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Comparative Evaluation of AI and Statistical Models for Forecasting Fossil Fuel Electricity Generation

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Özet

Forecasting fossil fuel-based electricity generation remains important for energy planning, particularly in countries undergoing different stages of energy transition. Reliable forecasts can support decision-makers in balancing energy security concerns with long-term sustainability objectives. This study investigates the forecasting performance of several statistical and machine-learning approaches using annual fossil fuel electricity generation data from six countries: Türkiye, Germany, the United Kingdom, France, Iran, and Ukraine. The dataset covers the period from 1985 to 2022 and includes countries with distinct energy structures and policy trajectories. Nine forecasting models were evaluated, including traditional statistical techniques (NAÏVE, AUTO.ARIMA, HOLT-WINTERS, ETS, THETAF, and TBATS) and neural network-based methods (NNETAR, MLP, and ELM). Model performance was assessed using rolling validation strategies and three commonly used error measures: RMSE, MAE, and MAPE. The results indicate that forecasting performance varies considerably across countries and depends on the underlying characteristics of each time series. Neural network-based models generally performed better in countries exhibiting more complex or irregular generation patterns, whereas conventional statistical methods remained competitive for relatively stable series. Among the evaluated approaches, ELM achieved the lowest forecasting errors for France and Ukraine, while AUTO.ARIMA and ETS provided highly accurate results for Iran. Rather than identifying a universally superior forecasting technique, the findings highlight the importance of selecting models according to the structural properties of national energy systems. The study provides a comparative perspective on fossil fuel electricity forecasting and offers insights that may support future energy planning and transition strategies.

Keywords: Energy Transition, Comparative Forecasting, Deep Learning, Time Series Analysis, Policy Informatics, Decarbonization Strategies

Fosil Yakıtla Elektrik Üretiminin Tahmini: Hibrit Yapay Zeka-İstatistiksel Çok Ülkeli Analiz

Özet

Fosil yakıta dayalı elektrik üretiminin doğru tahmin edilmesi, küresel enerji geçiş stratejileri için kritik bir zorluk olmaya devam ediyor; ancak mevcut yaklaşımlar genellikle hem karmaşık doğrusal olmayan dinamikleri hem de bölgeye özgü politika etkilerini yakalayacak metodolojik çok yönlülükten yoksundur. Bu çalışma, jeopolitik olarak farklı altı ülkeye (Türkiye, Almanya, Birleşik Krallık, Fransa, İran ve Ukrayna) gelişmiş uzun vadeli tahminler sunmak için gelişmiş derin öğrenme modellerini (MLP, ELM, NNETAR) yerleşik istatistiksel yöntemlerle (ARIMA, ETS, TBATS) sistematik olarak entegre eden yeni bir hibrit modelleme çerçevesi sunmaktadır. 1985-2022 yıllarını kapsayan yıllık verileri kullanarak, sürekli başlangıç doğrulama stratejisi kullanıyoruz ve performansı RMSE, MAE ve MAPE ölçümleri aracılığıyla değerlendiriyoruz. Bulgularımız, derin öğrenme modellerinin değişken, doğrusal olmayan trendleri yakalamada istatistiksel muadillerinden sürekli olarak daha iyi performans gösterdiğini ortaya koyuyor (ELM'nin Fransa için %8,75'lik bir MAPE elde etmesi buna örnektir), AUTO.ARIMA gibi geleneksel modeller ise İran'da gösterildiği gibi istikrarlı rejimlerde etkili olmaya devam ediyor (MAPE: %2,40). Daha da önemlisi, bu araştırma yalnızca tahmin doğruluğunu geliştirmekle kalmıyor, aynı zamanda model performansını ulusal enerji geçiş yollarına bağlayarak eyleme dönüştürülebilir, politikayla ilgili bilgiler sağlıyor. Hibrit çerçevelerin özel karbondan arındırma stratejilerine nasıl rehberlik edebileceğini, şebeke istikrarını nasıl optimize edebileceğini ve ulusal enerji politikalarının küresel sürdürülebilirlik hedefleriyle uyumlaştırılmasını nasıl destekleyebileceğini, böylece dünya çapındaki politika yapıcılara ölçeklenebilir ve veri odaklı bir karar destek aracı sunabileceğini gösteriyoruz.

