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Forecasting Electricity Generation and Assessing 2030 Energy Transition Scenarios: Evidence from Türkiye and Germany[1]

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ABSTRACT

Accurate electricity generation forecasting plays an important role in production planning, resource allocation, supply security, and long-term investment decisions. Since electricity systems require a continuous balance between supply and demand, forecasting errors may negatively affect operational efficiency and increase imbalance costs. At the same time, with the acceleration of the energy transition, not only short-term generation forecasts but also the evaluation of how future generation structures may evolve under different scenarios has become increasingly important. In this study, deep learning and boosting-based models were compared for Türkiye and Germany under 7-, 30-, and 365-day forecasting horizons, and the best-performing models were then used to generate BAU projections for 2030, which were evaluated together with the ST and EC scenarios reported by ENTSO-E. The findings showed that the GRU model produced more successful and consistent results for Türkiye, whereas boosting algorithms delivered stronger forecasting performance for Germany. The scenario comparisons also revealed that the BAU structure remained more dependent on fossil-based resources, while the ST and EC scenarios placed a clearer emphasis on the transition toward renewable energy. In this way, the study provides an integrated framework that supports both the evaluation of forecasting performance and the assessment of long-term energy planning alternatives.

Keywords: Electricity Generation Forecasting, Deep Learning, Boosting Algorithms, Scenario Analysis, Long-term Energy Planning
JEL-Classification: Q47, Q41, C45

1. Introduction

Electricity has become one of the most essential forms of energy in modern societies, supporting industrial activities, transportation systems, and daily life (Torres et al., 2022). Its importance continues to increase with the expansion of electrification, the growing adoption of electric vehicles, and the wider integration of renewable energy technologies into power systems. At the same time, maintaining a reliable and secure electricity supply has become more challenging due to the variability of generation sources and the continuous growth in demand. Since large-scale electricity storage is still limited in many systems, it is crucial to estimate generation needs as accurately as possible in order to match demand effectively.

Accurate electricity generation and demand forecasting is essential for maintaining supply security, supporting balanced production planning, reducing imbalance costs, and improving the efficient use of energy resources. However, electricity forecasting has become an increasingly challenging problem due

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to the growing share of renewable energy sources, weather-related variability, fluctuations in demand behavior, and the increasing complexity of power systems (Misiurek et al., 2025). Recent studies show that the need for accurate forecasting has become even more critical with the energy transition and that forecasting models should be adapted to the structure of the data.

Deep learning and boosting-based methods have emerged as strong alternatives in electricity forecasting, as they can capture nonlinear relationships and handle complex patterns more effectively than many conventional approaches. In particular, recent studies have shown that machine learning-based models can significantly improve electricity load forecasting performance when applied to large and heterogeneous energy datasets (Perçuku et al., 2025).

Projection studies are important not only for anticipating future generation or demand levels, but also for supporting infrastructure development, capacity planning, resource diversification, and long-term policy decisions in energy systems. Especially in a period marked by a rapid energy transition, the growing share of renewable resources and the increasing uncertainties in the system make forward-looking projections more strategic and necessary. Recent studies have also emphasized that long-term energy projections should be seen not merely as technical forecasts, but as essential decision-support tools for policy development and sustainable planning (Köse et al., 2025).

This study focuses on electricity generation forecasting for Türkiye and Germany by comparing deep learning and boosting-based methods under short-, medium-, and long-term prediction settings. In addition to evaluating model performance across different forecasting horizons, the study also extends the analysis toward 2030 by generating Business as Usual projections and comparing them with ST and EC energy scenarios on a resource basis. In this way, the study not only examines forecasting accuracy but also provides a broader perspective for understanding how future electricity generation structures may evolve under different pathways. The combined use of forecasting results and scenario comparisons is expected to provide a meaningful contribution to the literature, particularly in terms of linking data-driven prediction with long-term energy planning.

2. Related Works

Accurately forecasting energy consumption is of great importance for energy planning, resource management, and maintaining the balance between supply and demand. Electricity consumption is influenced by numerous uncertain and dynamic factors, such as irregular data fluctuations, measurement errors, variations in weather conditions, and calendar effects (Lin et al., 2020). This makes the forecasting process more complex. Some studies have employed traditional time series methods. Wang et al. (2012) used a seasonal ARIMA model for electricity demand forecasting in China. The results showed that optimized Fourier method combined with seasonal ARIMA performed better than the standalone seasonal ARIMA model. Rossi and Brunelli (2015) developed an electricity forecasting method to improve energy management in green data centers powered by renewable energy. The study specifically examined the Holt-Winters exponential smoothing approach. In another study, a linear regression-based model was proposed to forecast electricity consumption in Italy (Bianco et al., 2013). In the field of machine learning, forecasting models are generally addressed through tree-based methods and neural network-based approaches. Pang et al. (2022) proposed a random forest regression-based approach for monthly electricity consumption forecasting. In their study, influential variables were selected using the maximum mutual information coefficient, and the results showed that the proposed method achieved high prediction accuracy. In a study conducted in 2018, a hybrid short-term load forecasting model combining random forest and multilayer perceptron was proposed for predicting electrical load in a university campus. The results showed that the hybrid model outperformed the individual forecasting models (Moon et al., 2018).

In recent years, boosting-based algorithms and deep learning methods have been increasingly adopted to better learn the complex and nonlinear patterns involved in electricity forecasting. In particular, tree-based methods such as XGBoost, CatBoost, and Random Forest, together with deep learning models such as artificial neural networks, Long Short Term Memory (LSTM), GRU, and CNN, have become prominent in electricity consumption and generation forecasting studies. These methods offer important advantages in terms of handling multiple influencing variables simultaneously, learning temporal dependencies, and providing improved predictive performance in complex data structures. In some studies, the forecasting problem has been addressed through an input–output framework based on modeling the relationship between input and output variables, whereas in other studies, it has been handled directly within a time series forecasting framework. A summary of recent studies in the field of electricity forecasting is presented in Table 1.

Table 1 Summary of recent studies on electricity forecasting.

Ref.	Application	Forecast Horizon	Data Structure	Methods	Key Findings
Park and Hwang (2021)	Electricity load forecasting	Day-ahead (96 time points at 15 min intervals)	Multivariate time series with calendar, weather, and historical load data	Two-stage LightGBM + Attention-BiLSTM	The proposed two-stage model improved forecasting performance over the single S2S ATT-BiLSTM, achieving 3.23% lower MAPE
Torres et al. (2022)	Electricity consumption forecasting in Spain	4 hours	Univariate time series	Deep LSTM	The proposed deep LSTM model achieved the best performance among the compared methods, with a test MAPE of 1.4472%.
Dong et al. (2023)	Regional electricity consumption forecasting	Short-term	Input–output with external variables	XGBoost, K-means	XGBoost achieved higher prediction accuracy and better generalization performance than Random Forest
Zhang et al. (2023)	Electricity demand forecasting	Short-term	Input–output with weather variables	Hybrid CatBoost-PPSO	The hybrid CatBoost-PPSO model achieved the best short-term forecasting performance among the compared hybrid models, with a test MAPE of 7.15%.
Son and Shin (2023)	Electricity consumption forecasting	2, 7, 15, and 30 days	Multivariate time series with meteorological variables	Prophet, GRU, hybrid Prophet-GRU	The proposed hybrid Prophet-GRU model outperformed both Prophet and GRU, achieving a MAPE of 24.57% for 2-day forecasting.
Kim et al. (2023)	Peak electricity demand	21 days	Multivariate time series	1D-CNN + BiLSTM	The proposed 1D-CNN + BiLSTM model achieved relatively good forecasting performance, with WRMSSE values of 0.42 for electricity demand and 0.63 for SMP max.
Bai (2024)	Residential electricity consumption prediction	Short-term	Multivariate time series	GA-LSTM	The proposed GA-LSTM model outperformed GBRT, LSTM, RNN, and SVR, achieving a MAPE of 0.1856.
Zhao et al. (2025)	Renewable electricity	Short- and long-term	Multimodal data (time	CNN-Bi-GRU	The proposed CNN-Bi-GRU model outperformed ARIMA, GRU, and EEMD-ARIMA in both

	demand forecasting		series + textual data)		short- and long-term forecasting tasks, showing lower RMSE and MAPE values.
Archana et al. (2025)	Building energy prediction	Medium- to long-term	Multivariate building energy, weather, and time-label data	IDBO-CatBoost	The proposed IDBO-CatBoost model achieved the best performance, with MAE = 1.872, MAPE = 5.762
Kang (2026)	Building electricity consumption analysis in Seoul	Annual electricity consumption	Cross - sectional spatial urban form and socioeconomic data	XGBoost, SHAP	XGBoost and SHAP showed that covered area, population density, and floor area were the strongest predictors of building electricity consumption, while the effects of urban form were nonlinear and spatially heterogeneous.

