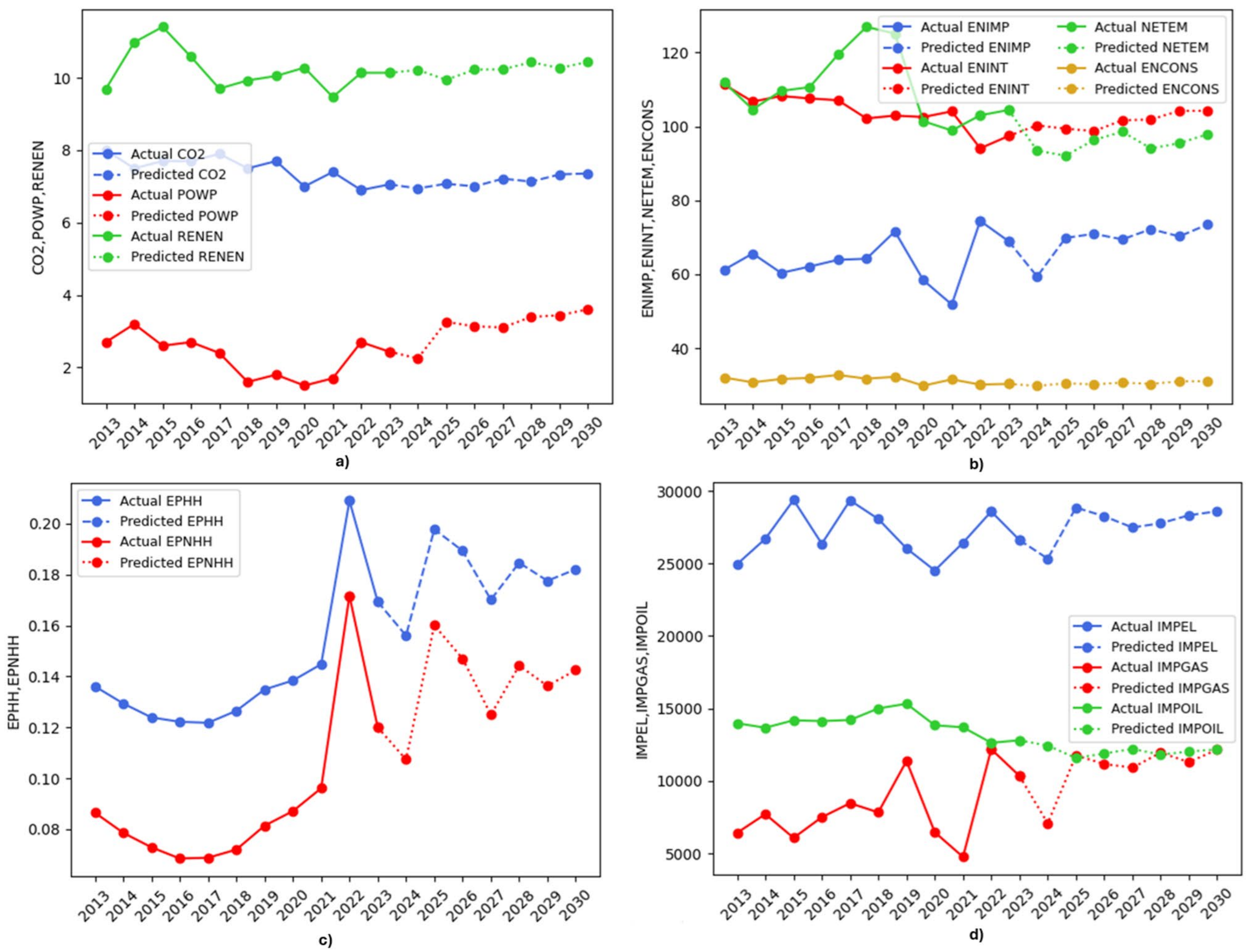


Fig. 7 Indicator predictions for Austria

(diagram *c*, indicators *IMPOIL, IMPEL, IMGAS*), a steady increase is expected to continue through 2030.

In light of the aforementioned factors, the potential for effective decarbonization in Belgium is likely to encounter several challenges, particularly illustrated by the escalating electricity costs and increasing energy imports. The anticipated rise in energy poverty is also significant. While the country's decarbonization policy has achieved notable milestones, its implications for economic competitiveness—especially regarding pricing and heavy reliance on energy imports—and, crucially, for the social well-being of citizens, could prove unfavorable.

Bulgaria

The predictions for Bulgaria (Fig. 9) are outlined as follows: The POWP indicator is projected to maintain its downward trajectory until 2030 (diagram *a*); CO_2 levels are anticipated to remain relatively stable, whereas *RENEN* is forecasted to rise (by approximately 15% by 2030). The *ENIMP* indicator, which reflects the import of energy products (diagram *b*) is expected to continue its downward trajectory in the coming years, while the *ENINT*, *NETEM* and *ENCONS* indicators are anticipated to remain relatively stable, with no notable changes. It is anticipated that energy product prices for households (*EPHH*) will remain relatively stable in the foreseeable future, a trend that does not extend to the prices of energy products for other consumer categories (*EPNHH*) (diagram c).

The import of gas (*IMPGAS*) is anticipated to follow a relatively stable trajectory (diagram d). In contrast, electricity imports are expected to exhibit steady growth (*IMPEL*), while significant fluctuations are forecasted for oil imports (*IMPOIL*). Stable values that describe the energy and environmental performance of the economy are noticeable (Zou et al. 2022), [47]. A significant reduction in energy poverty is also expected.

In summary, the evaluation of the acquired data suggests that by 2030, there will be no major advancements in the decarbonization of the Bulgarian economy, nor are any declines below the current level anticipated. The anticipated increase in the share of energy derived from

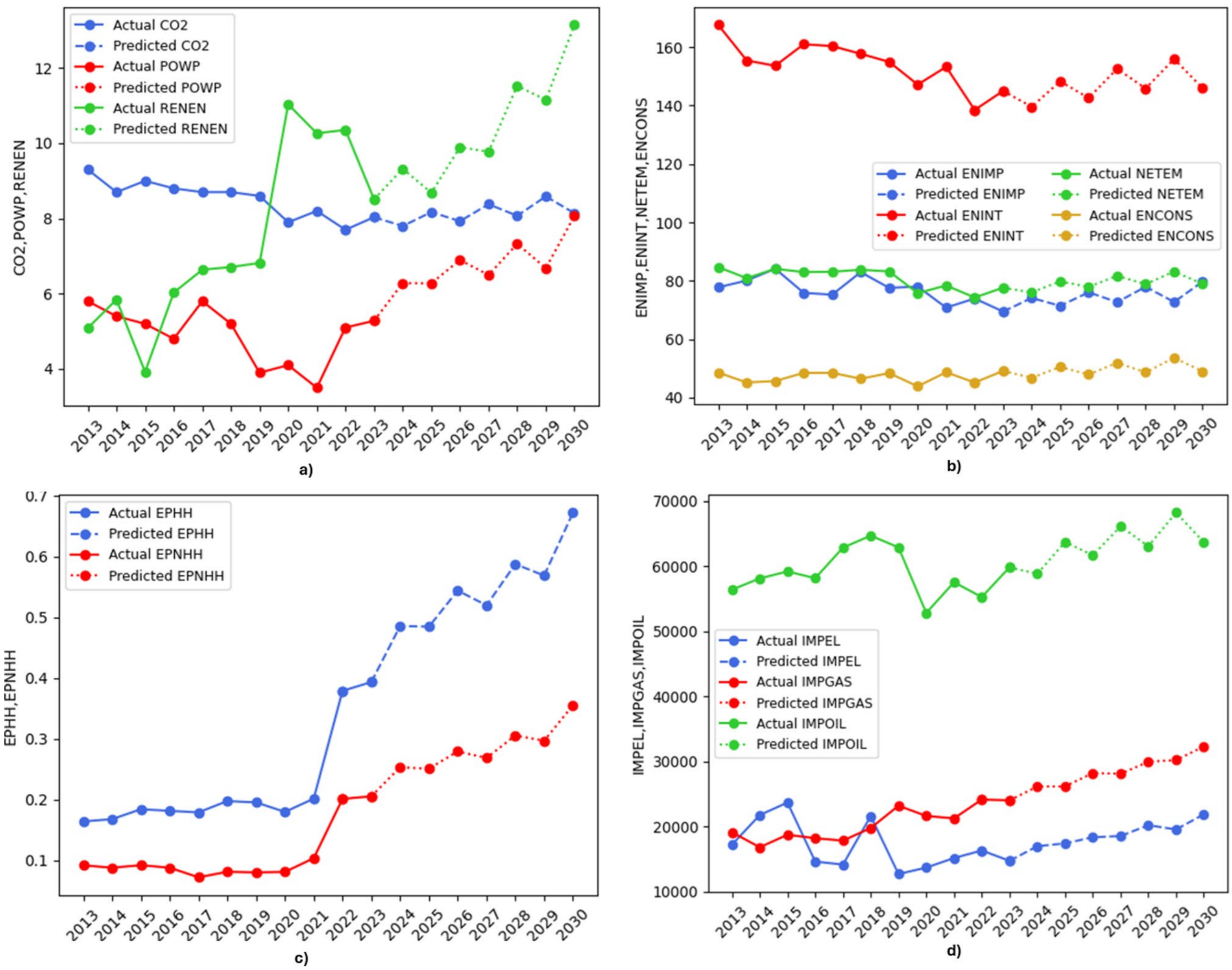


Fig. 8 Indicator predictions for Belgium

renewable sources is the only indicator likely to significantly influence the success of Bulgaria's decarbonization efforts by 2030.

Croatia

Indicator predictions for Croatia are presented below (Fig. 10). The first diagram (diagram *a*) indicates that significant fluctuations in the *POWP* and *RENEN* indicators are expected until 2030, reflecting the ongoing trends observed over the past decade. The CO_2 indicator is expected to remain relatively stable throughout this period. The second diagram (diagram *b*) shows that energy consumption (*ENCONS*) is projected to experience a moderate increase, with the *ENIMP* indicator reflecting similar trends. In contrast, the *NETEM* indicator is anticipated to exhibit significant fluctuations through 2030.

No notable changes in household electricity prices (*EPHH*) are anticipated; however, prices for other consumer categories (*EPNHH*) are expected to fluctuate more significantly, with a pronounced upward trend (*diagram c*). The predictions for these two indicators exhibit a six-year periodic pattern. The indicators representing oil and gas imports (*IMPOIL* and *IMPGAS*) display similar trends (*diagram d*), with a significant increase in gas imports anticipated. Conversely, electricity imports (*IMPEL*) are expected to fluctuate, following a six-year periodic pattern.

The forecast results suggest that Croatia is expected to experience an increase in energy source imports and electricity prices, which may significantly impact the social well-being of its citizens and the competitiveness of the national economy. This situation could be further aggravated by a projected decline in energy production from renewable sources. Conversely, the projections indicate that CO_2 emissions are expected to remain unchanged, which is certainly favorable in terms of decarbonization; however, it does not imply that significant progress can be expected in this area. It can be concluded that the primary challenge for future decarbonization efforts in

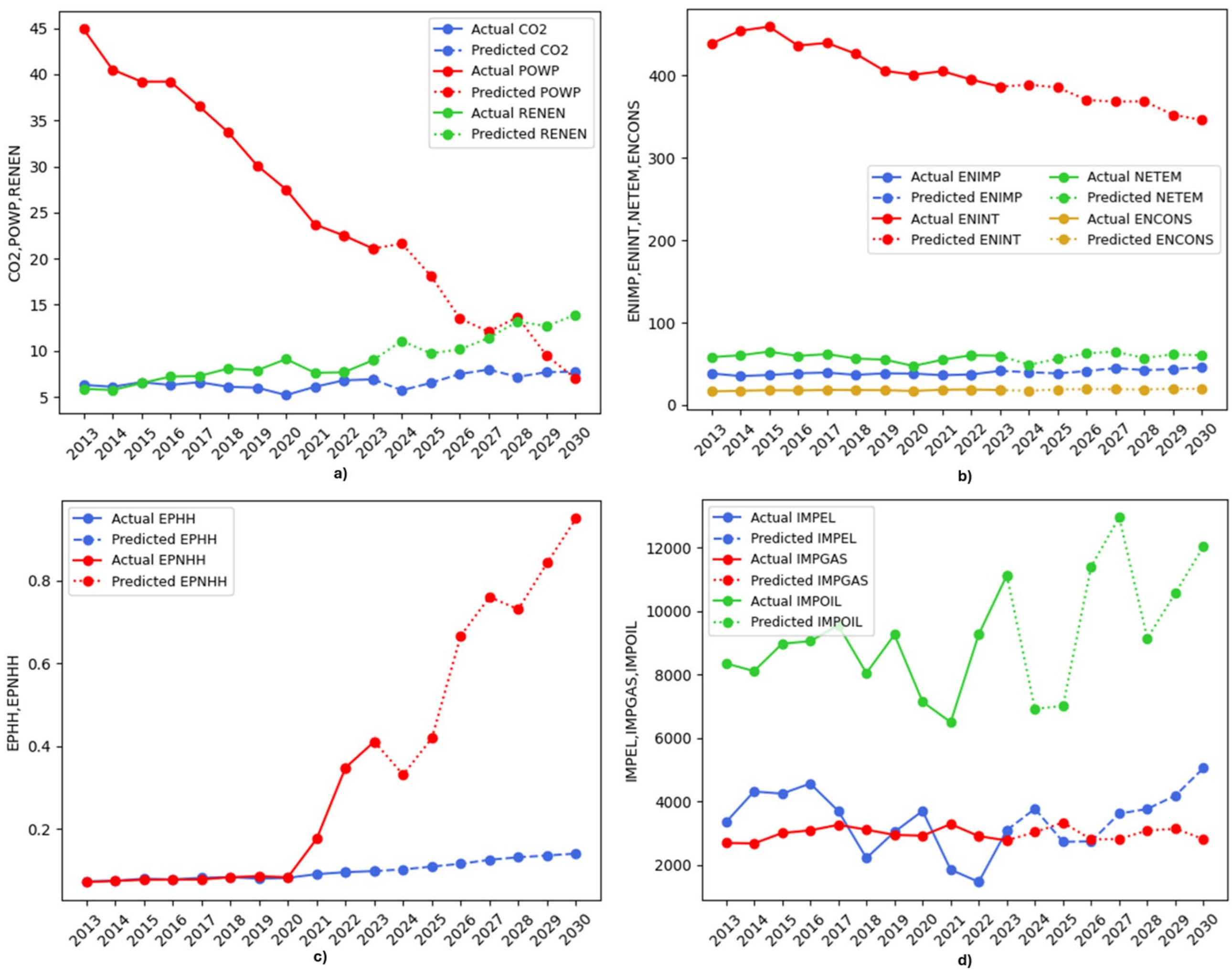


Fig. 9 Indicator predictions for Bulgaria

this country lies in electricity management. Although its consumption does not result in direct pollution, increasing demand, rising prices, and heavy reliance on imports pose significant concerns.

Cyprus

For Cyprus (Fig. 11), a significant increase in the share of energy from renewable sources (*RENEN*) is projected, while CO_2 levels are expected to remain largely unchanged (*diagram a*). Conversely, the *POWP* indicator is projected to experience continuous growth through 2030. The next diagram (*diagram b*) indicates a slight increase in energy imports (*ENIMP*), as well as energy intensity (*ENINT*). The *NETEM* indicator will continue to oscillate in four-year periods, with no significant increase anticipated. Conversely, the *ENCONS* indicator values for Cyprus are among the lowest across all 27 EU countries and have remained relatively stable throughout the observed period. Based on diagram *c*, it can be concluded that the electricity prices for *EPHH* and *EPNHH* are nearly identical, with a significant increase anticipated through 2030.

The final diagram (diagram *d*) illustrates that Cyprus does not engage in the import of gas or electricity (indicators *IMPEL* and *IMPGAS*). Oil imports (*IMPOIL*) are expected to fluctuate in the upcoming years leading up to 2030, yet these variations are not anticipated to be substantial when compared to the preceding decade. When comparing *IMPOIL* with other indicators, the pattern of changes closely resembles that of the *NETEM* indicator.

The main challenges for decarbonization in Cyprus lie in the anticipated rise in electricity costs, which will affect both the population and the economy. As an island nation, it is crucial to develop a tailored solution to address this issue, particularly by focusing on electricity generation from renewable sources. No significant changes in CO_2 values are expected for Cyprus until 2030. The factors previously mentioned are undoubtedly influenced by the structure of the country's economy, which is heavily reliant on tourism.