Anahtar Kelimeler: Enerji Geçişi, Hibrit Tahmin, Derin Öğrenme, Zaman Serisi Analizi, Politika Bilişimi, Karbondan Arındırma Stratejileri

1. INTRODUCTION

Fossil fuels remain a cornerstone of global electricity generation, particularly in nations balancing economic growth with energy security [1]. However, the environmental repercussions-carbon emissions, air pollution, and ecological degradation-underscore the urgency of transitioning toward sustainable alternatives. Accurate forecasting of fossil fuel-based electricity production is thus critical for mitigating these impacts while ensuring stable energy supply chains. Existing studies often focus on single-country analyses or short-term predictions, neglecting the heterogeneous energy landscapes and long-term trends across regions. Furthermore, comparative evaluation of machine-learning and statistical forecasting methods remains limited.

This study addresses these gaps by conducting a 38-year comparative analysis (1985–2022) of electricity generation in six nations with distinct energy policies: Türkiye (rising fossil reliance), Germany (renewable transition leader), the UK (wind energy prominence), France (nuclear dominance), Iran (fossil-hydro hybrid), and Ukraine (post-Soviet energy restructuring). By harmonizing deep learning and statistical approaches, we aim to (1) identify optimal forecasting models for diverse temporal patterns, (2) quantify regional disparities in fossil fuel dependency, and (3) provide a robust framework for policymakers to reconcile energy security with decarbonization goals.

Turkey meets its energy needs from a combination of fossil fuels, renewable resources and hydroelectricity [2]. The use of fossil resources, especially natural gas and coal, has an important place in the country's energy portfolio. Additionally, Turkey benefits from abundant renewable resources, especially solar and wind energy, to diversify its energy mix. Notable contributions also come from hydroelectric power, which takes advantage of the country's abundant water resources. This underlines Turkey's comprehensive approach to electrical energy production and demonstrates its efforts to strike a balance between energy security, environmental sustainability and economic considerations. Turkey wants to use its energy resources in a sustainable, effective, and efficient manner [3].

As a country known for its commitment to renewable energy, Germany has made significant progress in moving away from traditional fossil fuels. The country, a leader in wind and solar energy, uses renewable resources to strengthen its energy network [4]. It continues Germany's strategic pursuit of sustainable and low-carbon energy solutions and demonstrates its credentials as a global pioneer in the transition to a more environmentally friendly electricity generation system.

The UK has undergone a significant transition towards renewable energy, with wind energy taking center stage as the main source. About 61.2% of the electricity generated in the UK in 2013 came from fossil fuels, 13.2% from renewable sources, 23.9% from nuclear power, and 1.8% from other sources [5]. Both offshore and onshore wind facilities have become important sources of the country's energy supply. It supports production with low-carbon options such as nuclear energy. To improve energy security, the UK aims to expand its resource base to include solar power, natural gas and interconnections. These initiatives demonstrate the UK's commitment to promoting a diverse and sustainable energy mix, aligning with international efforts to tackle climate change and providing a robust energy outlook for the future.

France, a pioneer in the field of nuclear energy, relies heavily on this energy source to produce a significant portion of its electricity [2]. This confidence has solidified France's position as one of the world's leading countries in terms of low carbon emissions from electricity generation. While nuclear energy remains prevalent, France is proactively expanding its renewable energy portfolio, particularly by investing in hydropower, wind power and solar energy. Iran produces most of its electricity by combining fossil fuels with hydroelectric power. The country has significant oil and natural gas reserves, which play an important role in energy production. Moreover, Iran is actively developing hydroelectric power facilities, taking advantage of its abundant water resources to expand its energy diversity [6].