Electricity projection studies are important tools for ensuring energy supply security, supporting capacity planning, and guiding long-term investment decisions. By revealing future demand patterns under different scenarios, these studies contribute to the development of more robust energy policies. Rivera-González et al. (2019) examined electricity supply and demand projections for the Ecuadorian power generation system until 2040 and evaluated alternative scenarios using the LEAP model. The results showed that the sustainable power generation scenario offered a more efficient and environmentally favorable pathway by reducing emissions and production costs. Fields et al. (2024) developed electricity demand projections for Sierra Leone for the period 2023–2050 and evaluated base, high, and low demand scenarios. The study demonstrated that electricity demand can vary significantly under different socioeconomic and technical assumptions, highlighting the importance of scenario-based projections for energy planning. Bahta et al. (2025) used the LEAP model to analyze energy demand projections for Ethiopia for the period 2022–2060 and assessed changes in demand and emissions under different scenarios. The study showed that energy demand will increase in all scenarios and that scenario-based planning is critical for energy and climate policies.

3. Materials and Methods

3.1 Data Collection

In this study, daily time-series data obtained from two different data sources were used to develop electricity generation projections for the year 2030. Daily electricity generation data for Türkiye covering the 2009–2018 period were obtained from the Turkish Electricity Transmission Corporation (TEİAŞ), while daily electricity generation data for Germany covering the 2010–2018 period were obtained from Fraunhofer ISE. By utilizing approximately ten years of daily data for both countries, the goal was to enable the prediction models to capture not only short-term fluctuations but also seasonal patterns and long-term trends. In this context, prediction models extending through 2030 were developed using the obtained datasets. The electricity production time series for Türkiye and Germany are presented in Figure 1.

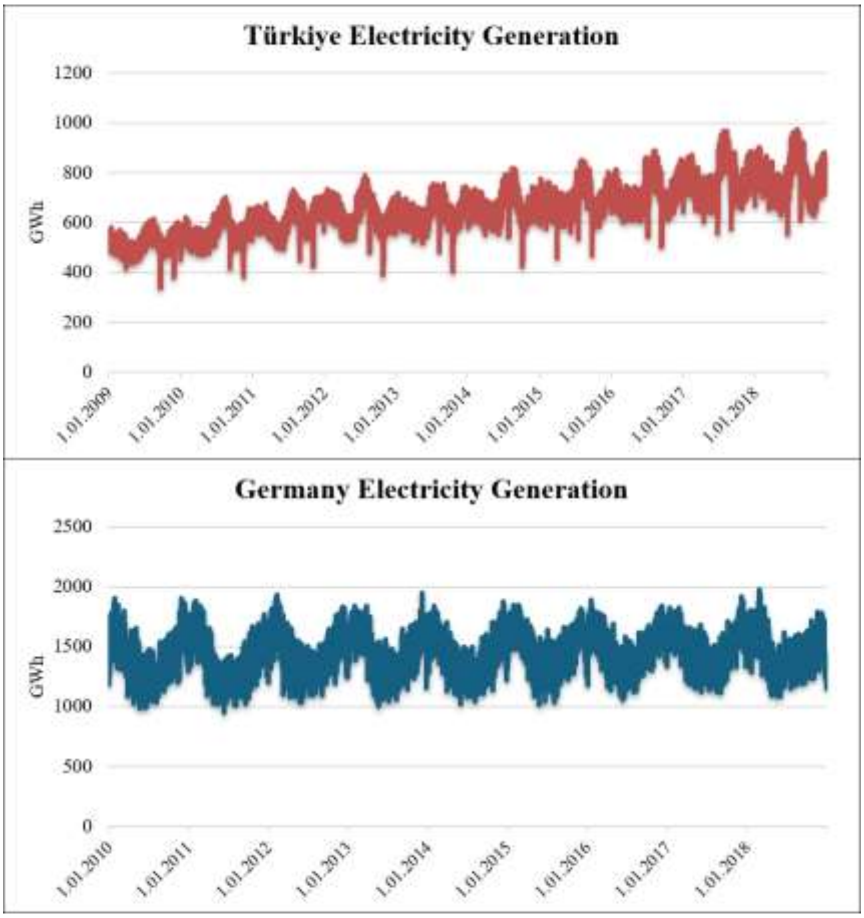


Figure 1 Daily electricity generation time series for Türkiye and Germany.

As shown in Figure 1, Germany's daily electricity generation is consistently higher than that of Türkiye. Additionally, the time series for Türkiye exhibits a noticeable upward trend over the study period, together with clear seasonal fluctuations. However, although Germany maintains a higher overall level of daily electricity generation, its series remains relatively stable in terms of long-term trend compared with Türkiye. Nevertheless, strong seasonal patterns are still evident in the German series. These observations indicate that the electricity generation structures of the two countries differ not only in magnitude but also in terms of trend behavior and temporal dynamics.

3.2 1D CNN Model

Convolutional Neural Networks (CNNs) are a type of deep learning architecture consisting of convolutional, pooling, and fully connected layers (Casolaro et al., 2023). These architectures are particularly notable for their ability to capture local patterns, share weights, and recognize similar patterns in the input at different locations. In the context of time series forecasting, 1D-CNN architectures can be utilized in the forecasting process by learning short-term dependencies and local temporal changes based on past observations.

Multi-step time series forecasting refers to the simultaneous or sequential prediction of values for multiple future time points (Cheng et al., 2020). In these terms, let h = 1, 2, …, H denote the forecasting horizon, or in other words, the number of forecast steps. One of the most commonly used approaches for multi-step forecasting in the literature is the recursive strategy. In the study as well, a recursive forecasting structure has been adopted to carry out the multi-step forecasting process.

In this study, 1D-CNN-based approach was used to forecast electricity generation time series. The model architecture was designed to predict the next time step based on fixed-length input windows composed of past observations. Each input sequence consists of the last L observations, and the window length is set to $L=30$. Accordingly, the input sequence can be expressed as in Equation 1:

$$X_t = [x_{t-L+1}, x_{t-L+2}, \dots, x_t] \quad (1)$$

where X_t denotes the input sequence fed into the model and x_t represents the electricity generation value at time t. The objective of the model is to predict the next time step based on this sequence:

$$\hat{x}_{t+1} = f(X_t) \quad (2)$$

where *f(·)* denotes the nonlinear mapping learned by the 1D-CNN model.

In the 1D-CNN architecture, the convolution operation extracts local temporal patterns from the input sequence sliding filters. A one-dimensional convolution operation can generally be formulated as in Equation 3:

$$z_t^{(k)} = \sigma\left(\sum_{i=0}^{q-1} w_i^{(k)}\, x_{t-i} + b^{(k)}\right) \quad (3)$$

where $z_t^{(k)}$ is the output of the k-th filter at time t, qdenotes the kernel size, $w_i^{(k)}$ represents the filter weights, $b^{(k)}$ is the bias term, and $\sigma(\cdot)$ is the activation function. In this study, the ReLU activation function was used in the convolutional layers.

The model architecture consists of two Conv1D layers, one MaxPooling1D layer, one GlobalAveragePooling1D layer, a dropout layer, and fully connected layers. The first convolutional layer contains 128 filters, while the second convolutional layer contains 64 filters. Pooling was applied to reduce the dimensionality of the feature maps and obtain more compact representations, after which Global Average Pooling was used to pass the extracted features to the dense layers. To mitigate overfitting, the dropout rate was set to 0.2. A single neuron was used in the output layer to generate the prediction for the next time step. The implemented architecture is explicitly defined in the code.

During training, Mean Squared Error (MSE) was adopted as the loss function. The loss function is given by:

$$MSE = \frac{1}{N} \sum_{j=1}^{N} (y_j - \hat{y_j})^2 \quad (4)$$

where y_j is the true value, $\hat{y}_j$ is the predicted value, and Nis the total number of samples. The Adam optimization algorithm was used to update the model parameters. In addition, an early stopping mechanism was employed during training to prevent overfitting when no further improvement was observed in the validation loss. The code confirms the use of Adam, MSE loss, and early stopping.

For multi-step forecasting, a recursive forecasting strategy was adopted. In this approach, the model first predicts one step ahead, and the predicted value is then appended to the input window to generate the next prediction. This process is repeated until the entire forecasting horizon is reached. Mathematically, this procedure can be expressed as follows:

$$\hat{x}_{t+1} = f(X_t) \quad (5)$$
$$\hat{x}_{t+2} = f([x_{t-L+2}, \dots, x_t, \hat{x}_{t+1}]) \quad (6)$$
$$\hat{x}_{t+h} = f([x_{t-L+h}, \dots, \hat{x}_{t+h-1}]) \quad (7)$$

where $h = 1,2, \dots, H$, and Hdenotes the total forecasting horizon. In this study, experiments were conducted for $H = 7$, $H = 30$, and $H = 365$. As also reflected in the code, the model was trained in a one-step-ahead manner and then transformed into a recursive multi-step forecasting framework during testing. The 1DCNN-based prediction architecture is shown in Figure 2.