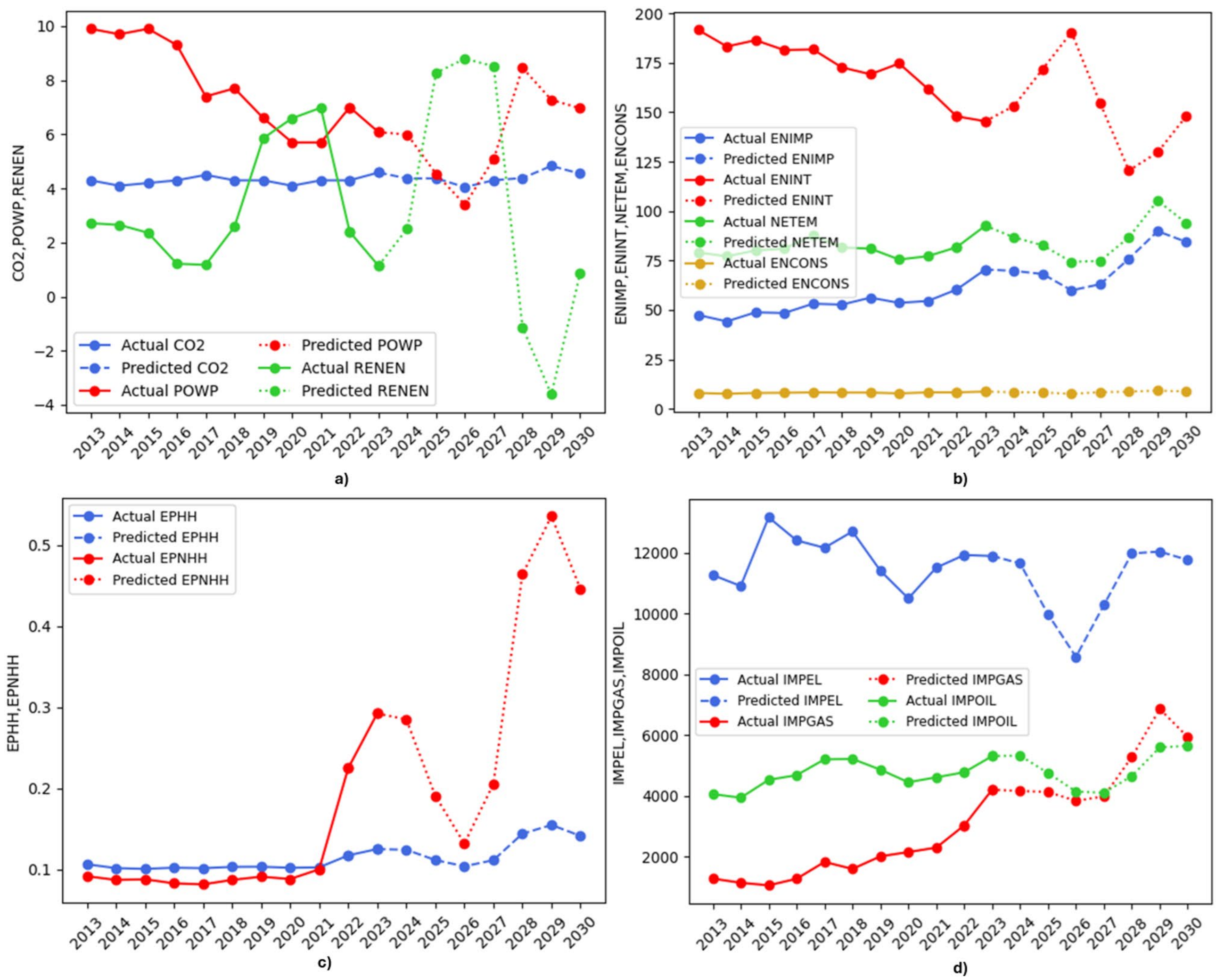


Fig. 10 Indicator predictions for Croatia

Czech Republic

The subsequent illustrations depict the prediction indicators for the Czech Republic (Fig. 12). The first diagram (diagram *a*) indicates that no significant changes in the CO_2*, indicator values are expected in the future,* whereas the *POWP* indicator is projected to exhibit an upward trend. The *RENEN* indicator is expected to continue fluctuating until 2030, though with reduced amplitudes*.* It is evident that there will be no significant changes in the *ENIMP, ENINT, NETEM*, and ENCONS indicators through 2030 (diagram *b*). Conversely, electricity prices (diagram *c*, indicators *EPHH* and *EPNHH*) showed a pronounced increase, especially between 2019 and 2022. The prediction suggests that the increase in electricity prices will be moderate and is expected to level off by 2028, after which a gradual decline is anticipated.

Diagram *d* presents data concerning indicators associated with energy imports. Significant variations in electricity imports are anticipated to persist (*IMPEL*), whereas gas and oil imports (indicators *IMPGAS* and *IMPOIL*) are projected to stabilize and exhibit a declining trend leading up to 2030.

The primary challenge for decarbonization efforts in the Czech Republic is its reliance on imported energy, which is further complicated by the unpredictability of pricing and overall supply stability. The findings suggest that the country's development policy will primarily emphasize enhancing economic competitiveness while striving to maintain the current levels of decarbonization indicators. However, it appears that substantial advancements are unlikely to occur.

Denmark

For Denmark (Fig. 13), a significant upward trend is anticipated for *POWP* and *RENEN* indicators. As for CO_2, despite a slight decline in the previous period, it is expected to reverse this trend and show a continuous increase until 2030 (diagram *a*). A modest decrease is

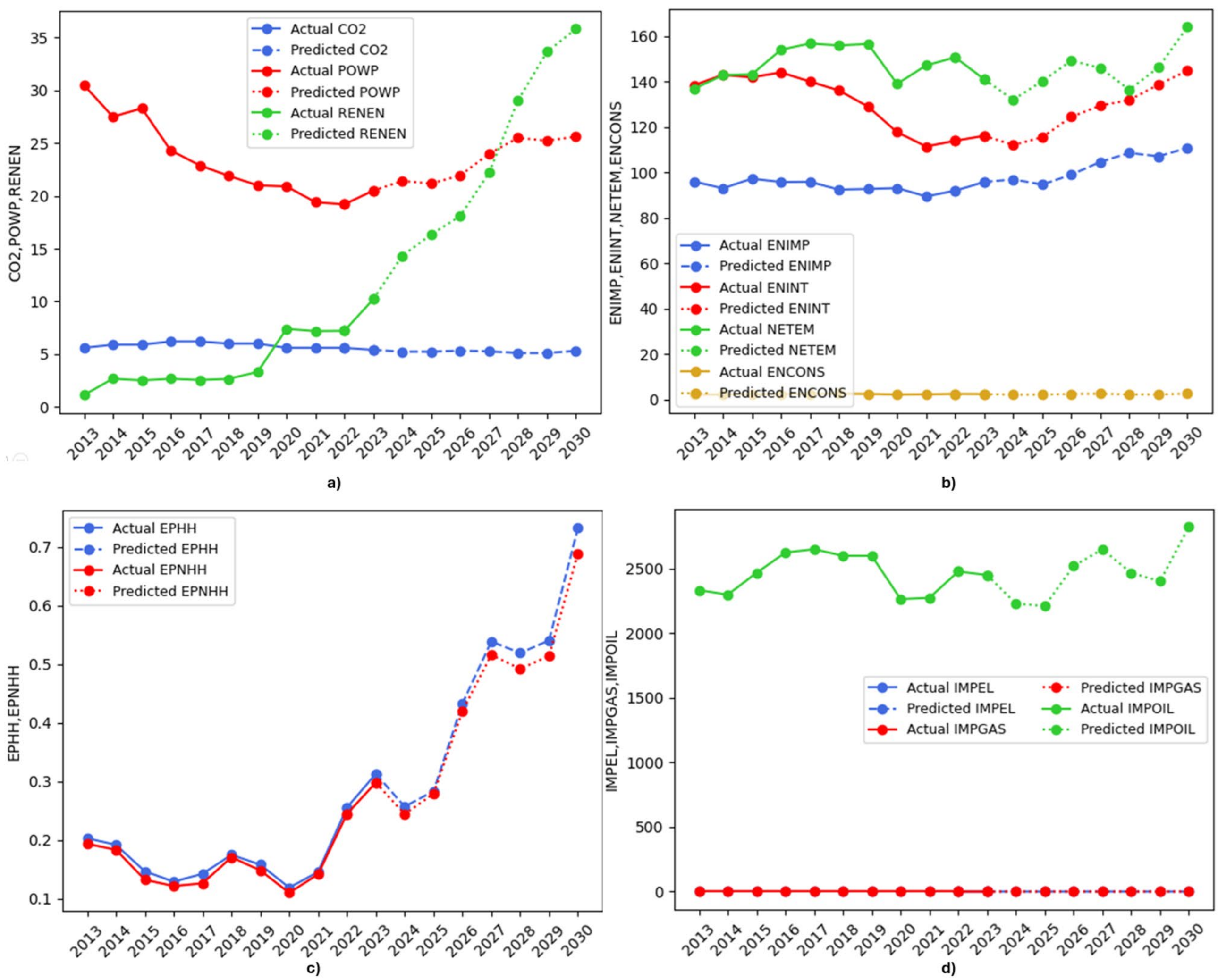


Fig. 11 Predictions for Cyprus

expected for the *ENCONS* indicator (diagram *b*), whereas *ENIMP* is forecasted to rise further, albeit with some variability, through 2030. The *ENINT* and *NETEM* indicators will maintain similar trends and are expected to reverse their previous decline from 2013 to 2022, showing an increase until 2030.

Electricity prices (*EPHH* and *EPNHH*) will continue the growth trend that began in 2020 (diagram *c*), with the rate of increase expected to slow down starting in 2027. The import of energy products is projected to continue its growth (indicators *IMPOIL* and *IMPGAS*, diagram *d*). Meanwhile, fluctuations in electricity imports are expected, with a slight decrease observed during the final three years of the period analyzed.

The primary obstacles that may influence the feasibility of Denmark's decarbonization include, firstly, the anticipated rise in electricity prices (impacting both the economy and the populace), alongside the expected growth in energy poverty. This indicates a pressing need to focus on the social dimensions of ongoing decarbonization efforts, as the recognized trends are likely to impact the competitiveness of the country's economy and, consequently, all other relevant indicators.

Estonia

Estonia (Fig. 14) made significant progress in the production of energy from renewable sources between 2017 and 2020 (the *RENEN* indicator, diagram *a*). Subsequently, a shift in trend occurred, and projections indicate that this indicator will persist in its decline until 2025, at which point it is expected to experience substantial growth until 2030. The projection indicates that CO_2 levels will rise until 2029, followed by a subsequent decrease. No substantial alterations are anticipated for the *POWP* indicator prior to 2030. Estonia is expected to maintain low, stable values for *ENCONS*, *ENIMP*, and *NETEM* (diagram *b*), while *ENINT* is projected to continue its slight increase until 2026, followed by stabilization and a slight

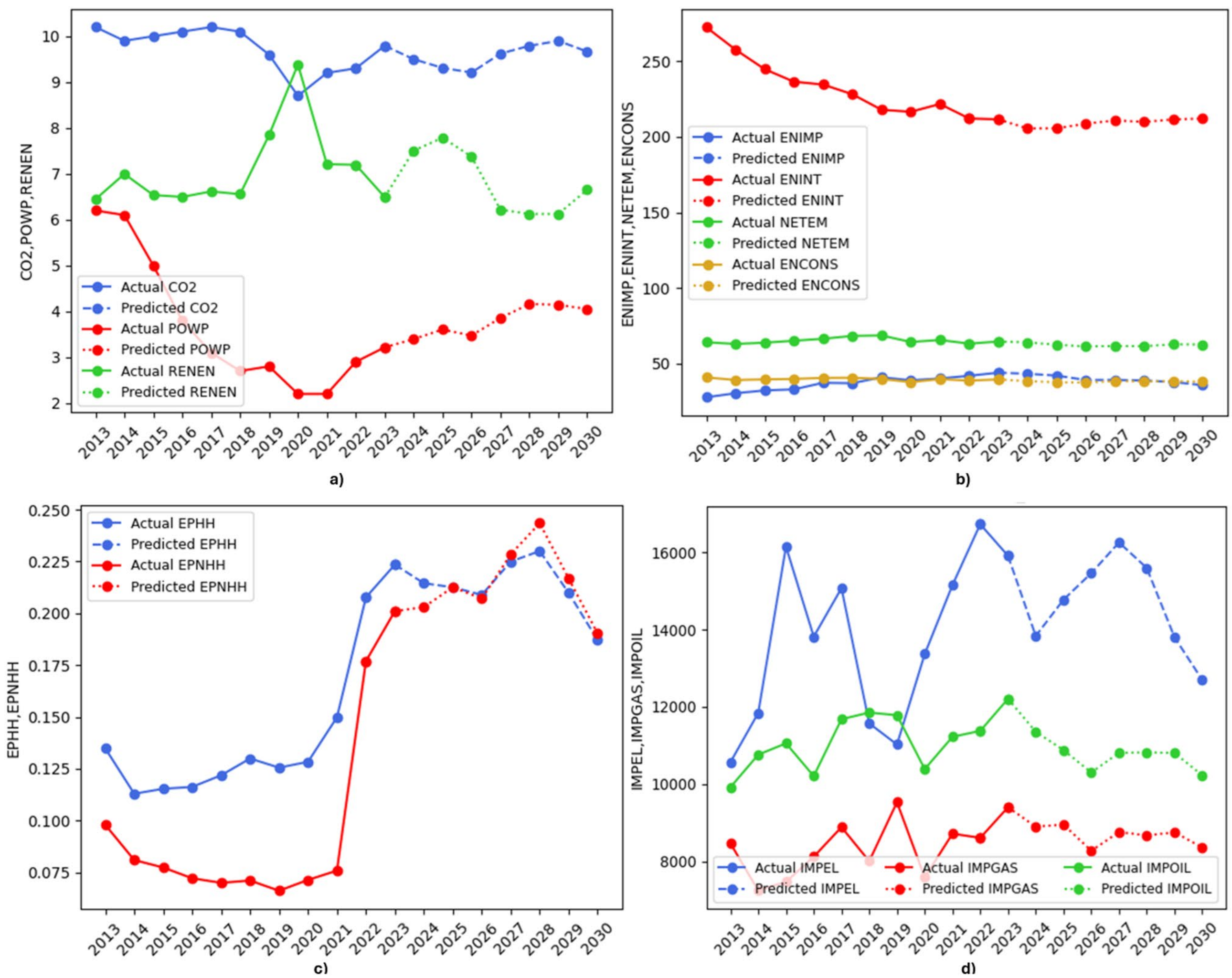


Fig. 12 Indicator predictions for the Czech Republic

decline until 2030. Electricity prices (indicators *EPHH* and *EPNHH*) peaked in 2022 (diagram *c*).

The predictions indicate a sustained growth trajectory for *EPHH* and *EPNHH*, with diminishing fluctuations anticipated until 2030. The import of oil and gas (*IMPOIL* and *IMPGAS*) is expected to remain stable, while the import of electricity (*IMPEL*) is projected to continue at the elevated levels observed in the previous period (diagram *d*).

The overall findings and forecasts indicate that Estonia is likely to experience considerable variations in anticipated trends, which will undoubtedly complicate the development planning process across all dimensions. The issues of energy poverty and electricity management are increasingly recognized as significant challenges impacting the country's economy, highlighting their critical role in the decarbonization process and overall management strategies.

Finland

Predictions for Finland generally show stable trends (Fig. 15). CO_2 and *POWP* show slightly decreasing trends, while a significant decrease is expected for *RENEN* by the end of 2030 (diagram *a*). Mild downward trends are also observed in the *ENIMP, ENINT, NETEM*, and *ENCONS* indicators (diagram *b*). Significant alterations are anticipated for the *EPHH* and *EPNHH* indicators (diagram *c*), which are forecasted to enter a state of permanent decline post-2025. Slight downward trends are also expected in the import of energy products, as indicated by the *IMPEL, IMPGAS,* and *IMPOIL* indicators (diagram *d*).