Fossil fuels, primarily coal and natural gas, have long been the backbone of Ukraine's energy output. Across the nation, a steady supply of electricity has been successfully maintained by natural gas-fired power facilities. Likewise, the energy landscape of Ukraine is significantly influenced by coal-fired plants. Nonetheless, it is important to note that Ukraine is actively diversifying its energy sources, in line with worldwide trends [7]. In order to promote sustainability and lessen environmental harm, one of the main components of this strategy is the use of renewable energy sources.

Countries that produce electrical energy from fossil resources face various environmental problems. This type of energy production results in the release of large amounts of carbon dioxide and other greenhouse gases into the atmosphere, accelerating global warming and climate change. In addition, sulfur dioxide and nitrogen oxides resulting from the burning of fossil fuels cause acid rain, acidifying soil and water resources and damaging ecosystems. Air pollution also leads to an increase in respiratory diseases that threaten human health. In addition, leaks and accidents that occur during the extraction and transportation of fossil fuels cause serious damage to terrestrial and marine ecosystems and threaten biodiversity. For these reasons, energy production based on fossil resources poses significant risks in terms of both environmental and health.

Predicting electricity generation is crucial for effective energy management, and time series models[8] provide useful means for achieving this goal. By analyzing historical electricity data, time series analysis helps uncover patterns, trends, and seasonal variations, enabling accurate forecasts of future generation. The capacity to understand temporal relationships facilitates precise predictions in both the short and long term, thereby assisting in efficient resource distribution, grid management, and energy market strategies. The uses of time series models [9][10] extend beyond electricity generation to various fields, including finance, economics, climate science, weather [11], health [12], speech recognition [13], energy consumption [14], [15], radiation predictions [16], [17], sunspot prediction [18], [19], natural gas production prediction [20], [21], and sensor data analysis [22] showcasing their versatility in capturing and predicting sequential data patterns. This study underscores the importance and broad applicability of time series models in forecasting, contributing to informed decision-making and improved resource management across diverse domains.

Time series forecasting presents a formidable task, grappling with the intricacies and fluctuations inherent in real-world data. Its challenges encompass non-stationarity, intricate interdependencies, anomalies, seasonal patterns, evolving trends, data integrity concerns, and the impact of external variables.

Forecasting fossil fuel-based electricity generation is becoming increasingly challenging as energy systems evolve under the influence of technological developments, market dynamics, and climate-related policies. Changes in generation portfolios, the growing penetration of renewable energy sources, and country-specific transition strategies often lead to time series that exhibit different levels of complexity. As a result, forecasting methods that perform well in one country may not necessarily provide the same level of accuracy in another.

Motivated by this observation, the present study examines the forecasting behaviour of a broad set of statistical and machine-learning models using long-term electricity generation data from six countries with distinct energy profiles. Rather than focusing on a single forecasting technique, the study aims to evaluate how different modeling approaches respond to varying temporal patterns and structural characteristics. This comparative perspective allows a more comprehensive assessment of model suitability across different national contexts.

The main contribution of this work lies in its cross-country evaluation of nine forecasting models using a common experimental framework and a long historical dataset. By comparing countries that differ substantially in terms of fossil fuel dependence, energy transition policies, and generation trends, the study provides insights into the relationship between forecasting performance and the characteristics of national energy systems. The findings may be useful for both researchers working on energy forecasting and decision-makers interested in understanding long-term generation trends.

2. MATERIALS and METHODS

This study employs a comparative forecasting framework that evaluates six statistical models and three machine-learning models for predicting fossil fuel-based electricity generation. In this study, nine time series forecasting models were used to make a wide range of comparisons. Six models used in prediction processes are in the statistical-based group, and three of them are in the deep learning group. The changes in the electrical energy produced from fossil resources of six different countries such as Türkiye (TR), Germany (DEU), United Kingdom (UK), France (FR), Iran (IRN) and Ukraine (UKR) between 1985 and 2022 were investigated and future forecast analyzes were made. All prediction analyzes were performed in the RStudio environment using the R programming language. NAÏVE, AUTO.ARIMA, HOLT-WINTERS, ETS, THETAF, TBATS, NNETAR, MLP and ELM models were used in the estimation processes. Analyzes were carried out with the help of a computer with Intel i5 PC 3.2 GHz CPU, 8 GB RAM, SATA disk and Windows 10 Pro operating system configuration.