A grid search procedure was conducted to determine the most suitable model hyperparameters, and the adopted parameter configuration was found to be appropriate based on the search results. Accordingly, key parameters such as sequence length, number of filters, and learning rate were selected based on the grid search experiments.

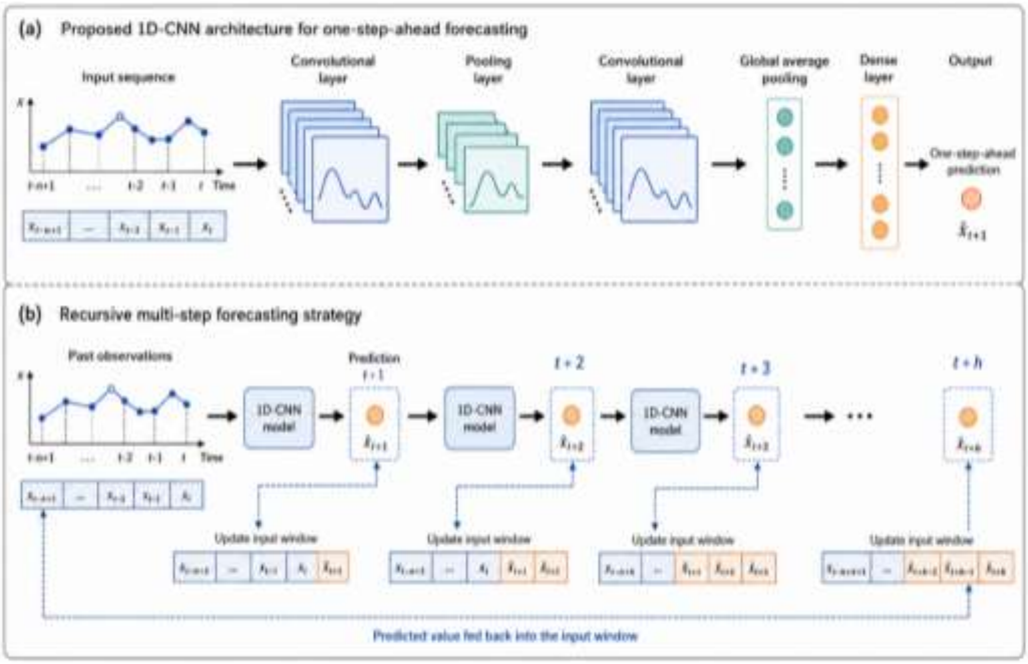


Figure 2 Proposed 1D-CNN forecasting framework: (a) the 1D-CNN architecture used for one-step-ahead prediction, and (b) the recursive multi-step forecasting strategy.

3.3 GRU Model

The Gated Recurrent Unit (GRU) is a recurrent neural network architecture widely used in time series and sequential data modeling (Sezgin et al., 2025). The GRU learns, through gating mechanisms, how much past information to retain and how to incorporate new information into the model. This architecture allows temporal dependencies to be modeled effectively and makes the training process more efficient. Due to its success in practical applications, the GRU has become one of the most frequently preferred methods for forecasting problems.

The operation of a GRU cell is defined through the update gate, reset gate, and candidate hidden state. While the update gate determines how much information from the previous state should be preserved, the reset gate controls the contribution of the past hidden state to the current computation. Based on these two mechanisms, the candidate hidden state is first generated and then used to compute the new hidden state. These operations can be expressed as follows (Önder et al., 2024):

$$z_t = \sigma(x_t W_z + h_{t-1} U_z + b_z) \tag{8}$$

$$r_t = \sigma(x_t W_r + h_{t-1} U_r + b_r) \tag{9}$$

$$\tilde{h}_t = tanh(x_t W_h + (r_t \odot h_{t-1}) U_h + b_h) \tag{10}$$

$$h_t = (1 - z_t) \odot \tilde{h}_t + z_t \odot h_{t-1} \tag{11}$$

Here, z_t denotes the update gate, r_t the reset gate, $\tilde{h}_t$ the candidate hidden state, and $h_t$the current hidden state. In addition, $W$and U represent the weight matrices, b denotes the bias terms, σ is the sigmoid activation function, and $\odot$ indicates element-wise multiplication. Through this mechanism, GRU effectively learns the balance between retaining past information and integrating new input, enabling it to model temporal dependencies efficiently.

The hyperparameters of the GRU model were determined through a grid search procedure in which different parameter combinations were systematically evaluated. Based on the experimental results, the sequence length, batch size, number of epochs, and learning rate were set to 30, 32, 50, and 0.001, respectively. The model architecture consisted of two GRU layers, with 128 units and a dropout rate of 0.4 in the first layer, and 64 units with a dropout rate of 0.2 in the second layer. A dense output layer with a single neuron was used to predict the next time step. The model was trained using the Adam optimization algorithm and the mean squared error loss function, while early stopping was applied based on improvements in validation loss. To evaluate multi-step forecasting performance, the model was implemented using a recursive forecasting strategy for forecasting horizons of 7, 30, and 365 days. The GRU-based prediction architecture is shown in Figure 3.

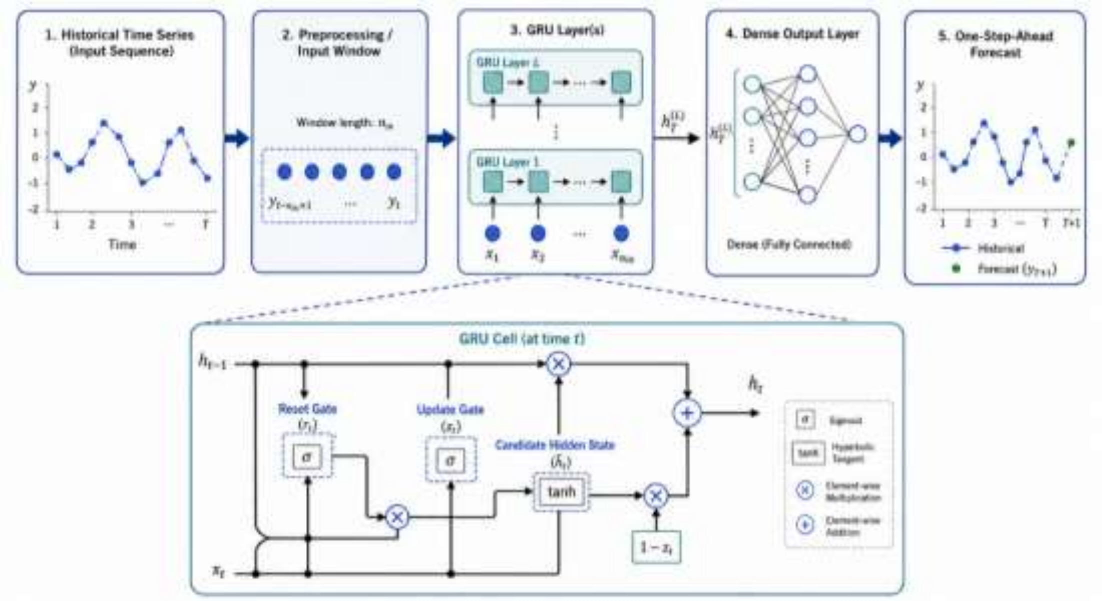


Figure 3 Proposed GRU-based forecasting framework and the internal architecture of a GRU cell.

3.4 XGBoost Regressor

XGBoost is an open-source library based on the gradient boosting framework, used for machine learning applications such as regression and classification (Nguyen et al., 2023). At the core of the algorithm lies the sequential construction of decision trees, which act as weak learners. Each new tree is trained to reduce the errors accumulated in previous steps, thereby gradually improving the model's overall prediction performance. Due to its flexible structure and high computational efficiency, XGBoost has become one of the most frequently used methods for prediction problems.

The core structure of XGBoost is based on the additive combination of decision trees, and the prediction for the *i-th* observation can be written as follows (Chen and Guestrin, 2016):

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{12}$$

where $\hat{y}_i$ is the predicted value, K is the number of trees, and $f_k(x_i)$ represents the output of the *k-th* decision tree.

The overall objective function in XGBoost consists of the training loss and a regularization term:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{13}$$

where $l(y_i, \hat{y}_i)$ denotes the loss function and $\Omega(f_k)$ is the regularization term used to control model complexity.