Considering the entire observed period, Finland maintains consistent values of the indicators, which presents a significant advantage when strategizing all facets of development, including decarbonization. Unlike other countries, Finland anticipates a decrease in electricity prices, as well as a reduction in the imports of electricity, oil, and gas. This will significantly impact the stability

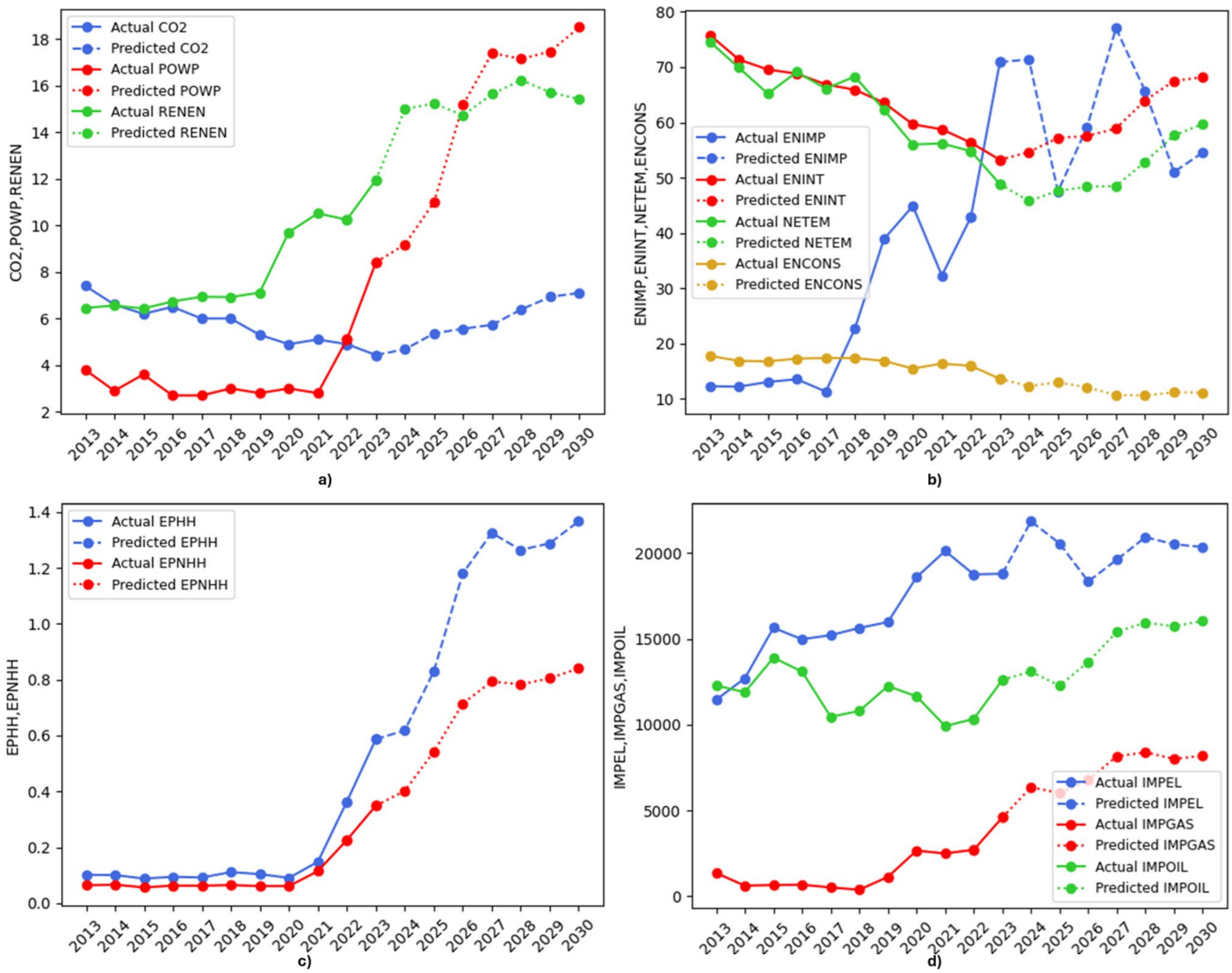


Fig. 13 Indicator predictions for Denmark

of the country's energy-economy-environment nexus and the continued progress of the decarbonization process.

France

Significant alterations are anticipated for the observed indicators in France (Fig. 16). Aside from CO_2, which is anticipated to experience a slight decrease, the *RENEN* indicator is projected to see substantial growth through 2030. *POWP* is expected to maintain its moderate growth trend in the future as well (diagram *a*). A significant decrease in energy consumption (*ENCONS*), a slight increase in energy imports (*ENIMP*) and a continued slight decline in *ENINT* and *NETEM* (diagram *b*) are expected. During the observed timeframe, a greater sustained increase in *EPHH* and *EPNHH* is anticipated compared to the preceding decade (diagram *c*). A similar trend is expected for electricity imports (*IMPEL*), while milder growth with fluctuations is anticipated for other energy sources (*IMPOIL* and *IMPGAS*) (diagram *d*).

Significant fluctuations in various indicators, along with a sharp rise in electricity prices and imports and the anticipated surge in energy poverty, will present major challenges for France's decarbonization strategy moving forward.

Germany

For Germany, the predictions show that some indicators will undergo significant changes, while others will continue the trends observed in the previous ten years (Fig. 17). The *RENEN* and *POWP* indicators are expected to experience significant growth by the end of 2030, while the CO_2 trend is projected to remain relatively stable (diagram *a*). Predictions for *ENINT* and *ENCONS* indicate a slight decline; *ENIMP* is expected to continue its growth, while *NETEM* will remain nearly unchanged compared to the previous decade (diagram *b*). As in France, the predictions for the *EPHH* and *EPNHH* indicators suggest a sharp increase in electricity prices (diagram *c*). Similarly, the prediction for electricity imports (*IMPEL*) follows the

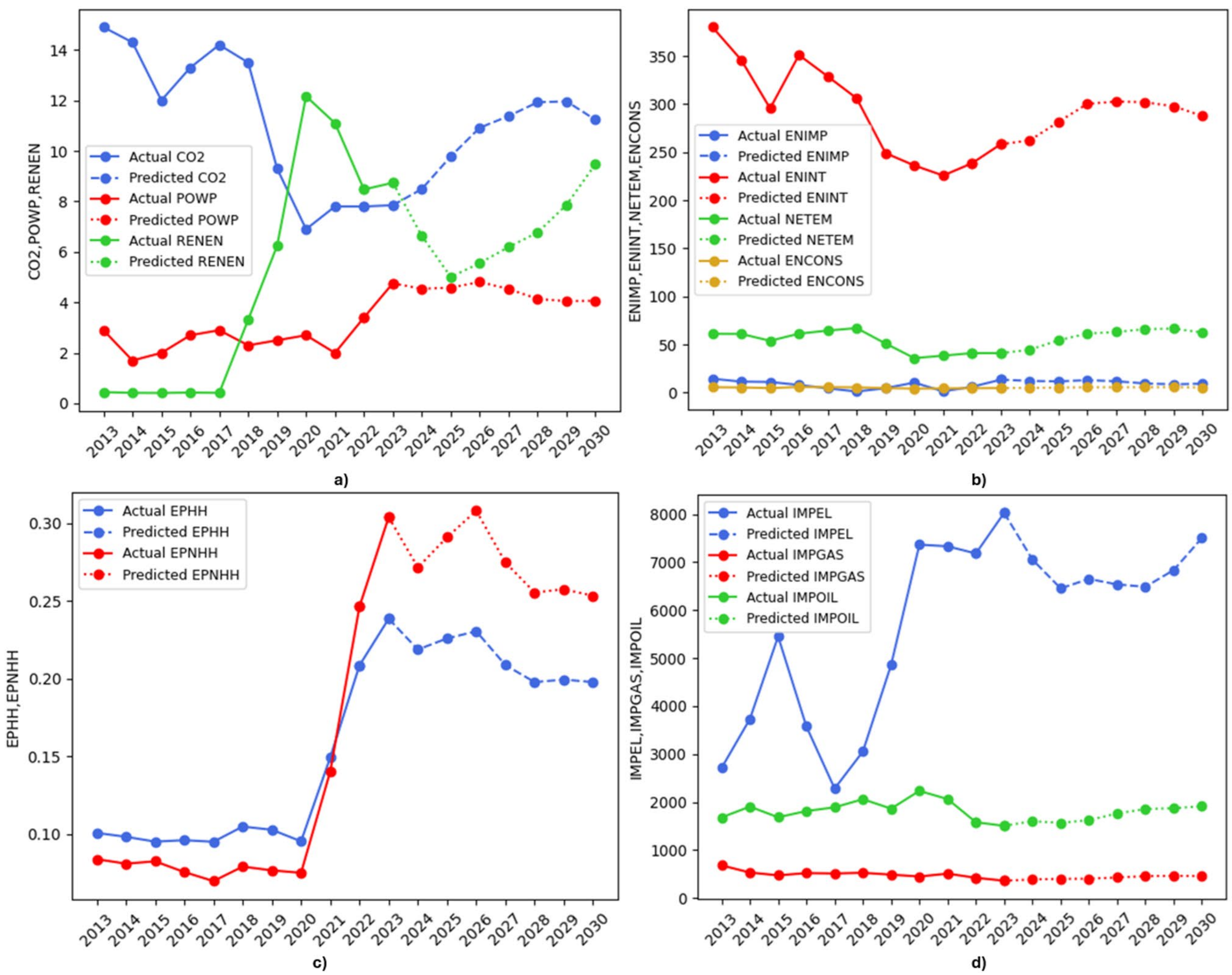


Fig. 14 Indicator predictions for Estonia

same upward trend. The import of other energy products (*IMPOIL* and *IMPGAS*) is expected to show modest growth accompanied by fluctuations (diagram *d*).

After 2022, the German economy faces many complex challenges, primarily related to problems in gas imports. Additional complications are anticipated due to the projected rise in electricity prices, which will not only affect the economy but also contribute to an expected increase in energy poverty. An increase in renewable energy share is expected, but not enough to meet population and economic needs. In this context, the decarbonization of the German economy will largely rely on effective management of the key aspects mentioned above.

Greece

The following are the predicted trends for the indicators in Greece (Fig. 18). CO_2 and *RENEN* are expected to grow slightly, while *POWP* is projected to remain stable until 2028 (diagram *a*). Except for energy consumption (*ENCONS*), significant growth is forecasted for the indicators *ENIMP, EININT*, and *NETEM* (diagram *b*). Electricity prices (*EPHH* and *EPNHH*) are expected to continue their rapid growth trend until the end of 2026. Afterward, they are expected to slightly decline until the end of 2030 (diagram *c*). For oil imports (*IMPOIL*), the prediction indicates significant growth, following a similar trend to *ENIMP* and *EININT*, while the import of other energy products (*IMPEL* and *IMPGAS*) is expected to remain stable (diagram *d*).

To date, Greece has experienced a measured level of success in the decarbonization of its economy, characterized by a modest initial decrease followed by a rise in energy intensity (which is associated with energy imports) and relatively consistent CO_2 emissions. The future poses significant challenges, primarily due to rising electricity prices, which are expected to impact on the competitiveness of the national economy—particularly considering its strong dependence on tourism.

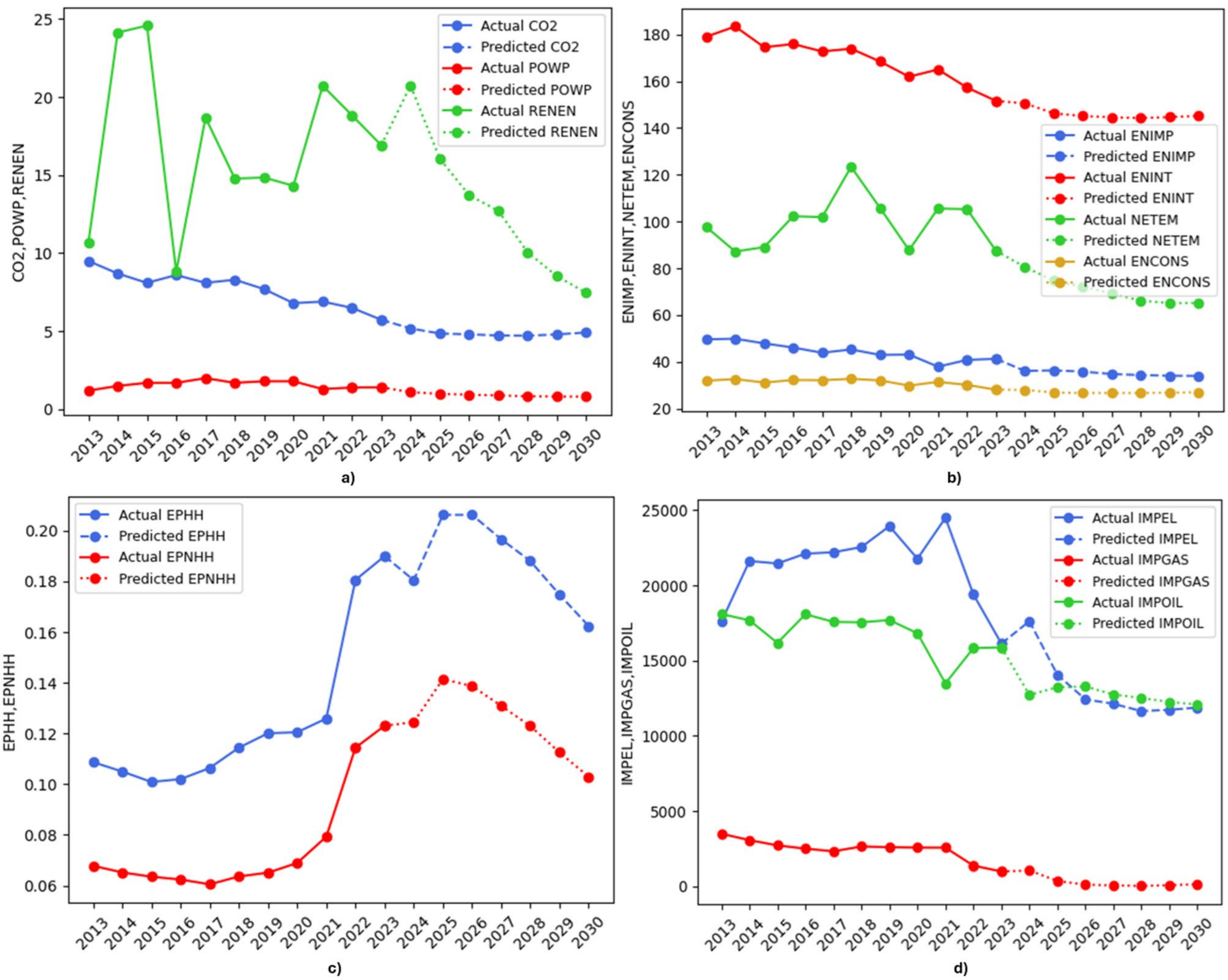


Fig. 15 Indicator predictions for Finland

Hungary

The indicator predictions for Hungary (Fig. 19) show year-to-year fluctuations for most variables. Apart from CO_2, *RENEN* and *POWP* have shown periodic fluctuations since 2020. These fluctuations are expected to continue until 2030 (diagram *a*). On the other hand, the indicators *ENCONS, ENINT, ENIMP*, and *NETEM* are expected to remain relatively stable (diagram *b*). Electricity prices for households (*EPHH*) are projected to stay unchanged, reflecting the significance of social policy—while prices for other consumers (*EPNHH*) are expected to show substantial fluctuations (diagram *c*). Imports of electricity and gas (*IMPEL* and *IMPGAS*) are predicted to continue oscillating similarly to previous decades, with *IMPOIL* showing only minor changes (diagram *d*).

Ireland

The predictions for Ireland (Fig. 20) indicate significant fluctuations in *POWP* and *RENEN*, while CO_2 is expected to show only minor oscillations (diagram *a*). In contrast, indicators such as *ENINT, ENIMP, ENCONS*, and *NETEM* are projected to change only slightly by the end of 2030 (diagram *b*). Both *EPHH* and *EPNHH* are expected to exhibit considerable fluctuations following a similar pattern (diagram *c*). Apart from electricity imports (*IMPEL*), which are projected to remain relatively stable, the import of other energy products (*IMPOIL* and *IMPGAS*) is expected to undergo slight, periodic variations (diagram *d*).