The regularization term for each tree is defined as:

$$\Omega(f_k) = \gamma T + ½ \lambda \sum_{j=1}^{T} w_j^2 \tag{14}$$

where T is the number of leaves, w_j is the score assigned to leaf j, γ is the penalty for the number of leaves, and λ is the regularization coefficient.

In the XGBoost model, lag variables of 1, 2, 3, 4, 5, 6, 7, 14, 21, 28, 30, 60, 90, and 365 days were defined, and rolling mean and rolling standard deviation features for 7 and 30 days were also included. In addition, calendar-based features such as day of the week, day of the month, month, week of the year, day of the year, and weekend information were incorporated into the model. The number of estimators, maximum depth, learning rate, subsample ratio, and colsample_bytree ratio were set to 500, 8, 0.05, 0.8, and 0.8, respectively. The XGBoost model was implemented using a recursive forecasting strategy for forecasting horizons of 7, 30, and 365 days, where each predicted value was fed back into the input structure for the subsequent forecasting step. The hyperparameters of the XGBoost model were determined through a grid search algorithm. The XGBoost model architecture is shown in Figure 4.

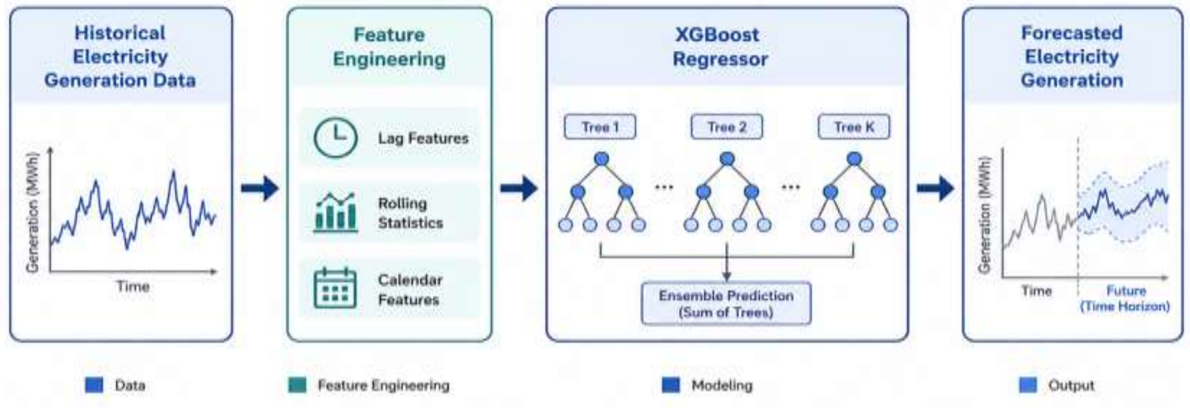


Figure 4 XGBoost-based framework for electricity generation forecasting.

3.5 CatBoost Regressor

CatBoost is a boosting-based machine learning algorithm that has attracted considerable attention due to its strong predictive performance and its ability to improve the gradient boosting framework (Wu and Huang, 2024). It has been successfully applied in a variety of prediction problems and is particularly effective in handling structured tabular data. In this study, CatBoost was employed as one of the forecasting models for electricity generation prediction. Its tree-based structure enables the model to capture complex nonlinear relationships among lagged variables, rolling statistics, and calendar-based features. In addition, CatBoost includes mechanisms that help reduce overfitting and improve generalization performance, making it a suitable choice for time series forecasting tasks based on engineered input features. The CatBoost model architecture is shown in Figure 5.

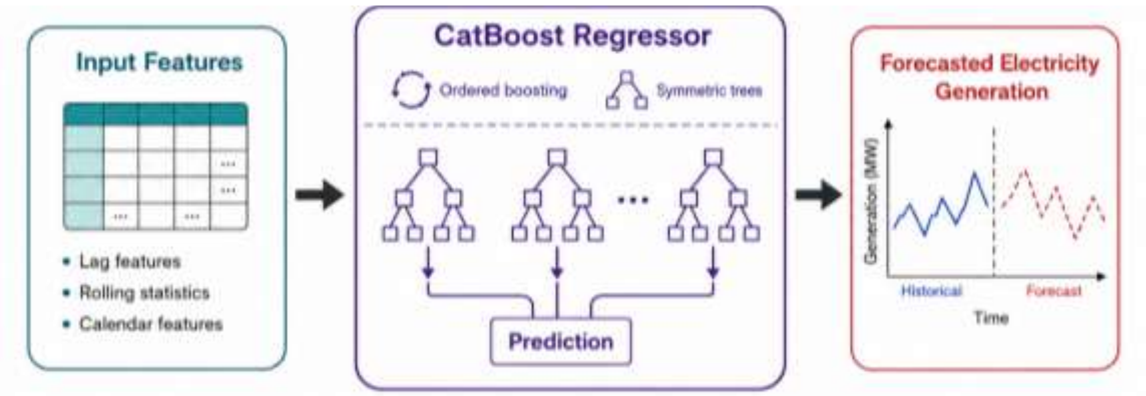


Figure 5 CatBoost-based framework for electricity generation forecasting.

In CatBoost, the final prediction is obtained as the additive sum of decision trees:

$$\hat{y}_i = \sum_{k=1}^{M} f_k(x_i) \tag{15}$$

where $\hat{y}_i$ denotes the predicted value for the i-th observation, M is the total number of trees, and $f_k(x_i)$ is the output of the *k-th* tree. Thus, the final prediction is formed by the sequential contribution of all weak learners. (Prokhorenkova et al., 2018).

The objective function in CatBoost can be written as the sum of the loss function and the regularization term:

$$L(F) = \sum_i l(y_i, F(x_i)) + \sum_k \Omega(f_k) \tag{16}$$

where $l(y_i, F(x_i))$ denotes the loss function measuring the prediction error, and $\Omega(f_k)$ represents the regularization term controlling model complexity. This formulation aims to improve predictive accuracy while reducing overfitting. (Prokhorenkova et al., 2018)

At each boosting iteration, the model is updated by adding a new tree to the existing ensemble:

$$F_{\mathrm{m}}(x) = F_{\mathrm{m-1}}(x) + \alpha \cdot h_{\mathrm{m}}(x) \tag{17}$$

where $F_m(x)$ is the updated model at iteration m, $F_{m-1}(x)$ is the model from the previous iteration, $h_m(x)$ is the newly added tree, and α is the learning rate.

The lag variables, rolling statistics, and calendar-based features used in the CatBoost model were defined in the same way as in the XGBoost model. In terms of model parameters, the number of iterations, tree depth, learning rate, subsample ratio, and rsm ratio were set to 500, 8, 0.05, 0.8, and 0.8, respectively. In addition, RMSE was used as both the loss function and the evaluation metric, while Bernoulli bootstrap was adopted as the sampling strategy. The CatBoost regressor was implemented using a recursive forecasting strategy and evaluated for forecasting horizons of 7, 30, and 365 days. At each forecasting step, the predicted value was fed back into the input structure to generate the subsequent prediction in the multi-step forecasting process.

3.6 Energy Development Plans

Energy development plans are of great importance in terms of countries' economic growth, industrialization processes, and sustainable development goals. For this reason, many energy agencies and international organizations prepare energy projections covering the next 10, 20, and 30-year periods to outline future trends in production, demand, and capacity development. These projections contribute not only to ensuring energy supply security but also to the formulation of investment plans, the identification of infrastructure needs, and the shaping of energy policies. Especially when considering the increase in renewable energy investments, changes in consumption patterns, and technological transformation, long-term energy forecasts become even more critical for decision-makers.

The electricity generation structures of Türkiye and Germany were analyzed in terms of the use of different energy sources. In this context, the Business as Usual (BAU) scenario, which reflects the current generation trends of the countries, was compared with the 2030 Sustainable Transition (ST) and European Commission (EC) scenarios presented by the European Network of Transmission System Operators for Electricity (ENTSO-E, 2018). Thus, the study aimed not only to evaluate the current generation structure but also to examine the possible changes in the electricity generation mix under different future scenarios.

First, the BAU scenario was constructed to represent a situation in which the existing energy mix in electricity generation remains unchanged over time. This scenario also serves as a baseline reference for evaluating alternative scenarios. In this context, electricity generation forecasts up to 2030 were obtained using the best-performing forecasting model, and the BAU scenario was then formulated by considering the current shares of different energy sources in each country's electricity generation mix. In this way, the evolution of total electricity generation under the existing source distribution was revealed.

Second, the ST scenario represents a structure in which the energy transition progresses more rapidly and carbon emissions are reduced through an economically feasible transition process. In this scenario, the share of high-carbon sources such as coal and lignite in the electricity generation sector is projected to decrease, with increased use of lower-carbon or renewable energy sources in their place. Additionally, the shift of certain energy uses in other sectors, such as transportation and logistics, toward the electricity system is also taken into account. However, in the ST scenario, this transition occurs at a relatively more controlled and gradual pace. This scenario aims for a production structure with lower carbon intensity by 2030, and in the long term, emission reductions are expected to be supported by technological advancements and the widespread adoption of new energy applications.

Third, the European Commission (EC) scenario represents a policy-based framework shaped in line with the European Union's 2030 climate and energy targets. This scenario is based on a structure developed within the impact assessment studies published in 2016 and designed to be consistent with the 2030 targets. Under the EC scenario, the electricity generation system is expected to evolve toward a lower-carbon structure, with greater energy efficiency and a generation mix aligned with broader climate objectives. In this context, the EC approach was included in the analysis as a scenario reflecting the European Union's policy orientation and energy transition goals when evaluating electricity generation projections for 2030.

4. Results and Analysis

4.1 Comparative Evaluation of Forecasting Models

In the first stage of the study, forecasting models were developed to analyze electricity generation patterns in Türkiye and Germany under short-, medium-, and long-term prediction settings. For this purpose, forecasting horizons of 7, 30, and 365 days were examined, and the predictive performances of the models were compared accordingly. The performance metric results obtained for these forecasting horizons are presented in Tables 2 and 3. The performance values presented in the tables represent the mean and standard deviation obtained over five different seeds.

The results presented in Tables 2 and 3 indicate that forecasting performance varies depending on both the country and the prediction horizon. For Türkiye, the GRU model achieved the best performance across all forecasting horizons. For horizon=7, GRU produced the lowest error values with an MAE of 28.3, an RMSE of 44.4, and a MAPE of 3.7%. For horizon=30, it maintained its superiority with an MAE of 47.1, an RMSE of 65.1, and a MAPE of 5.9%. In long-term forecasting, namely horizon=365, GRU again outperformed the competing models with an MAE of 118.6, an RMSE of 140.6, and a MAPE of 14.3%. Although CatBoost and 1DCNN generated results close to GRU in some cases, GRU remained the most consistent and accurate model overall for the Türkiye dataset.

For Germany, the findings reveal a different pattern. At horizon=7, XGBoost and CatBoost achieved the same MAPE value of 4.4%, while XGBoost showed a slight advantage with a lower MAE (65.6) and RMSE (83.7). At horizon=30, CatBoost delivered the best overall performance with an MAE of 68.5, an RMSE of 86.3, and a MAPE of 4.6%. A similar trend was observed for horizon=365, where CatBoost again ranked first with an MAE of 76.1, an RMSE of 95.4, and a MAPE of 5.1%. In contrast, the error values of 1DCNN and GRU increased more noticeably for the Germany dataset, particularly under the long-term forecasting setting.

Overall, the findings suggest that the GRU-based approach was more suitable for Türkiye, whereas CatBoost provided more accurate results for Germany, especially in medium- and long-term forecasting. This once again highlights that the most appropriate forecasting model may vary depending on the structural characteristics of the dataset and the forecasting horizon.

Table 2 Forecasting model performance for Türkiye at different horizons.

Methods	Horizon=7			Horizon=30			Horizon=365		
	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)
XGBoost	52.2±1.3	73.7±1.0	6.5±0.2	89.9±3.6	113.4±3.6	11.1±0.4	209.9±7.5	226.0±7.2	25.7±0.9
CatBoost	38.3±0.6	56.9±0.8	4.7±0.1	52.3±1.5	71.5±1.9	6.5±0.2	159.2±5.1	178.2±5.7	19.4±0.7
1DCNN	39.0±6.0	53.6±5.6	4.9±0.7	55.2±11.7	71.9±11.3	6.8±1.4	155.5±28	173.6±29.6	18.9±3.4
GRU	**28.3±1.5**	**44.4±0.6**	**3.7±0.1**	**47.1±7.8**	**65.1±7.1**	**5.9±0.9**	**118.6±32.5**	**140.6±34.6**	**14.3±3.9**

Table 3 Forecasting model performance for Germany at different horizons.

Methods	Horizon=7			Horizon=30			Horizon=365		
	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)
XGBoost	**65.6±0.4**	**83.7±0.6**	**4.4±0.0**	68.7±0.1	86.4±0.3	**4.6±0.0**	86.6±5.5	113.5±8.1	6.0±0.4
CatBoost	65.7±0.3	83.8±0.6	**4.4±0.0**	**68.5±0.4**	**86.3±0.4**	**4.6±0.0**	**76.1±1.5**	**95.4±1.4**	**5.1±0.1**
1DCNN	79.8±0.9	105.5±1.4	5.5±0.1	94.6±5.6	121.5±6.3	6.5±0.5	195.5±31.1	241.3±36.4	13.8±2.5
GRU	75.7±0.8	99.0±0.8	5.2±0.0	89.2±0.7	115.5±1.6	6.1±0.1	135.0±13.3	166.9±17.1	8.9±0.9

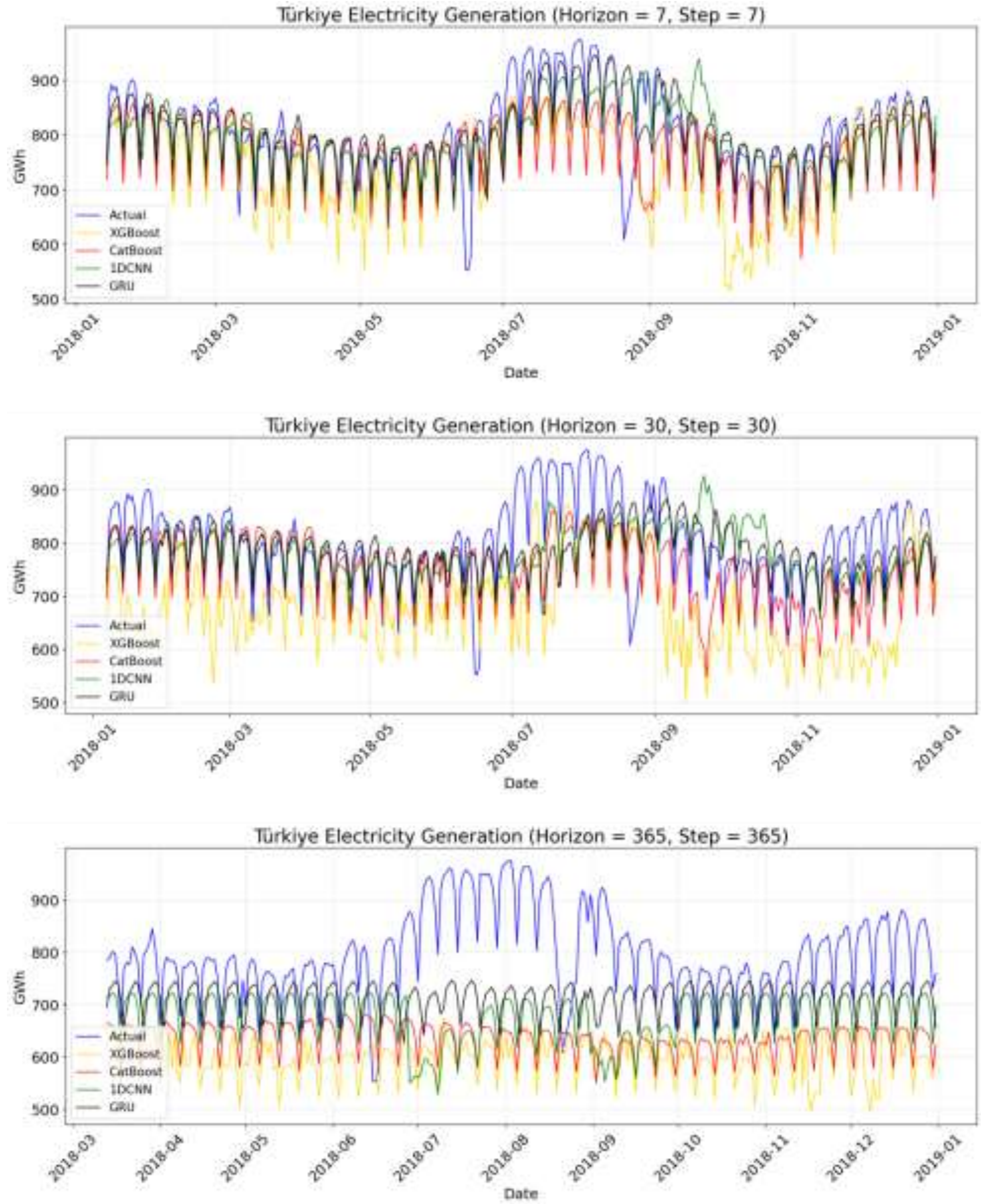


Figure 6 Actual and predicted electricity generation values for Türkiye under the 7, 30, and 365-day forecasting horizons based on the best seed.