Energy and environmental indicators influencing the decarbonization of Hungary's economy have fluctuated considerably over the observed period. However, no major changes are anticipated in energy product imports—though this will largely depend on the European Union's future relationship with the Russian Federation. Future measures should be directed toward stabilizing and increasing the production of renewable energy, curbing electricity price growth, and further reducing the energy intensity of the economy. By monitoring key trends and balancing development policies, we

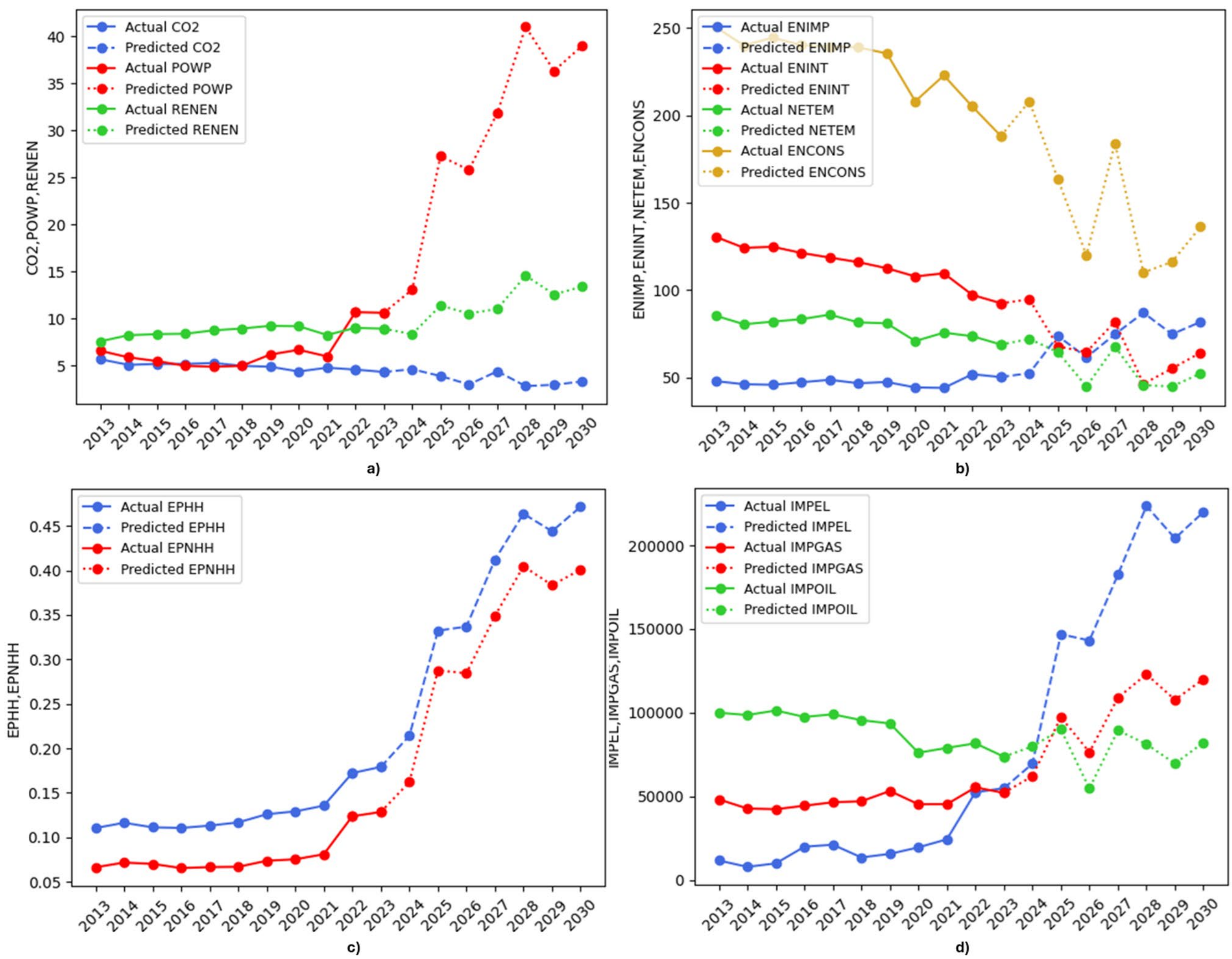


Fig. 16 Indicator predictions for France

can expect continued success in decarbonizing the Hungarian economy without compromising the economy's competitiveness or the social well-being of citizens.

Italy

Indicator predictions for Italy (Fig. 21) suggest significant growth in *RENEN* and CO_2 emissions, with an expected increase in *POWP* by 2027, followed by a slight decline toward the end of the observed period (diagram *a*). Growth is forecasted for *ENIMP*, *ENCONS*, and *NETEM*, while *ENINT* is expected to follow a similar trend to the previous decade (diagram *b*). Electricity prices (*EPHH* and *EPNHH*) are projected to continue their rapid growth until the end of 2030 (diagram *c*). Energy product imports are expected to remain relatively unchanged (diagram *d*).

The management of the decarbonization process in the Italian economy faces—and will continue to face—numerous challenges, primarily reflected in the expected growth trends of various indicators that impede progress. These indicators include rising electricity prices and imports, increased gas and oil imports, and a further rise in the economy's energy intensity. In this context, planning for future progress requires regular reassessment and a thorough analysis of various factors, allowing Italy to begin recording positive signs of its economic decarbonization.

Latvia

Predictions for Latvia (Fig. 22) indicate trend changes for most indicators. With the exception of CO_2, which remains relatively unchanged, *POWP* and *RENEN* exhibit opposite trends with fluctuating patterns until the end of 2030 (diagram *a*). Energy imports and consumption (*ENIMP* and *ENCONS*) are expected to remain stable, while *NETEM* and *ENIMP* will shift their previously opposing trends (diagram *b*). Trend changes are also forecasted for *EPHH* and *EPNHH*, with both expected to decline until the end of 2028 before starting to increase again (diagram *c*). The import of electricity (*IMPEL*) will

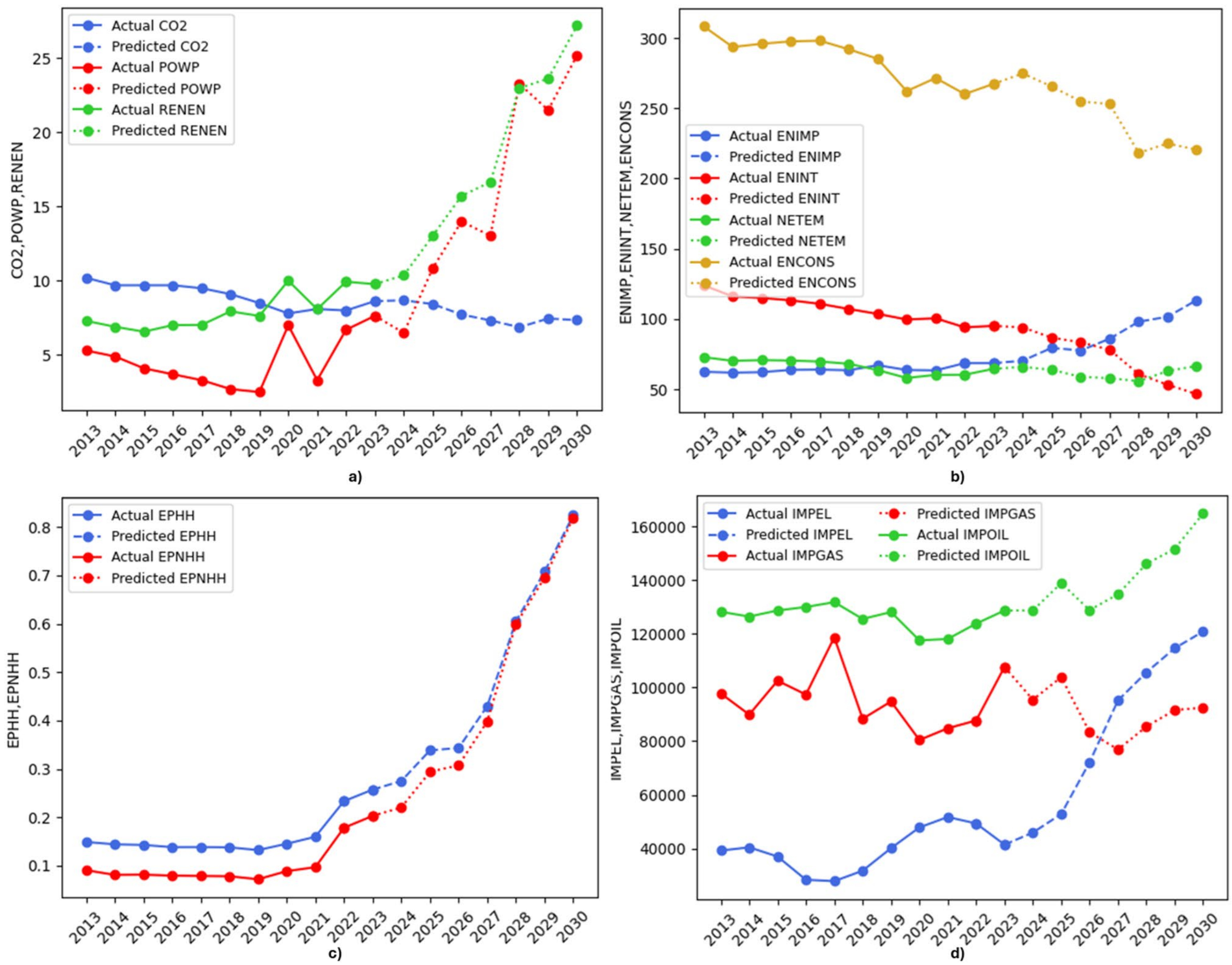


Fig. 17 Indicator predictions for Germany

follow a similar pattern to *EPHH* and *EPNHH*, dropping until the end of 2028 before rising again. Imports of gas and oil (*IMPGAS* and *IMPOIL*) will fluctuate with minor changes (diagram *d*).

In contrast to most EU countries, forecasts indicate a downward trend in electricity prices and a slight decrease in overall energy imports. As energy poverty diminishes and CO_2 emissions are projected to remain stable, it can be inferred that the transition toward a decarbonized economy in this country will occur in a steady manner without significant economic, social, or environmental hurdles. The most significant challenges that could impact the above are likely to be of a geopolitical nature.

Lithuania

Forecasts for Lithuania (Fig. 23) indicate significant changes in most indicators. The year 2026 marks a key turning point in several trends. As in many other countries—except in the case of CO_2—the *POWP* indicator is expected to follow a downward trend until 2026, after which it will begin to rise. In contrast, *RENEN* is projected to maintain a steady upward trajectory from 2024 through the end of the observed period (diagram *a*). *ENCONS* and *ENIMP* are expected to remain stable, while *ENINT* is predicted to follow a similar curve to *POWP*. *NETEM* will show a slight downward trend over the forecasted period (diagram *b*). Electricity prices (*EPHH* and *EPNHH*) are projected to rise significantly until 2026, followed by a decline (diagram *c*). Energy product imports in Lithuania are expected to fluctuate considerably. *IMPEL* is forecasted to drop sharply, while *IMPOIL* and *IMPGAS* will exhibit less dramatic changes. However, after 2026, *IMPOIL* is expected to rise, whereas *IMPGAS* is likely to decline (diagram *d*).

The process of managing the decarbonization of the Lithuanian economy has proven to be a complex and multifaceted challenge over the observed period. In the future, CO_2 levels are expected to stabilize, although fluctuations in other related indicators are likely to persist. A positive indicator is the expected decrease in electricity

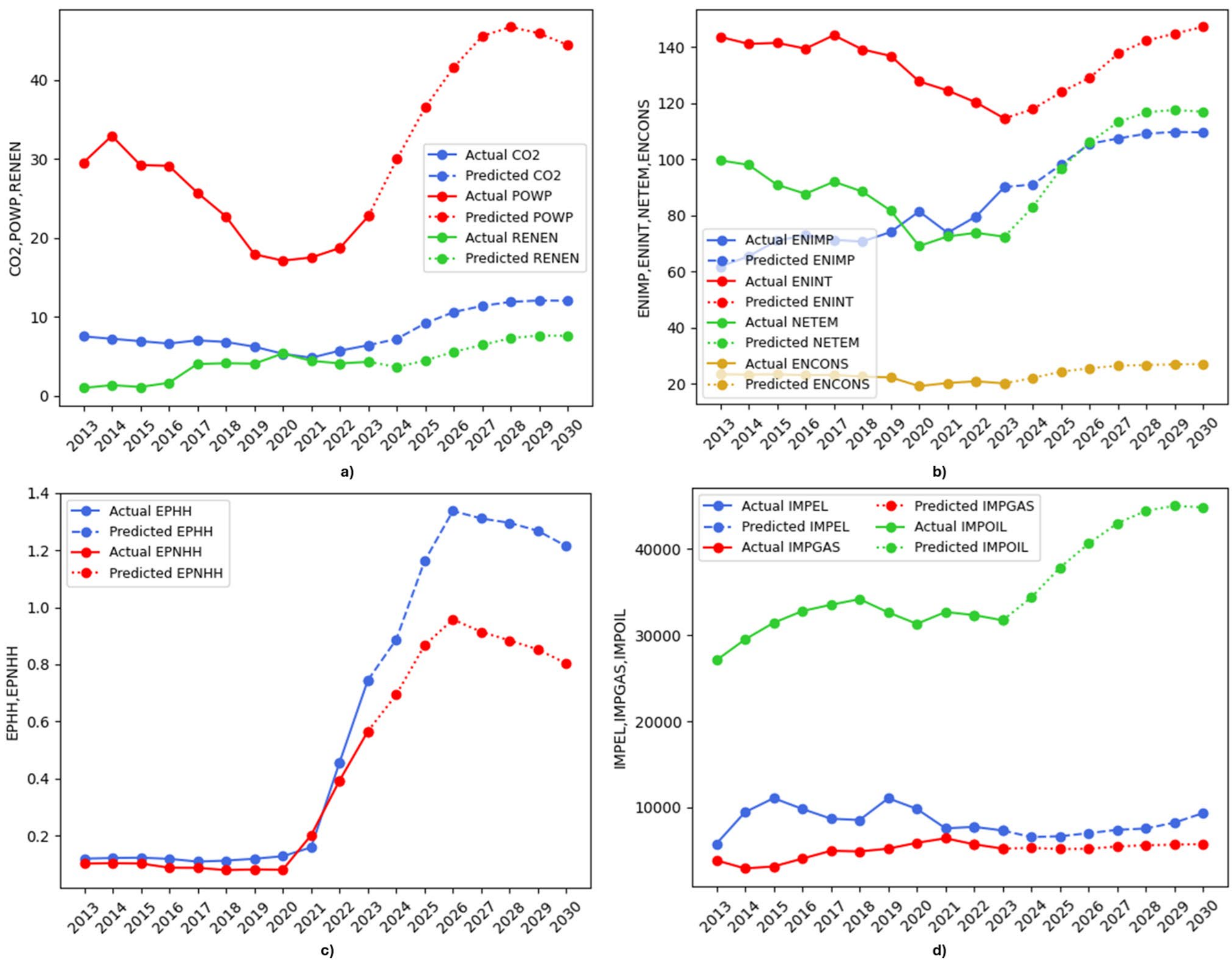


Fig. 18 Indicator predictions for Greece

and gas imports, accompanied by a relatively small increase in oil imports. In addition, a downward trend in electricity prices and energy poverty is noticeable. Considering the above, it is realistic to expect limited progress in decarbonization; however, no significant negative trends are anticipated. Therefore, future development policy should focus on maintaining existing efforts while carefully planning new initiatives—particularly considering complex geopolitical developments.

Luxembourg

Unlike the previously described predictions, those for Luxembourg reveal different patterns (Fig. 24). Most indicators show significant changes both in the past decade and throughout the forecast period. The indicators CO_2, *POWP*, and *RENEN* are expected to reverse their trends in 2027 and 2028, with all three beginning to decline by the end of 2030 (diagram *a*). In contrast, *ENCONS* and *ENIMP* are not projected to undergo notable changes during the observation period, while *ENINT* and *NETEM* are expected to continue the oscillating trends observed over the past decade (diagram *b*). Additionally, significant trend shifts are anticipated for *EPHH* and *EPNHH*. Unlike in other countries, the changes in *EPHH* are not closely linked to those in *EPNHH* (diagram *c*). No major changes are expected in the import levels of energy products—*IMPEL*, *IMPGAS*, and *IMPOIL* (diagram d).

The economy of Luxembourg is driven by electricity-intensive services rather than fossil fuel-based industries. Given the shifting trend in electricity prices, the high reliance on electricity imports, and the fluctuating share of renewable energy sources, energy management efforts should be concentrated in this segment.