Figures 6 and 7 present the comparisons between the actual and predicted values obtained from the best seed. For Türkiye, the results indicate that the models were generally able to capture the overall pattern under horizon=7 and horizon=30. Among them, the GRU model produced forecasts that were closer to the peaks and troughs of the actual series and showed a more consistent alignment with the observed values. At horizon=365, certain pattern distortions became visible for all models. Nevertheless, GRU still remained closer to the actual series dynamics than the competing methods and followed the overall trend more successfully in the long-term setting.

The results for Germany point to a stronger forecasting structure. As shown in Figure 6, the patterns in the Germany dataset were learned more effectively, particularly under the short- and medium-term settings, and the predicted series remained highly consistent with the actual values. For horizon=7 and horizon=30, the boosting-based methods, especially XGBoost and CatBoost, reflected the fluctuations and periodic behavior of the actual series quite successfully. More importantly, under horizon=365, the deterioration observed for Türkiye did not appear as strongly in the Germany dataset. On the contrary, the boosting algorithms were still able to preserve the underlying pattern to a large extent and maintain a strong fit with the actual series. This suggests that the structural characteristics of the Germany dataset were more effectively captured by tree-based methods.

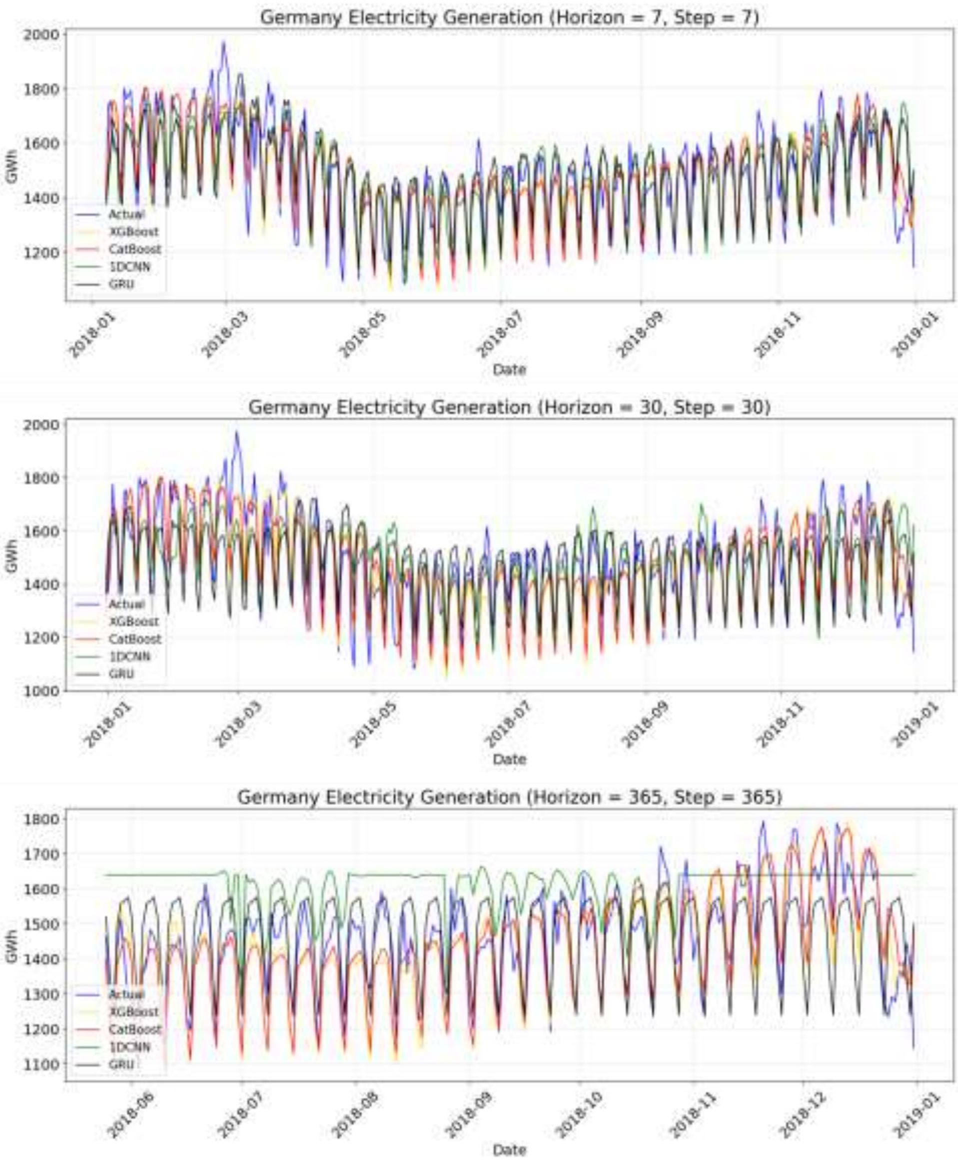


Figure 7 Actual and predicted electricity generation values for Türkiye under the 7, 30, and 365-day forecasting horizons based on the best seed.

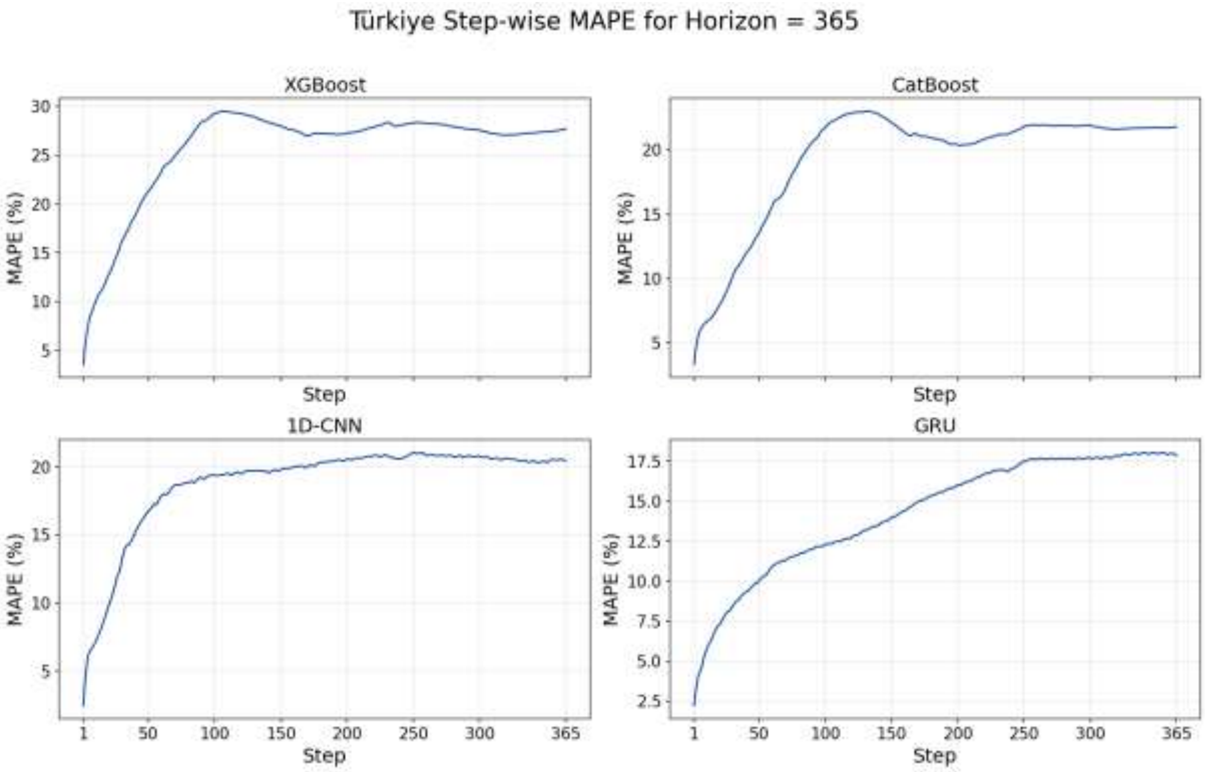


Figure 8 Step-wise MAPE values of the forecasting models for Türkiye under horizon=365.