Malta

Despite notable changes in the past, the predictions for Malta indicate only minor changes in most indicators through to 2030 (Fig. 25). This can be attributed to Malta's status as a small island located in the southern

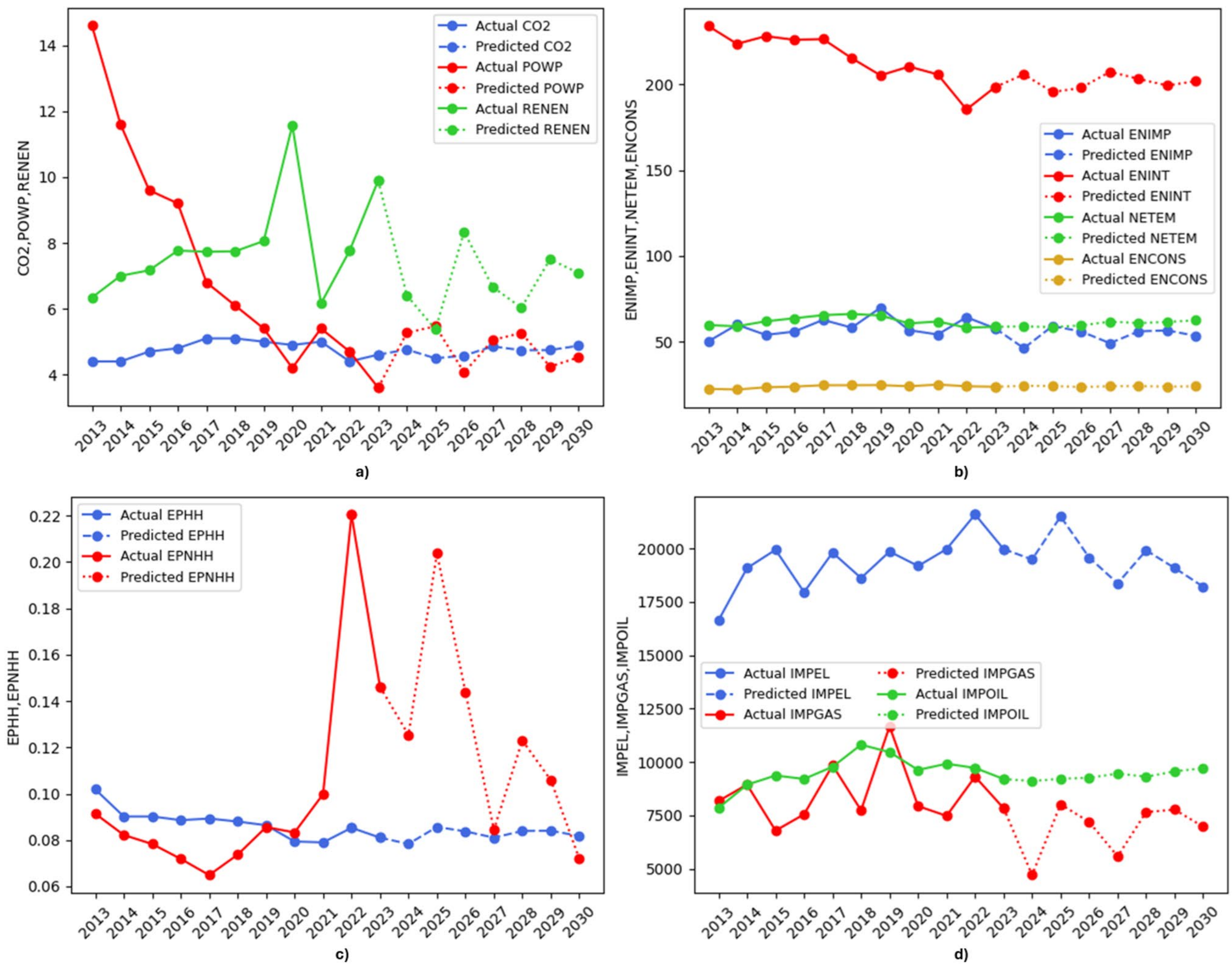


Fig. 19 Indicator predictions for Hungary

Mediterranean, with a relatively small population primarily employed in tourism and related service sectors. Unlike Cyprus, Malta imports all types of energy products; however, significant shifts in these imports are not expected. Overall, most indicators are projected to remain relatively stable throughout the forecast period.

Malta has so far achieved moderately positive results in certain aspects of decarbonization: the CO_2 emission levels have remained stable, with slight improvements in the energy intensity of the economy—pointing to a clear direction for future efforts. Forecasts for indicators influencing Malta's decarbonization suggest that significant fluctuations are unlikely, which will greatly ease the overall management of the transition.

Poland

Another interesting forecast concerns Poland (Fig. 26). The fluctuations observed exemplify the typical patterns of indicators throughout the projected timeframe. With the exception of *ENIMP* and *IMPOIL*, which are projected to show gradual increases, all other indicators are expected to undergo annual trend changes. CO_2 and *POWP* are expected to diverge in trends from *RENEN* (diagram *a*). Similarly, *ENINT*, *NETEM*, and *ENCONS* are anticipated to exhibit synchronous trend changes (diagram *b*). The same pattern is observed for *EPHH* and *EPNHH* (diagram *c*). Finally, *IMPEL* and *IMPGAS* will display annual trend changes, but in contrasting directions (diagram *d*).

The entire observed period for Poland is characterized by significant oscillations across all selected indicators. This pattern can hinder the management of the decarbonization process, especially in light of the additional challenges posed by changes in the EU's energy policy. As a result, further decarbonization efforts in Poland are likely to be particularly challenging.

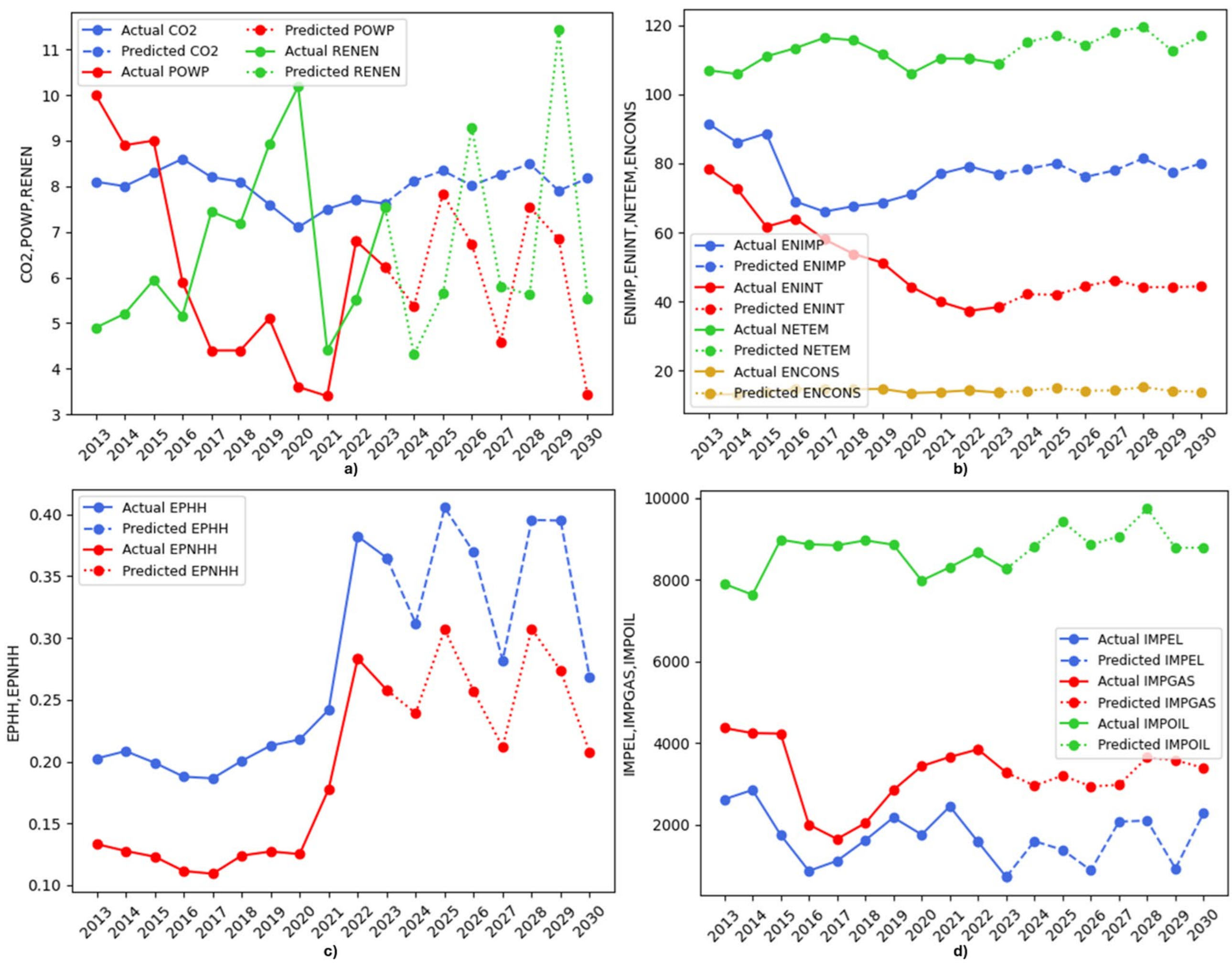


Fig. 20 Indicator predictions for Ireland

Portugal

Significant growth is a common characteristic in the predictions for Portugal (Fig. 27). *POWP* and *RENEN* are expected to exhibit growth, while CO_2 is projected to increase slightly (diagram *a*). Slight growth is anticipated for *ENIMP, ENINT*, and *ENCONS*, whereas *NETEM* is expected to grow rapidly until 2027, after which it will begin to decline through to the end of 2030 (diagram *b*). The growth of electricity prices (*EPHH* and *EPNHH*), which began in 2022, will continue rising until 2026, before gradually reversing and declining toward the end of 2030 (diagram *c*). Similar trends are predicted for the imports of energy products (*IMPEL, IMPOIL*, and *IMPGAS*). After significant growth through 2026, these imports are expected to start declining toward the end of the observed period (diagram *d*).

CO_2 emission values and total energy imports are the only two indicators for which no significant changes are anticipated in the future. The rise in electricity prices will impact both the competitiveness of the economy and the social well-being of citizens, while the expected increase in energy imports presents specific challenges for managing the decarbonization process. This context underscores the need for careful planning and caution moving forward.

Romania

In the predictions for Romania (Fig. 28), some indicators show minor changes, while others exhibit significant growth. *POWP* is expected to experience substantial growth until 2028, after which its trend will shift. In contrast, *RENEN* and CO_2 are anticipated to remain largely unchanged (diagram *a*). The same pattern applies to *ENCONS, NETEM*, and *ENIMP*, while *ENINT* is projected to begin growing toward the end of 2030 (diagram *b*). The growth of electricity prices (*EPHH* and *EPNHH*), which began in 2022, is expected to continue rising until 2028. After that, the trends will reverse and decline through to the end of 2030 (diagram *c*). *IMPOIL* is expected to continue rising, while no significant changes

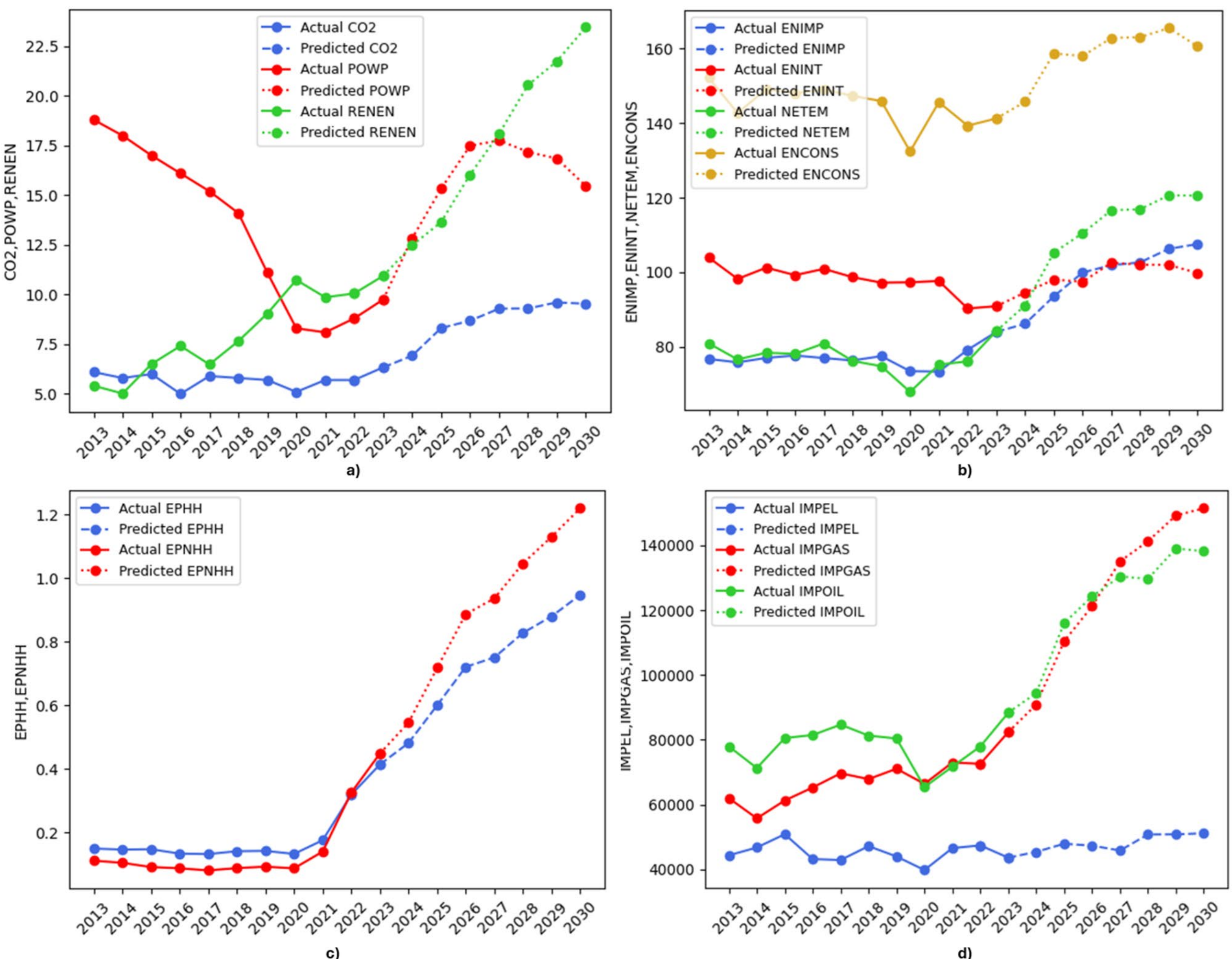


Fig. 21 Indicator predictions for Italy

are anticipated for *IMPGAS*. Finally, *IMPEL* will grow until 2026, after which it will begin to decline (diagram *d*).

An increase in energy intensity, electricity prices, and energy poverty is expected, with no significant changes anticipated in CO_2 levels. Despite large fluctuations and changes in the values of individual indicators, no alterations are expected in this key indicator of decarbonization success. As a result, no significant progress in this regard is anticipated until 2030.

Slovakia

The predictions for Slovakia show significant variation across indicators (Fig. 29). Some indicators are expected to experience considerable changes, while others are projected to follow existing trends, similar to those observed in the past. Large periodic changes are anticipated for *POWP* and *RENEN*, while CO_2 is expected to maintain a trend of minor changes (diagram *a*). Minor changes are predicted for *ENIMP*, *ENINT*, *ENCONS*, and *NETEM* (diagram *b*). Significant periodic changes are expected for *EPHH*, with especially notable fluctuations in *EPNHH* (diagram *c*). Oscillations are also expected for *IMPEL* and *IMPGAS*, while *IMPOIL* is expected to remain relatively stable (diagram *d*).

Based on current and projected trends for the selected indicators, Slovakia most closely resembles Poland. Both countries are expected to experience significant yearly oscillations and trend changes in their economies, which complicate the management of decarbonization—a process ultimately measured by carbon neutrality. CO_2 levels are expected to remain stable for the most part, with no significant impact from other indicators.

Slovenia

The indicator predictions for Slovenia (Fig. 30) show much more stability compared to those for Slovakia. A steady, significant growth is expected for *RENEN* and *POWP*, while CO_2 is projected to experience only minor changes (diagram *a*). Similarly, *ENINT* and *NETEM* are

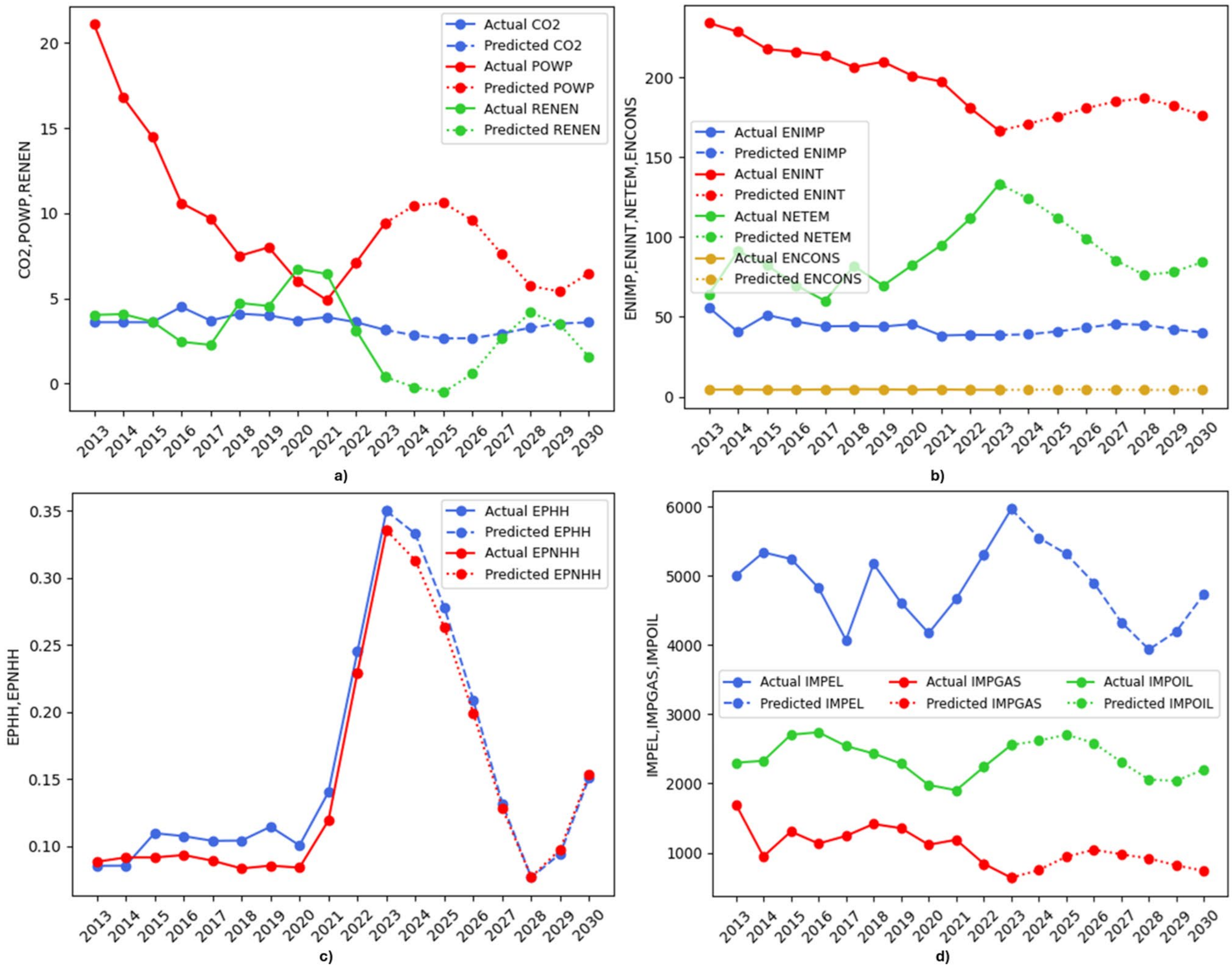


Fig. 22 Indicator predictions for Latvia

expected to show consistent growth, while *ENIMP* and *ENCONS* are likely to remain largely unchanged (diagram *b*). Electricity prices (*EPHH* and *EPNHH*) are also projected to increase (diagram *c*). The same trends are expected for *IMPEL* and *IMPGAS*, while *IMPOIL* is expected to remain stable (diagram *d*).