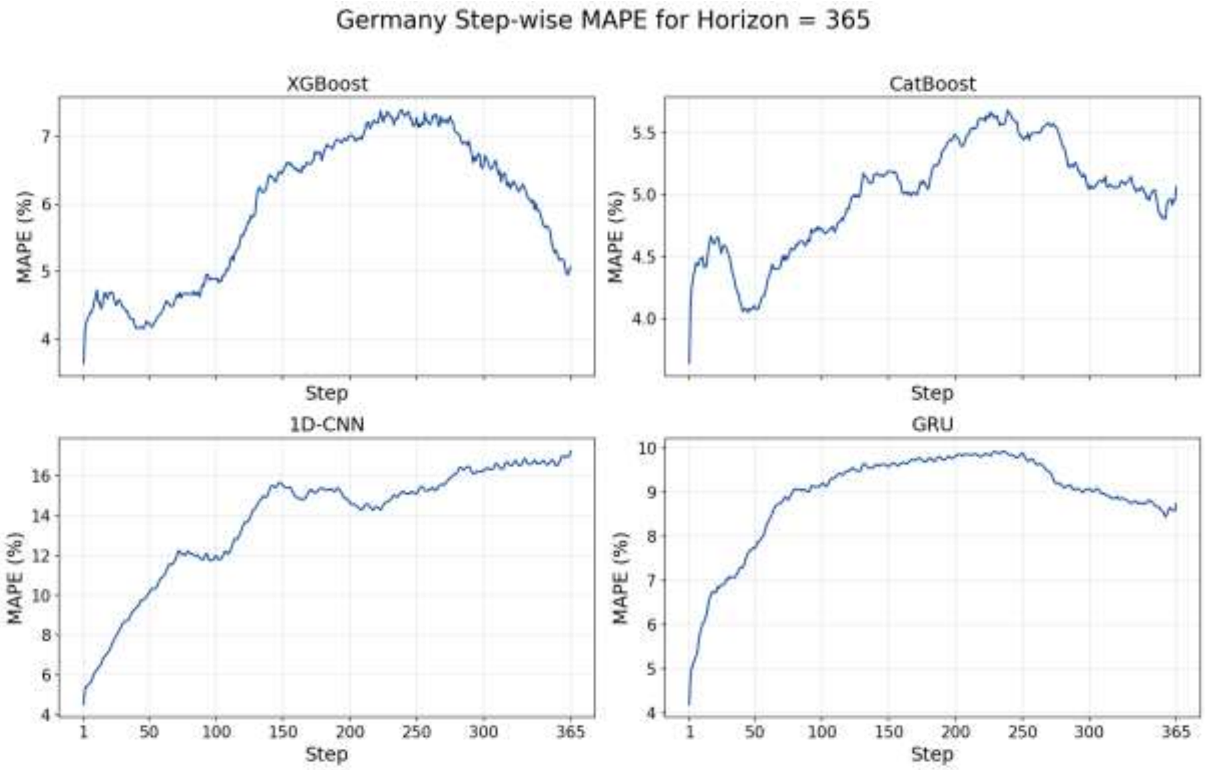


Figure 9 Step-wise MAPE values of the forecasting models for Germany under horizon=365.

Figures 8 and 9 illustrate the step-wise MAPE variation of the models for horizon=365. For Türkiye, the error values generally increased as the forecast step became longer, while the GRU model exhibited a lower and more controlled rise in error compared to the other methods. XGBoost and CatBoost showed earlier and more pronounced increases in error, whereas 1D-CNN and especially GRU provided a more stable pattern. For Germany, the step-wise error profile appeared more balanced. In particular, the partial decline in MAPE observed after certain forecast steps for the boosting-based models indicates that these methods were able to preserve the underlying pattern over the long horizon and moderate error growth to some extent. These findings suggest that GRU was more robust for long-term forecasting in the Türkiye dataset, whereas XGBoost and CatBoost were more successful in controlling step-wise error for the Germany dataset.

4.2 Comparison of 2030 Electricity Generation Scenarios

In the second stage of the study, Business as Usual (BAU) projections for 2030 were generated using the developed forecasting models and compared with the Sustainable Transition (ST) and European Commission (EC) 2030 scenarios obtained from ENTSO-E reports. This comparison made it possible to evaluate the differences between the generation structure expected under the continuation of current trends and the alternative scenarios shaped by policy and transition-oriented pathways. Thus, the analysis addressed not only forecasting performance but also the possible scenario divergences in the context of long-term energy planning.

As shown in Figures 10 and 11, the BAU projections obtained using the best-performing forecasting models indicate a gradual increase in annual electricity generation for both countries over the 2028–2030 period. For Türkiye, annual generation is projected to reach 384,419.7 GWh in 2028, 390,208.8 GWh in 2029, and 397,645.9 GWh in 2030. For Germany, annual generation is expected to rise from 532.889 TWh to 534.754 TWh over the same period. These findings suggest that, under the continuation of current trends, both countries are likely to experience an upward trajectory in electricity generation, although the increase appears to be more pronounced in Türkiye and more moderate and stable in Germany.

These forecasts are important not only for estimating annual total generation amounts but also for supporting future period-based electricity planning. In particular, anticipating generation trends for the coming years can provide decision-makers with an important reference for issues such as capacity planning, resource allocation, supply security, and the balance between demand and generation. In this respect, the obtained projections can contribute to both operational and strategic planning processes in the energy system.

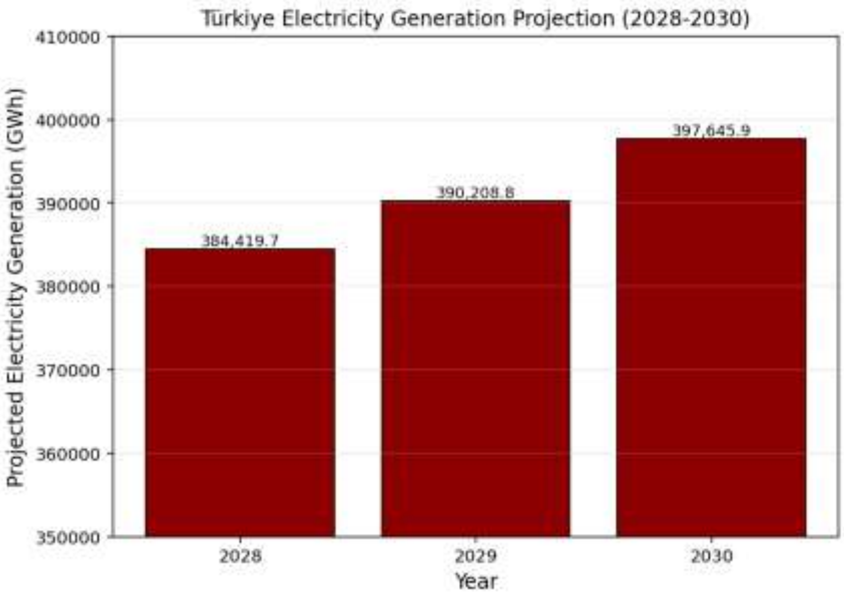


Figure 10 BAU projection of annual electricity generation for Türkiye for the 2028–2030 period.