An increase in the share of energy from renewable sources is expected, but this will be accompanied by a rise in energy poverty. It is projected that the prices in the economy will experience a more rapid increase by 2030 compared to those for the population, alongside an anticipated rise in electricity imports. However, the expected stability in CO_2 levels indicates that no significant progress is anticipated in the decarbonization of the Slovenian economy.

Spain

The predictions for Spain show significant changes across all indicators (Fig. 31). Additionally, the trends of these indicators are expected to shift over the forecast period. For most indicators, changes are projected to occur over a three-year period. The trends for CO_2 and *POWP* are expected to show moderate yet opposite movements, while *RENEN* is anticipated to undergo significant changes within a three-year period (diagram *a*). The projections for *ENIMP, ENCONS*, and *NETEM* indicate similar oscillating patterns, while *ENINT* is expected to follow a different, opposing trend (diagram *b*). A similar oscillating pattern of significant changes is predicted for electricity prices (*EPHH* and *EPNHH*) (diagram *c*). Finally, the import of energy products (*IMPEL, IMPOIL*, and *IMPGAS*) is expected to undergo periodic changes, with *IMPEL* anticipated to reverse its trend (diagram *d*).

Across the entire sample, Spain exhibits the largest proportional oscillations among the indicators that describe the environmental and energy aspects of the economy. Additionally, electricity prices have been volatile and are expected to remain so with an upward trend until 2029. These trends are likely to influence both the Spanish economy and the social position of its

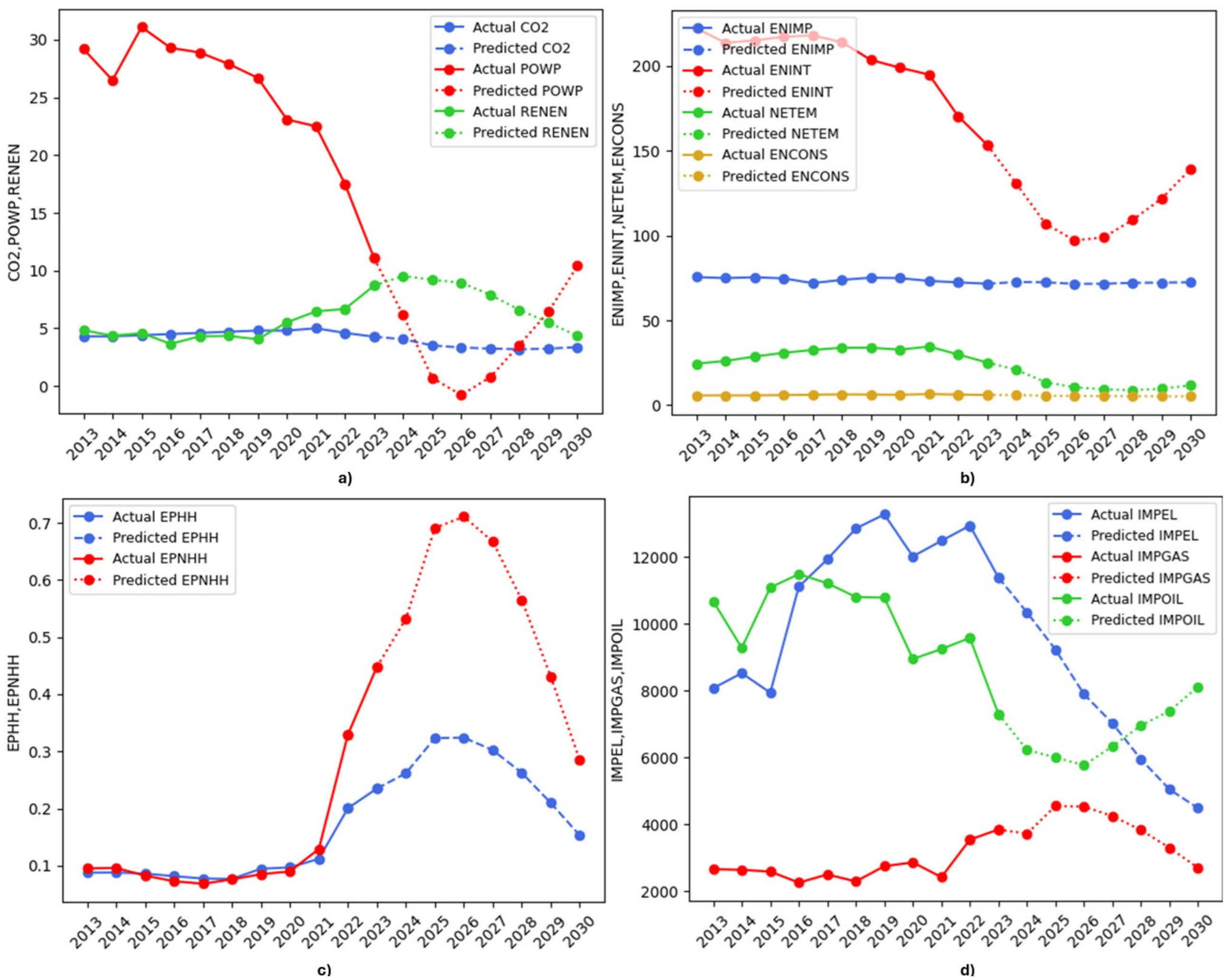


Fig. 23 Indicator predictions for Lithuania

citizens, highlighting the need for focused management in the decarbonization of the Spanish economy moving forward.

Sweden

The indicator predictions for Sweden show greater stability and fewer trend changes compared to those previously presented (Fig. 32). CO_2 and *POWP* are expected to experience minor changes, while *RENEN* is projected to maintain a slightly descending trend (diagram *a*). *ENIMP*, *ENINT*, and *ENCONS* are expected to have minor changes, while *NETEM* is predicted to undergo slightly more fluctuations without a noticeable trend (diagram *b*). Both *EPHH* and *EPNHH* are expected to follow a declining trend through to the end of 2030, with similar patterns of change (diagram *c*). The prediction for electricity imports (*IMPEL*) shows a slightly ascending trend that fluctuates annually (diagram *d*).

IMPOIL is expected to experience minor yearly changes without a noticeable trend, while *IMPGAS* is projected to remain almost the same throughout the entire forecast period. These trends suggest stability in key energy and environmental indicators that significantly influence the decarbonization process. However, no significant changes are expected in CO_2 levels.

Discussion

The decarbonization of Europe constitutes a strategic decision that entails intricate transformations within the economy and society. This initiative is designed for the long term, extending to 2050, and thus presents a significant challenge for governance. This is particularly evident when considering the events that transpired shortly after its adoption, including the COVID-19 pandemic, the crisis in Ukraine and the Middle East, and the change of administration in the United States, all of which have had a direct impact on the EU economy. Consequently, the ramifications of the transition to a low-carbon economy are currently difficult to assess realistically. The geopolitical landscape significantly impacts the supply chains that

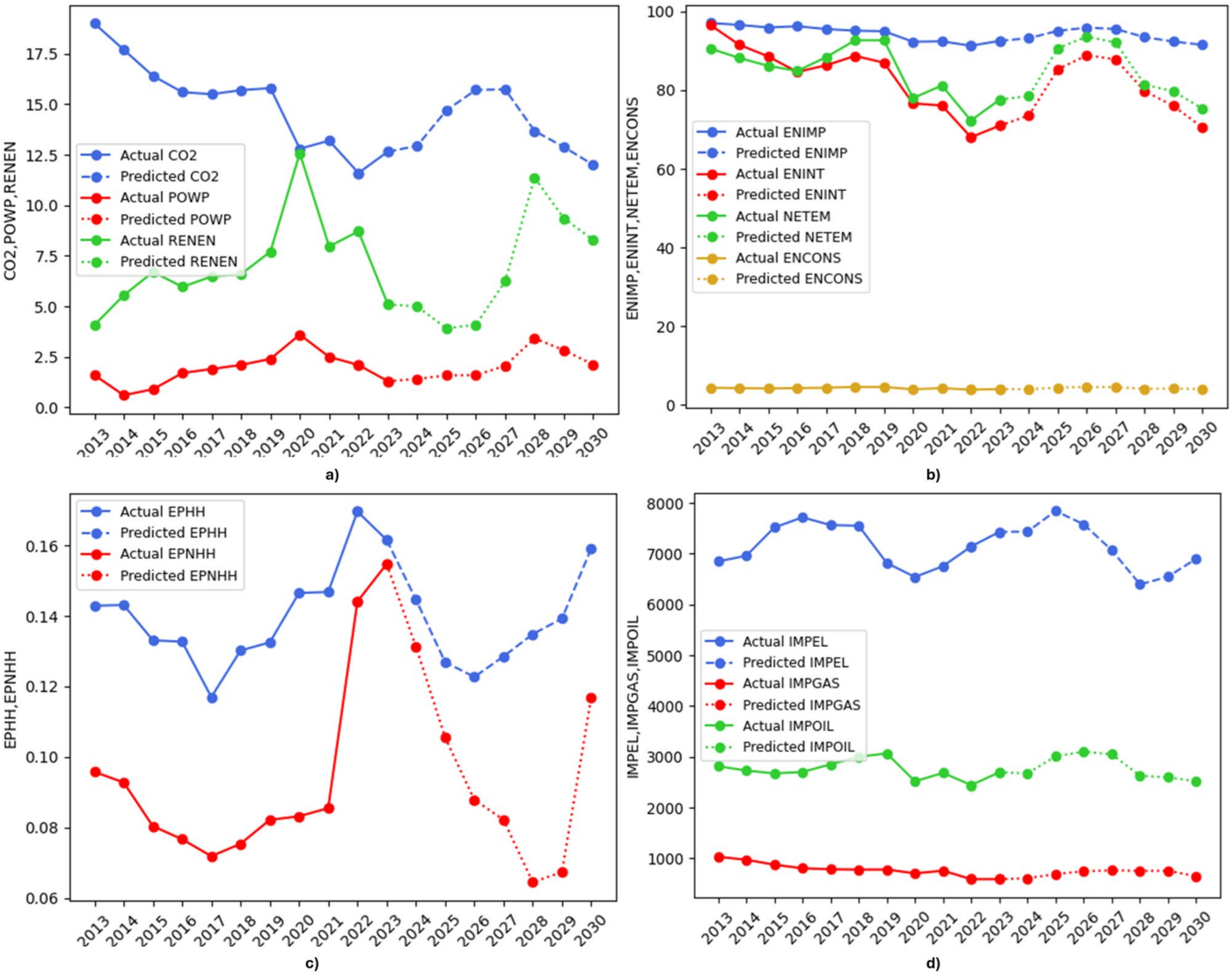


Fig. 24 Indicator predictions for Luxembourg

the EU has depended on for many years. The design and adoption of the decarbonization strategy through the EU Green Deal certainly took these factors into account. The new circumstances have not led to changes in the European Commission's position on the direction of development, despite differing views among member states. However, it is essential to develop new and/or modified frameworks for managing this process, which unfolds under a wide range of diverse and changing factors both within and outside the EU.

The research indicates that carbon dioxide emissions, a key measure of decarbonization success, did not show significant changes during the observed and predicted periods. During the period for which data is available (2013–2022), CO_2 values remained very stable, a trend that continues thereafter. The EU Green Deal was adopted in 2019, and it is unrealistic to expect significant changes to be felt immediately. However, it is evident that since its adoption, unfavorable trends have emerged in key decarbonization indicators, primarily driven by the rise in energy prices. The geopolitical shifts that emerged post-2022 significantly influenced the core principles of decarbonization, notably the halt of natural gas imports (regarded as a more environmentally friendly energy option from the Russian Federation) and the discontinuation of rare earth mineral imports (which are crucial for manufacturing processes) from the People's Republic of China (as of 2024).

In addition, significant changes have occurred in the parliaments of certain European countries, where political actors have highlighted the shortcomings of decarbonization and its negative impact on their national economies. Public sentiment regarding decarbonization is showing a shift toward greater negativity. Countries aspiring to EU membership lag behind in all aspects of decarbonization and are unable to independently finance, implement, and monitor the necessary measures. Countries that relied entirely on fossil fuel supplies from the Russian Federation and whose economies are based on energy-intensive industries find themselves in a

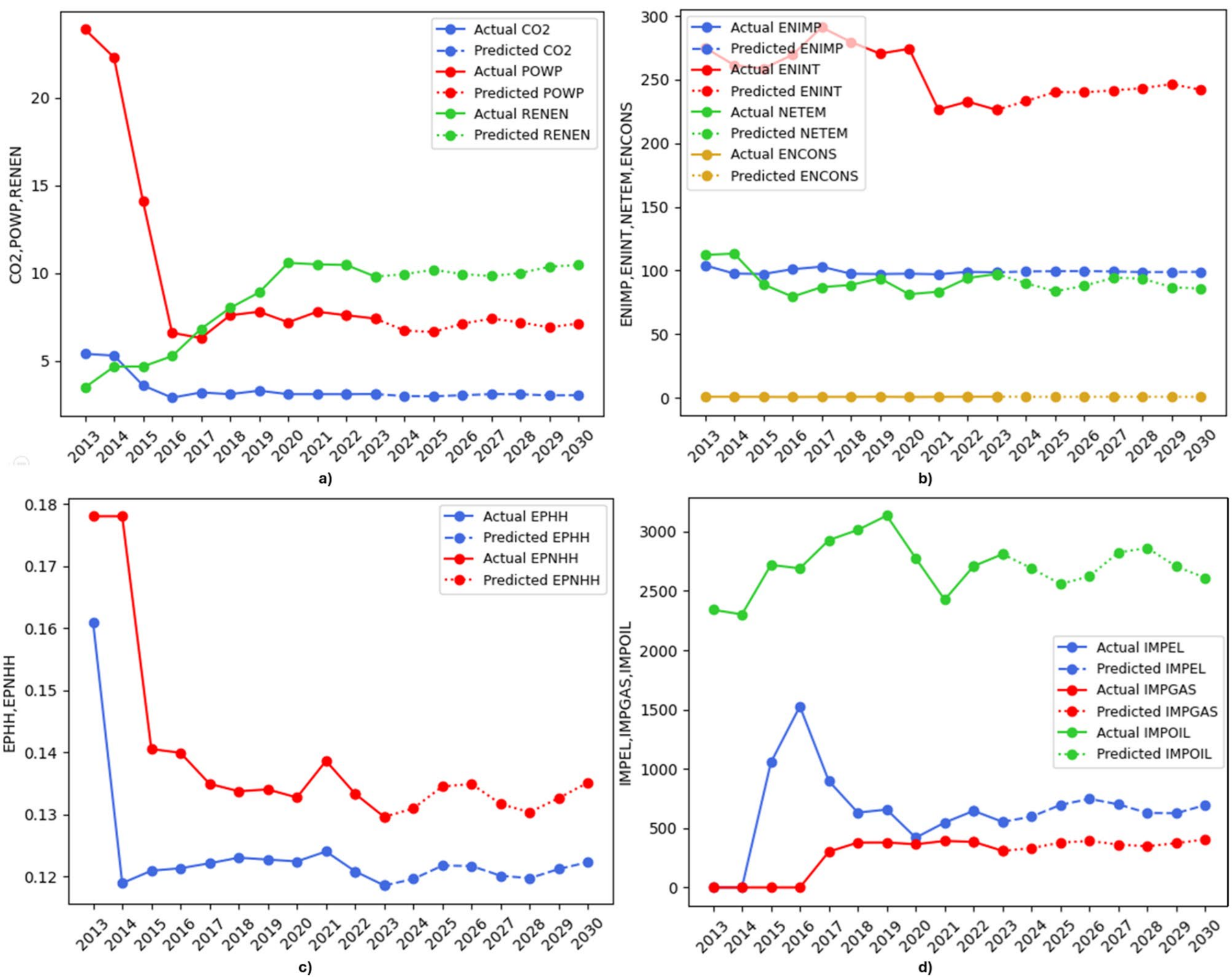


Fig. 25 Indicator predictions for Malta

particularly unfavorable position. On one hand, these countries must find new energy sources; on the other, they must reduce the share of energy-intensive industries, which will lead to a decrease in employment both in these industries and in coal mines. As a result, delays in the comprehensive and consistent implementation of decarbonization were observed in these countries up until 2022, and it is unrealistic to expect rapid turnarounds in the future.