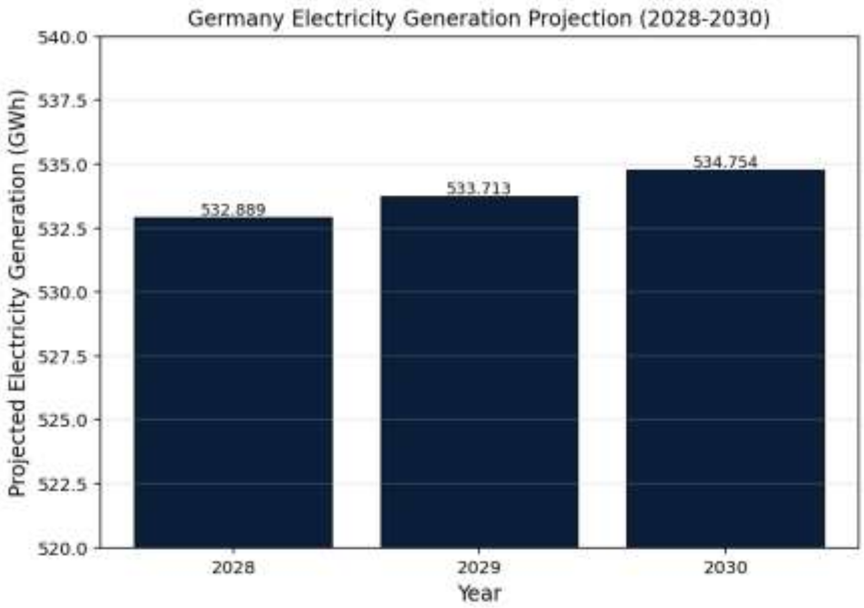


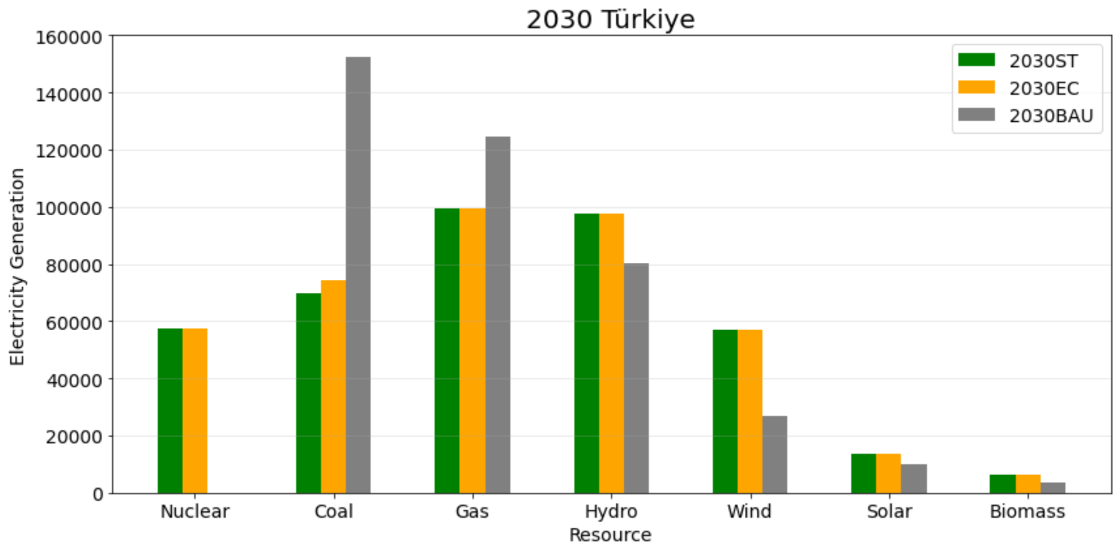
Figure 11 BAU projection of annual electricity generation for Germany for the 2028–2030 period.

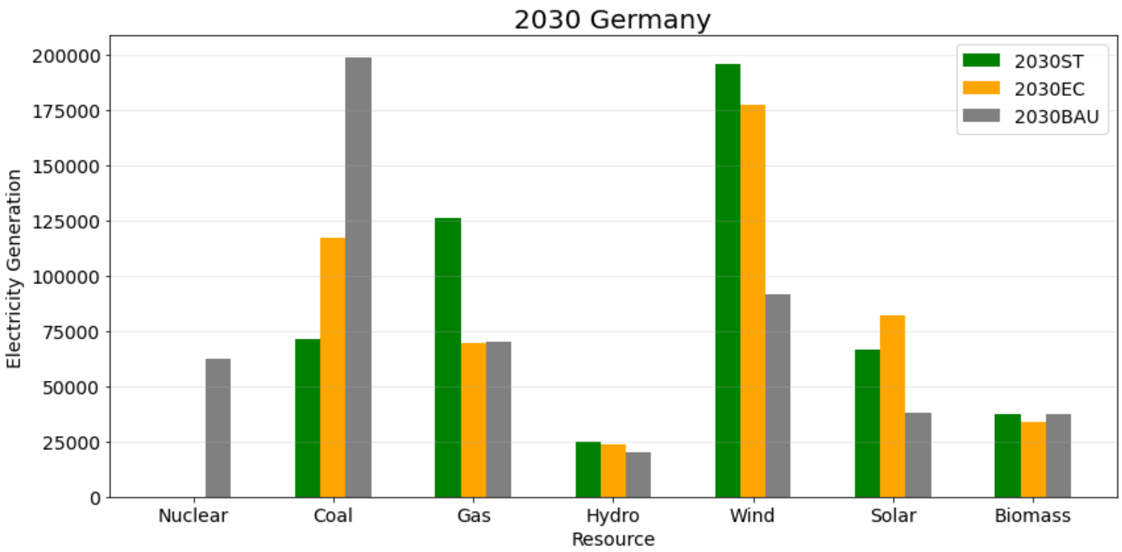
In constructing the BAU 2030 projection, the resource-based electricity generation shares observed in the final year of the dataset were preserved, and the resulting structure was compared with the ST and EC scenarios. The comparative findings are illustrated in Figures 12 and 13.

Figure 12 shows that, for Türkiye, the BAU projection points to a noticeably higher dependence on coal and natural gas in 2030 compared with the ST and EC scenarios. Under the BAU case, coal generation rises to approximately 150 thousand GWh, while natural gas reaches around 125 thousand GWh, both of which are clearly above the levels suggested by the ST and EC pathways. In contrast, hydropower remains close to 100 thousand GWh in both the ST and EC scenarios but stays around 80 thousand GWh in the BAU projection. A similar pattern is observed for wind power: while ST and EC both remain near 55 thousand GWh, BAU falls to roughly 30 thousand GWh. Overall, the ST and EC scenarios present a relatively similar and transition-oriented structure for Türkiye, whereas the BAU projection reflects a more carbon-intensive electricity mix driven primarily by coal and natural gas.

Figure 13 reveals a much sharper divergence between the BAU projection and the ST and EC scenarios for Germany. A key difference is that nuclear generation is completely eliminated in both the ST and EC scenarios, whereas the BAU structure still retains approximately 65 thousand GWh of nuclear output. Coal generation is another major point of separation: it remains very high in the BAU case at nearly 199 thousand GWh, compared with about 70 thousand GWh in ST and 117 thousand GWh in EC. On the renewable side, wind power reaches approximately 195 thousand GWh in the ST scenario and 175 thousand GWh in the EC scenario, while the BAU projection remains much lower at around 90 thousand GWh. A similar contrast appears in solar generation, which lies in the range of roughly 70–80 thousand GWh in ST and EC but remains close to 40 thousand GWh under BAU. These findings indicate that, for Germany, the ST and EC scenarios imply a much stronger transition away from fossil and nuclear dependence, whereas the BAU structure preserves a larger share of the existing conventional generation mix.

Overall, while the BAU projections for both countries reflect the resource structure that would emerge if current trends continue, the ST and EC scenarios represent more transformation-focused alternatives shaped by policy interventions. In Turkey, the ST and EC scenarios exhibit a structure that is quite similar to one another, while the BAU scenario diverges from these two scenarios, particularly in terms of coal and natural gas. In Germany, however, the divergence is much more pronounced; specifically, the complete phase-out of nuclear power and the significant strengthening of renewable sources in the ST and EC scenarios present a different perspective on energy transition compared to the BAU approach. However, the ST and EC scenarios also contain certain internal differences; this indicates that energy transition can be shaped not through a single path, but through various combinations of policies and technologies.





5. Conclusion

Accurate electricity forecasting plays a critical role in energy planning by supporting generation planning, reducing imbalance costs, improving resource allocation, and guiding long-term investment decisions. Since supply and demand must be kept in constant balance in electricity systems, reliable forecasts are of great importance not only for short-term operational efficiency but also for medium- and long-term infrastructure planning, capacity expansion decisions, and energy transition strategies. Therefore, the development and comparison of forecasting methods make significant contributions to understanding future generation patterns and supporting more effective and sustainable electricity planning.

In this study, deep learning and boosting-based algorithms produced strong forecasting results for both countries. The findings showed high predictive accuracy in short- and medium-term horizons and indicated that even under the highly challenging horizon=365 setting, the models were still able to achieve a reasonably good level of performance. In particular, the GRU model exhibited a more consistent and robust structure for the Türkiye dataset, whereas boosting algorithms produced stronger results for Germany. This demonstrates that the most suitable forecasting model depends not only on the selected method itself but also on the structural characteristics of the dataset and the forecasting horizon.

From the perspective of scenario comparisons, the BAU projections for both countries reflect a structure that remains closer to the continuation of the existing generation mix, where fossil-based resources retain a relatively stronger position. In contrast, the ST and EC scenarios present a more transition-oriented framework in which renewable energy sources, particularly wind, solar, hydro, and biomass, become more prominent. Especially for Germany, the complete elimination of nuclear generation in the transition scenarios and the higher contribution of renewable sources clearly highlight the policy-driven nature of the energy transition.

In future studies, it is recommended that models incorporate not only historical production data but also additional inputs such as economic indicators, population growth, energy demand, installed capacity, renewable energy investments, and country-specific energy policy plans in order to obtain more robust and reliable long-term forecast results. Such multi-variable structures can contribute to reducing uncertainty, particularly in long-term projections, and to obtaining more realistic results. Furthermore, expanding scenario analyses to consider not only production volumes but also environmental impact, such as carbon and water footprints by source, presents an important area of research. This would enable energy planning to be evaluated not only in terms of supply and cost, but also from broader sustainability and environmental perspectives.

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