The study further indicated several unfavorable forecasts regarding ongoing decarbonization efforts in Europe, particularly highlighting the growing demand for energy imports, especially in the most industrially advanced countries: Germany, France, and Italy. Major issues with electricity supply already exist and are expected to persist in most countries, as demand exceeds domestic production. Meanwhile, decades of investment in renewable energy sources have not demonstrated their ability to significantly mitigate the impact of the energy crisis that the EU is facing. Moreover, a notable trend of rising energy poverty is expected even in the wealthiest EU countries.

Only Austria, Belgium, Croatia, and Cyprus are projected to show relative stability in the values of the selected indicators. It is crucial to highlight that, even in these countries, a reduction in CO_2 emission levels is not anticipated, despite the fact that their economies are predominantly service-oriented and do not heavily rely on fossil fuel consumption. Only Finland and Sweden are consistently projected to make progress in their decarbonization efforts.

Each study that includes indicators of sustainable development has its own methodological limitations and specificities. The selection of indicators is subjective in nature but is based on the research goal, and the values are sourced from official data. The accuracy of input values is consistently subject to examination. In light of this, it is crucial to continually enhance the data collection system within the statistical services of each country. This applies especially to European countries that are not

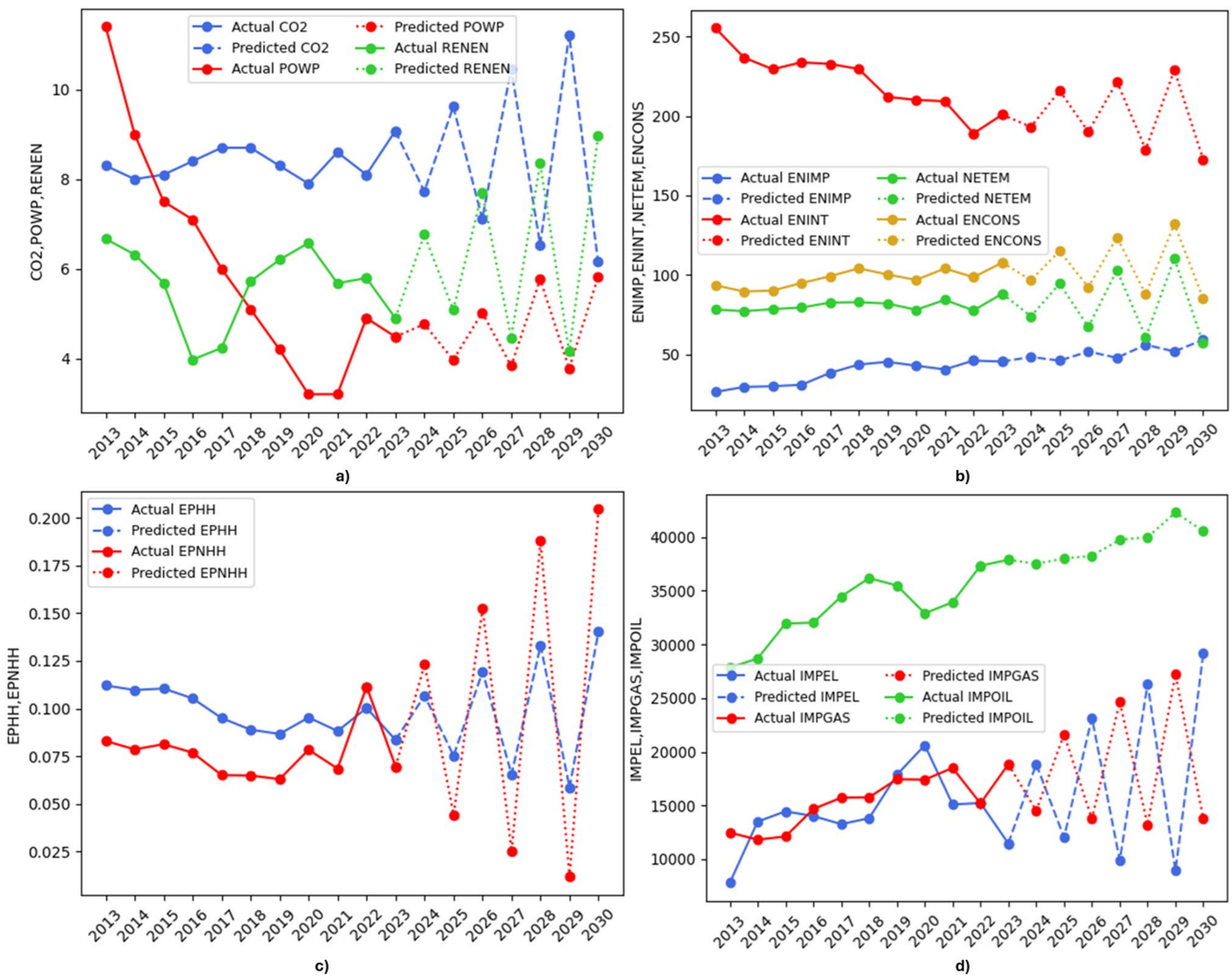


Fig. 26 Indicator predictions for Poland

EU members, as Europe's decarbonization efforts also encompass them.

In the presented predictions, a machine learning model was employed. The stochastic nature of the data, along with its multidimensionality—reflected in a large number of indicators (features) and their sequentially (time series), as well as the large number of observed countries—necessitated the use of LSTM recurrent neural networks instead of models based on probability distributions or regression analysis. It was found that in scenarios where sudden changes in indicators occur due to geostrategic events and/or shifts in national politics, the application of machine learning in predicting decarbonization-related indicators yields acceptable and reasonable results. Each prediction is analyzed by subject matter experts (SMEs) based on their existing knowledge and experience. However, SMEs have pointed out certain limitations, particularly related to anomalies in the reliability of official data for individual countries.

The proposed prediction model is recommended for future research on Europe's decarbonization success, as it can be continuously improved and adapted. This can be achieved through updating training and validation data, as well as modifying machine learning model parameters. Additionally, the model is flexible in the event of changes to the indicators under consideration. For example, new indicators can be added, and existing ones can be removed. Moreover, one or more indicators can be replaced by derived features (e.g., a new feature extracted via principal component analysis). These types of changes do not significantly affect the prediction model.

Conclusions

The main goal of this research is to evaluate the effectiveness of the EU's current decarbonization efforts, as outlined in the EU Green Deal, with predictions extending to 2030, using machine learning methods. This goal was established based on the need to assess the efficiency of the decarbonization implementation and make forecasts,

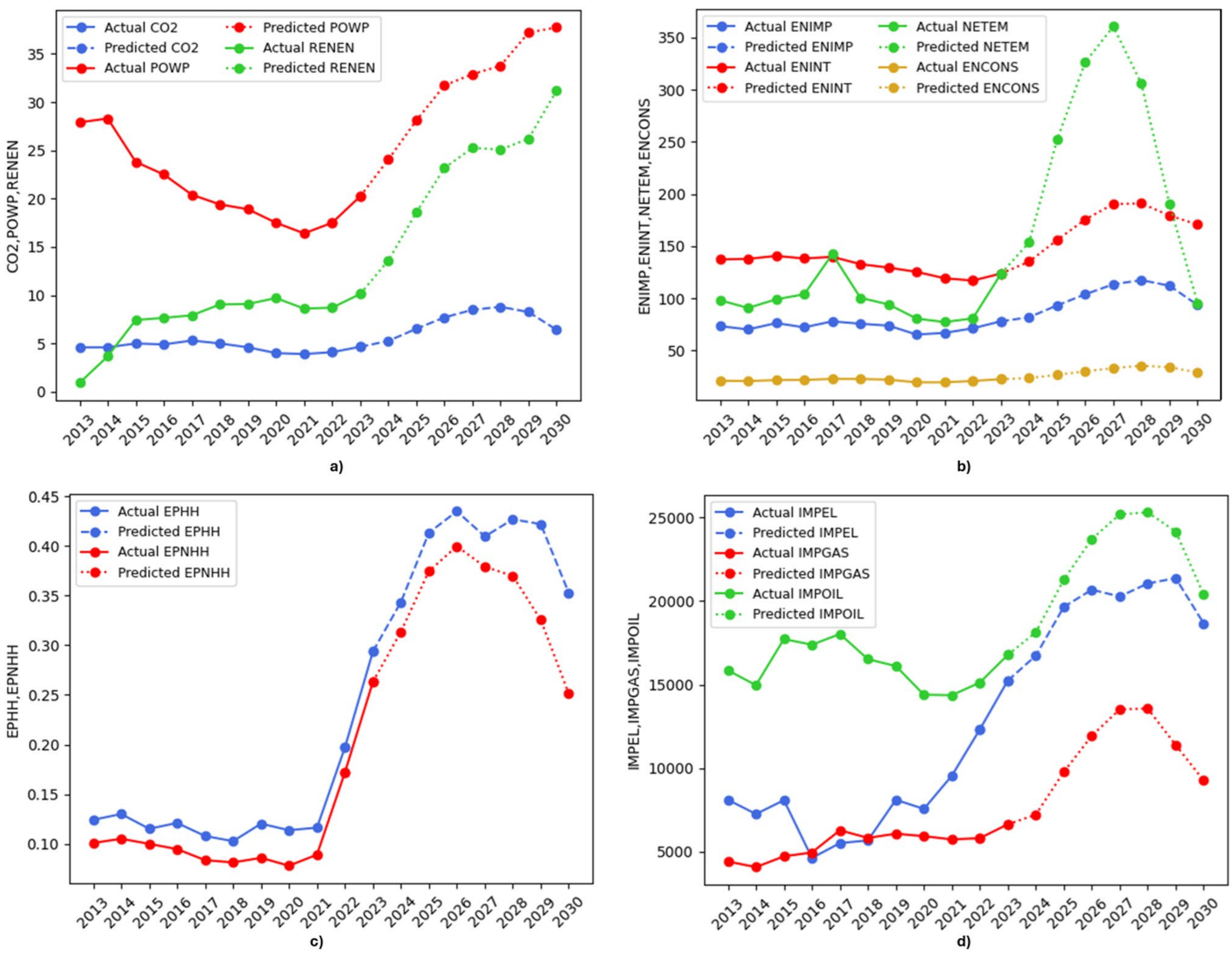


Fig. 27 Indicator predictions for Portugal

as the EU is facing numerous international changes and internal conflicts. These factors will likely impact the success of this complex and costly endeavor, which has significant implications for both the European economy and the social position of its citizens.

The research included data on 13 indicators collected from 2013 to 2022, covering a sample of 27 EU countries.

The research results indicate that CO_2 emissions have remained steady throughout the period. However, significant changes are expected in certain indicators that strongly influence the decarbonization of the economy—particularly the supply and pricing of energy products, the combustion of which accounts for the largest share of CO_2 emissions. The forecast shows that, with the exception of Finland and Sweden, all EU countries will experience a high degree of volatility in the aforementioned indicators. This volatility will significantly complicate the formulation of public policies and raise doubts about the effectiveness of the decarbonization process's implementation.

It is important to note that the EU Green Deal serves as the official long-term development strategy of the EU. Therefore, member states are obligated to implement it in practice. However, significant objections have been raised by certain member states, citing the practical impossibility of consistently applying the strategy and its related activities. These concerns are especially relevant in light of the cessation of natural gas supplies from the Russian Federation and the shortage of rare earth materials from the People's Republic of China.

Considering the results of this and similar research, it is unrealistic to expect that decarbonization activities will proceed as planned. A multi-year delay in the anticipated reduction of CO_2 emissions is therefore expected. On the other hand, most countries are facing decreased economic competitiveness, rising energy poverty, and social challenges, primarily due to increasing energy prices and the overall cost of living. Continued insistence on the consistent implementation of the decarbonization process, given the current circumstances the EU is facing, could lead to even greater turmoil within the Union

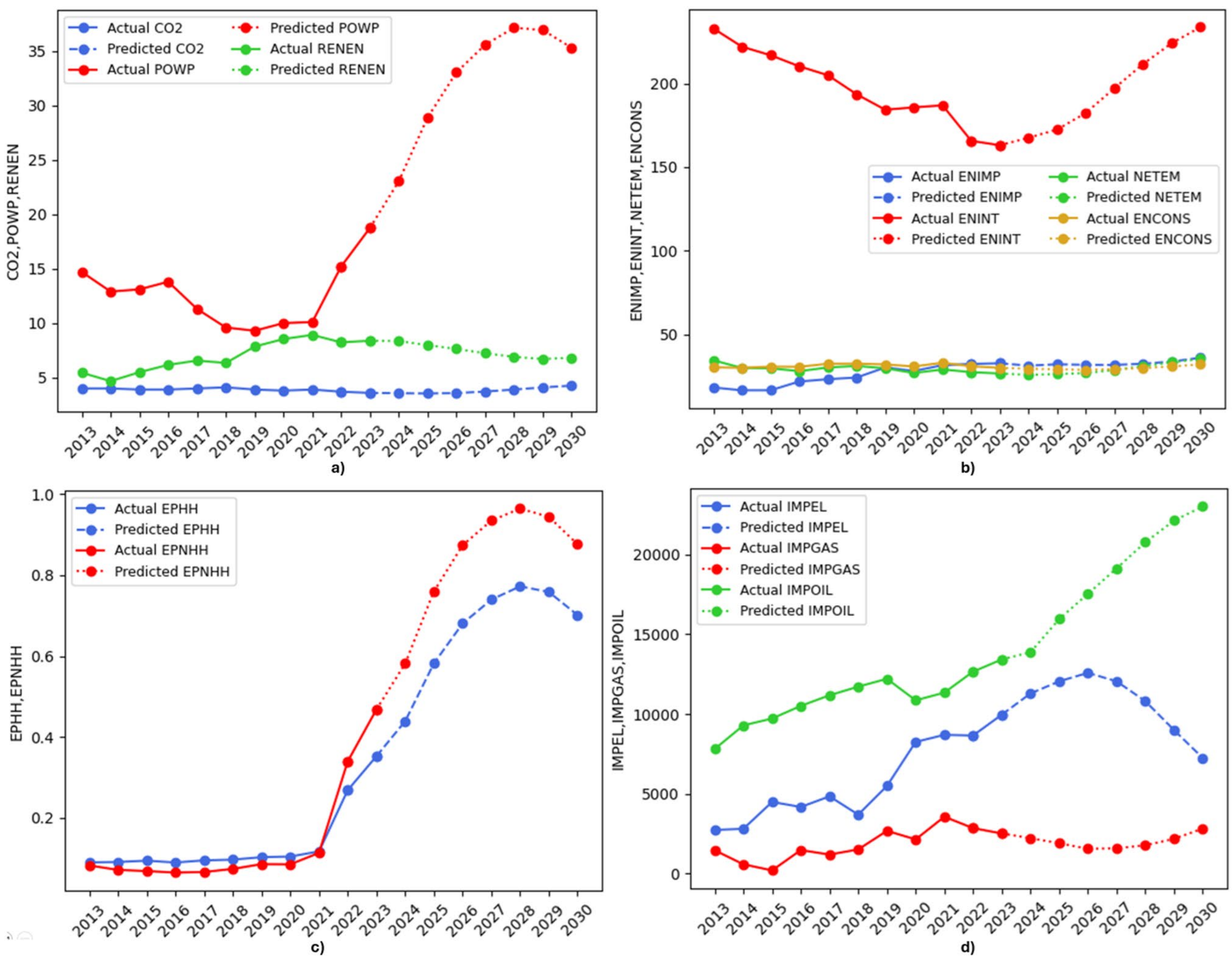


Fig. 28 Indicator predictions for Romania

and increased citizen dissatisfaction. This, in turn, could undermine the long-term stability, solidarity, and unity of the EU.

The conclusion that further decarbonization in the EU will unfold under the influence of complex changes is, therefore, unmistakable. The endeavor to enhance environmental quality is undoubtedly a fundamental value and necessity for all individuals and societies. However, it appears that the initiative to decarbonize the economy across the European continent may be overly ambitious and founded on unrealistic assumptions and expectations.

Consequently, future research should enhance the comprehensive understanding of the overall decarbonization strategy from multiple perspectives. Firstly, it is necessary to define new inputs that will facilitate the formulation of realistic and attainable objectives, taking into account the shifts that have occurred following the COVID-19 pandemic, which have further complicated the landscape post-2022. The above highlights the need for strong interdisciplinarity in future work, along with the application of artificial intelligence methods. This opens up the possibility of working with multidimensional data from different countries, organized in time series, and featuring a large number of indicators. The proposed model serves as a solid foundation for improving predictions in conditions of great uncertainty. It provides results that are valuable for shaping new policies, making decisions, monitoring, and forecasting future trends. Of particular importance is the development of new methodologies based on artificial intelligence, which will enable the monitoring of decarbonization success. These methodologies will also help identify necessary corrections in the management of the decarbonization process based on the results obtained.

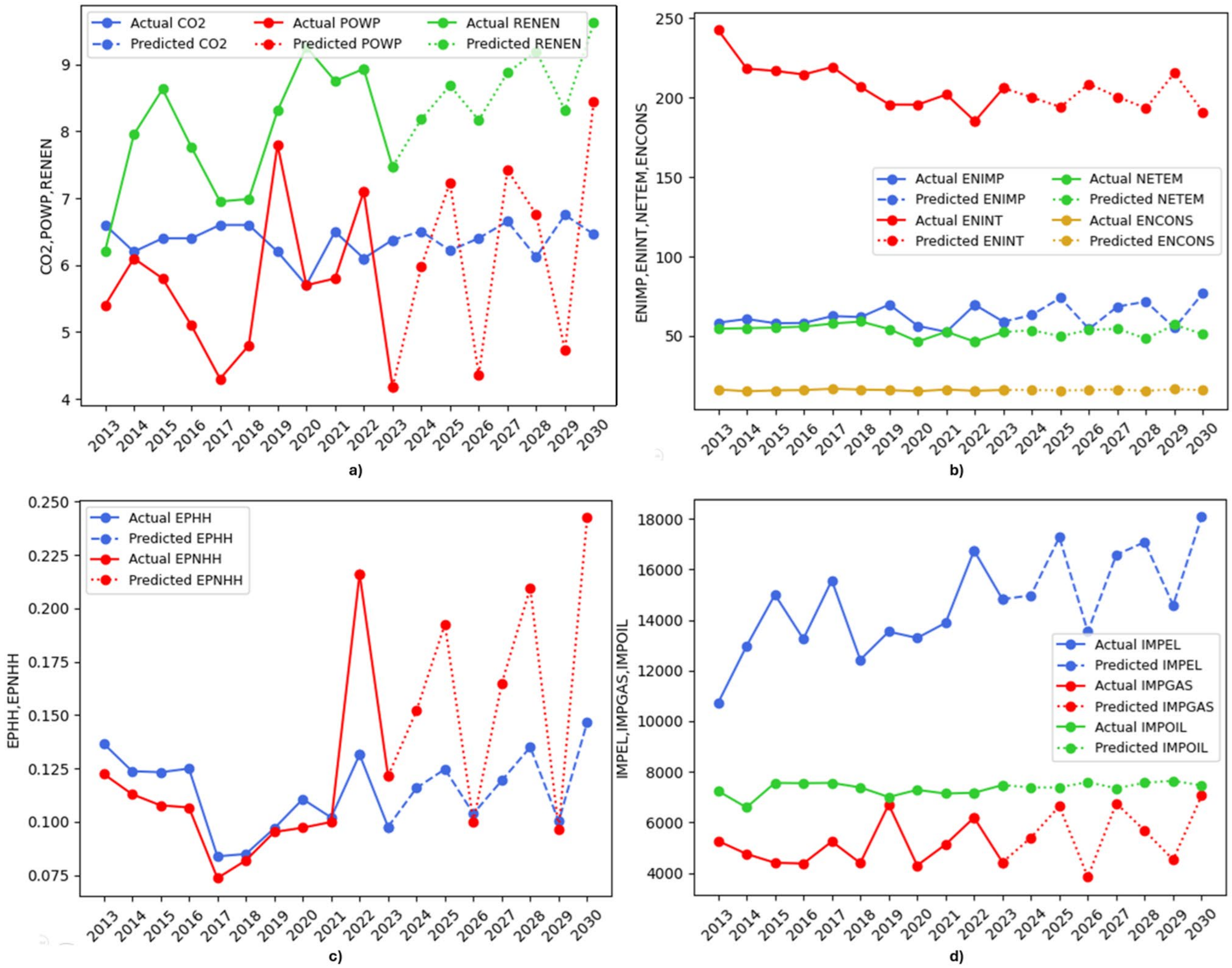


Fig. 29 Indicator predictions for Slovakia

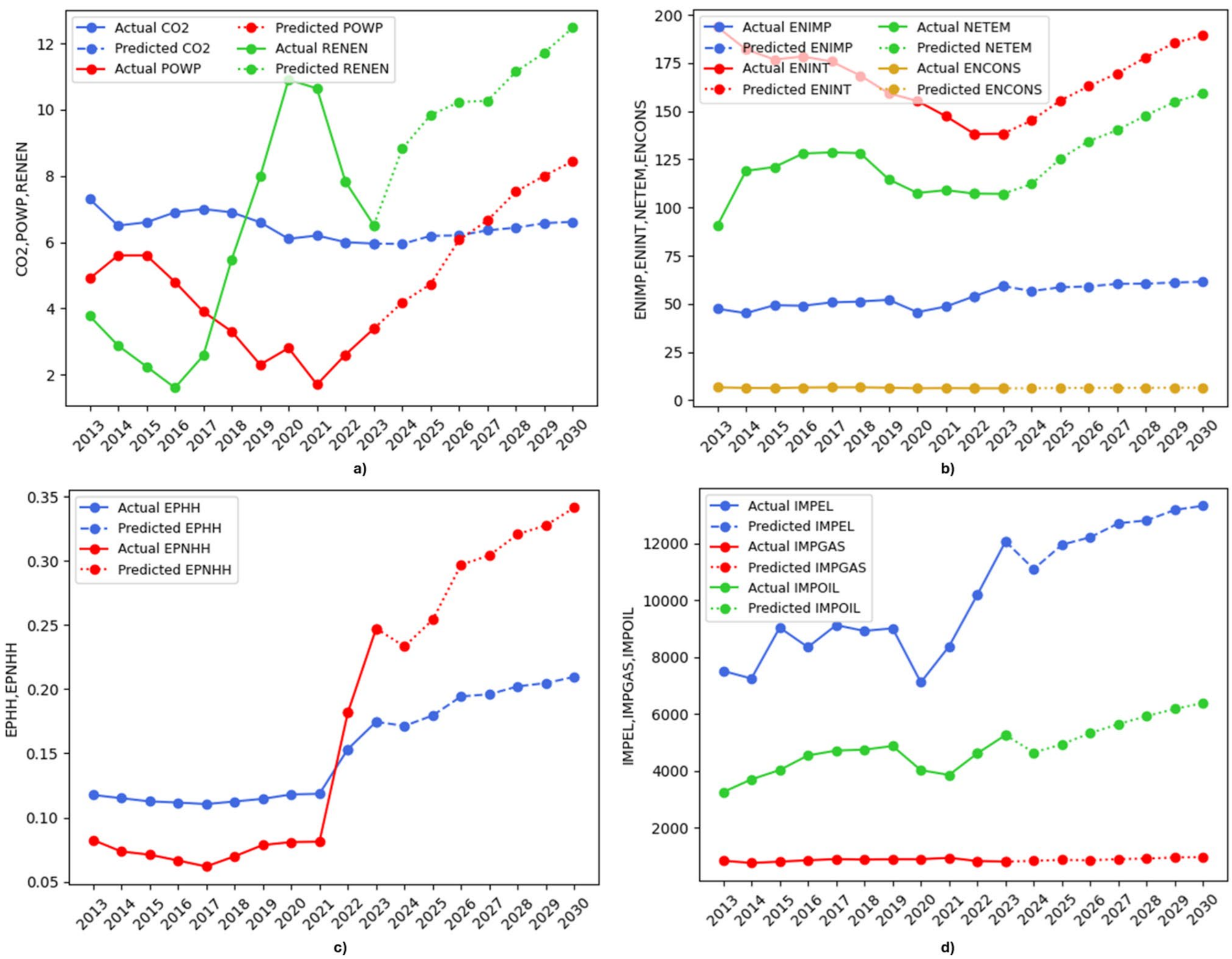


Fig. 30 Indicator predictions for Slovenia

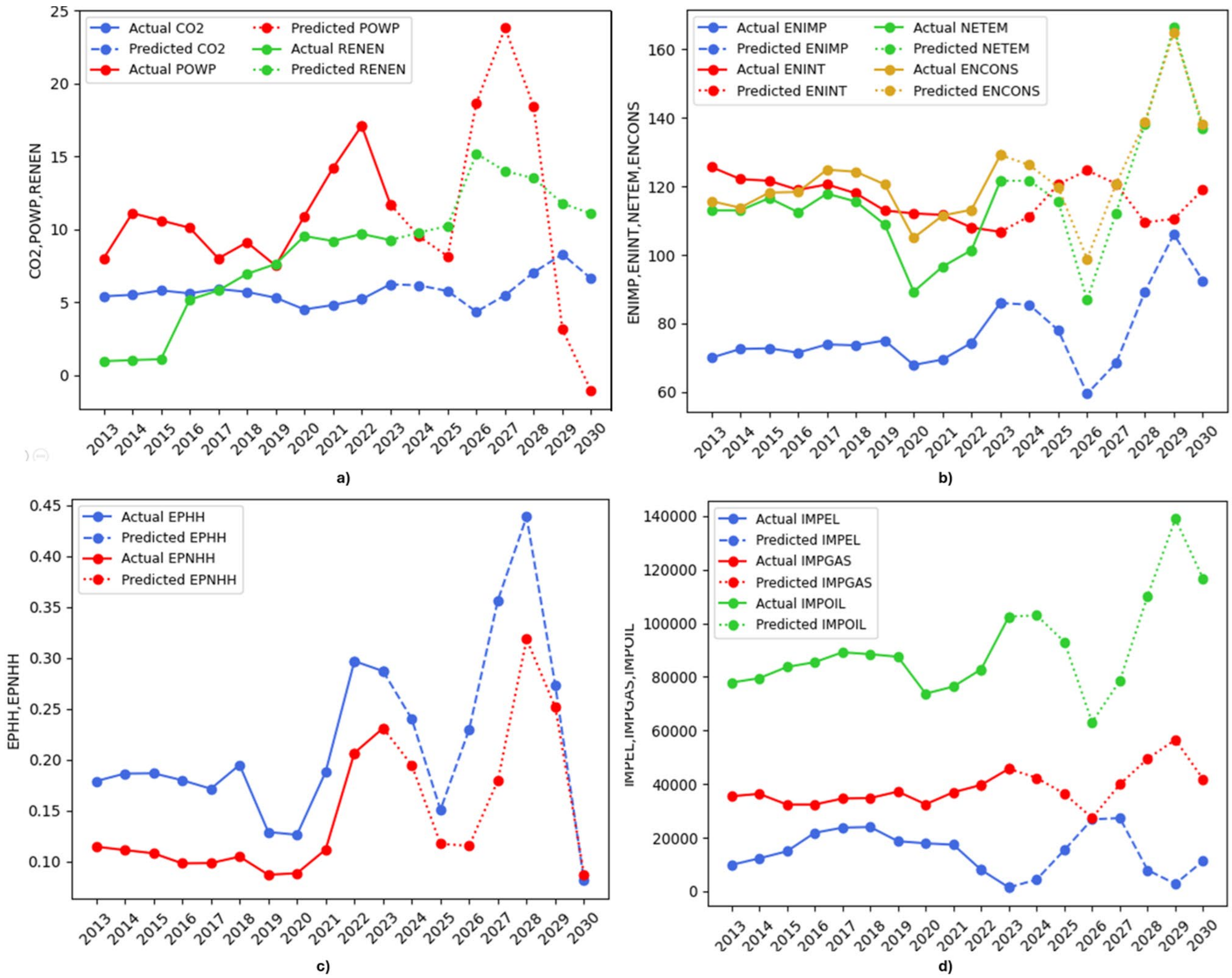


Fig. 31 Indicator predictions for Spain

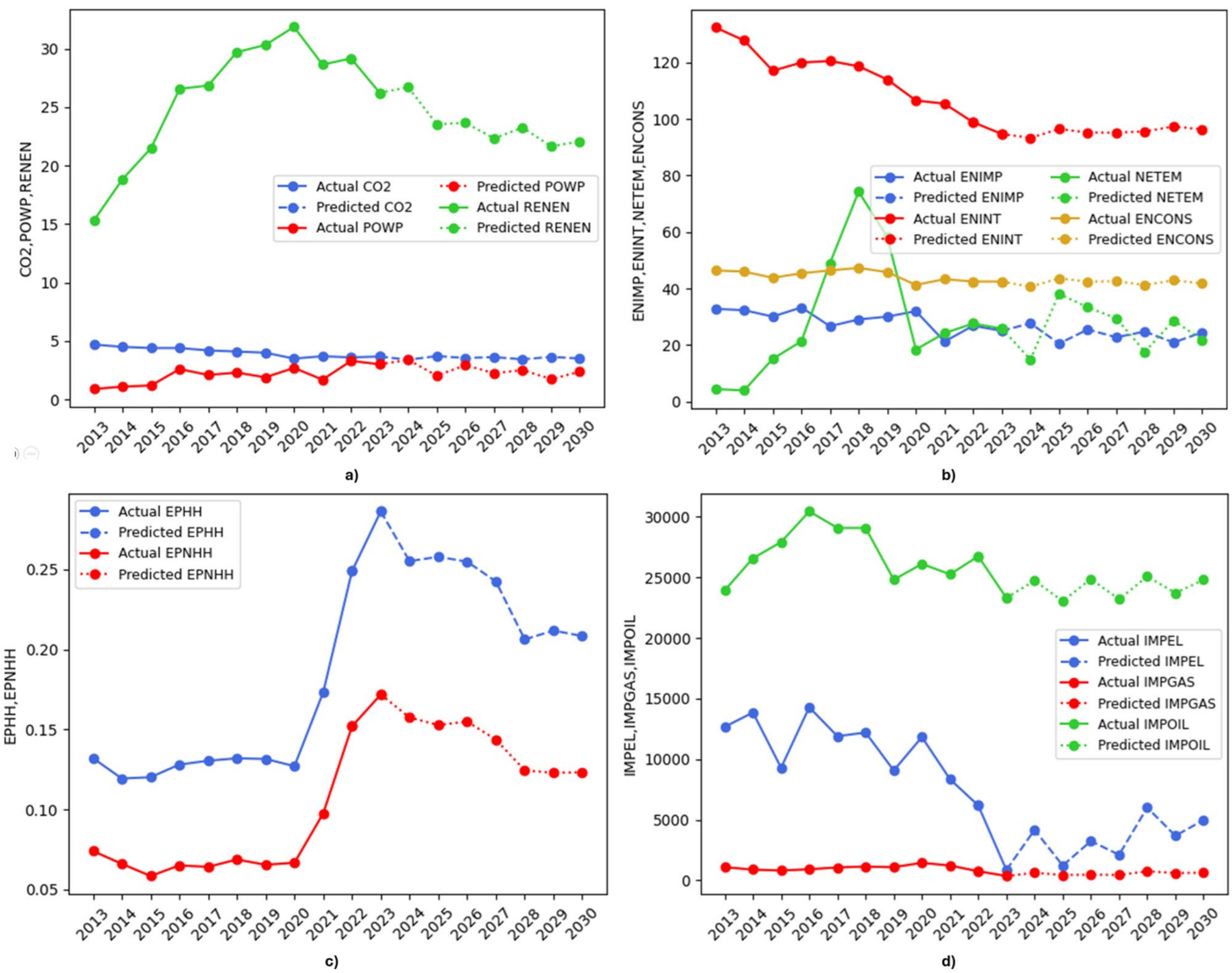


Fig. 32 Indicator predictions for Sweden

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Author contributions
MR and GŠ prepared a draft of the study. GŠ completed data processing. SF participated in literature review. All authors read and approved the final manuscript.

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Declarations

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Consent for publication
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Competing interests
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