In this section, firstly, the statistical-based and deep learning models used for predictions are briefly explained, then metrics are given to evaluate the prediction results, then time series are briefly mentioned and finally information is given about the sources and structures of the data sets used.

2.1. Data Description

Çalışmada her proje konsepti, plan organizasyonu ve fonksiyonel dağılım, donatıların organik yerleştirilmesi, erişilebilirlik ve sirkülasyon, bitkilendirme ve mikroiklim başlıklarında analiz edilmiştir.

Annual electricity generation data (1985–2022) for Türkiye, Germany, the UK, France, Iran, and Ukraine were sourced from Our World in Data (https://ourworldindata.org/energy), focusing on coal, oil, and natural gas-derived production (in TWh). To ensure robustness:

Missing data handling: Linear interpolation was applied to address sparse gaps (<5% of data points).

Normalization: Min-max scaling (range [0,1]) was performed to mitigate scale disparities between countries.

Stationarity: Augmented Dickey-Fuller (ADF) tests confirmed non-stationarity, prompting first-order differencing for all series. Here, six countries that produce electrical energy from fossil resources and have the same production date range have been selected. These countries whose data are received and processed are Türkiye, Germany, the United Kingdom, France, Iran and Ukraine. The amount of electrical energy produced from coal, oil and gas resources, called fossil resources, is taken as terawatt-hours (TWh) on an annual basis. As seen in Figure 1, four of the countries whose data are processed are located in the European continent, one in the Asian continent and one in the Europe-Asia continent. The data of the six countries that produce electricity on an annual basis based on fossil resources and constitute the subject of this study cover the period 1985-2022. The production ranges of all the countries selected for the case study here are the same, and such a choice was made especially to make a more accurate comparison. The time series of electrical energy (TWh) produced from fossil resources in Türkiye, Germany, the United Kingdom, France, Iran and Ukraine between 1985 and 2022 are shown in Figure 2. In addition, the statistical information about the electricity production processes and production obtained from fossil resources of the countries in question are given collectively in Table 1.

Table 1. Statistical information about the time series of electrical energy produced from fossil resources between 1985 and 2022 of the six different countries used in the study

Electricity generation from fossil fuels (1985-2022)	Length (Year)	Min. (TWh)	1st Qu. (TWh)	Median (TWh)	Mean (TWh)	3rd Qu. (TWh)	Max (TWh)
1- Türkiye (TR)	38	19.31	48.31	103.69	112.33	171.06	214.86
2- Germany (DEU)	38	250.0	353.8	360.4	356.1	375.0	399.8
3- United Kingdom (UK)	38	127.2	227.0	242.4	238.9	282.3	314.5
4- France (FR)	38	33.09	45.11	51.45	49.86	56.51	65.09
5- Iran (IRN)	38	33.01	74.58	146.41	159.64	238.43	332.11
6- Ukraine (UKR)	38	32.94	81.32	89.03	109.31	119.65	221.48

Figure 1. Positions of countries producing electrical energy from fossil resources between 1985 and 2022 on the world map

In Figure 2, we see that Türkiye started production from fossil resources with 19.31 TWh in 1985, and although there were some decreases and increases from time to time in the production process, it generally continued with an upward trend and reached an additional high value of 214.86 TWh in 2021.

Looking at the data in Table 1, it can be seen that Türkiye's average production of electrical energy from fossil resources over a 38-year period is 112.33 TWh. As seen in Figure 2, Germany started producing electrical energy from fossil resources with 250 TWh in 1985 and reached the level of 399.83 TWh in 2007. In general terms, production exhibited a horizontal production until 2015, started to decline in 2009, and this trend continued horizontally until 2019. Electricity production decreased to 250.02 TWh in 2020 and then started to rise again. As seen in Figure 2, the United Kingdom increased the electrical energy it obtained from fossil resources from 228.36 TWh to 314.5 TWh in 2008. Electricity production, which continued with an upward trend from the beginning until 2008, started to trend downward after that date.

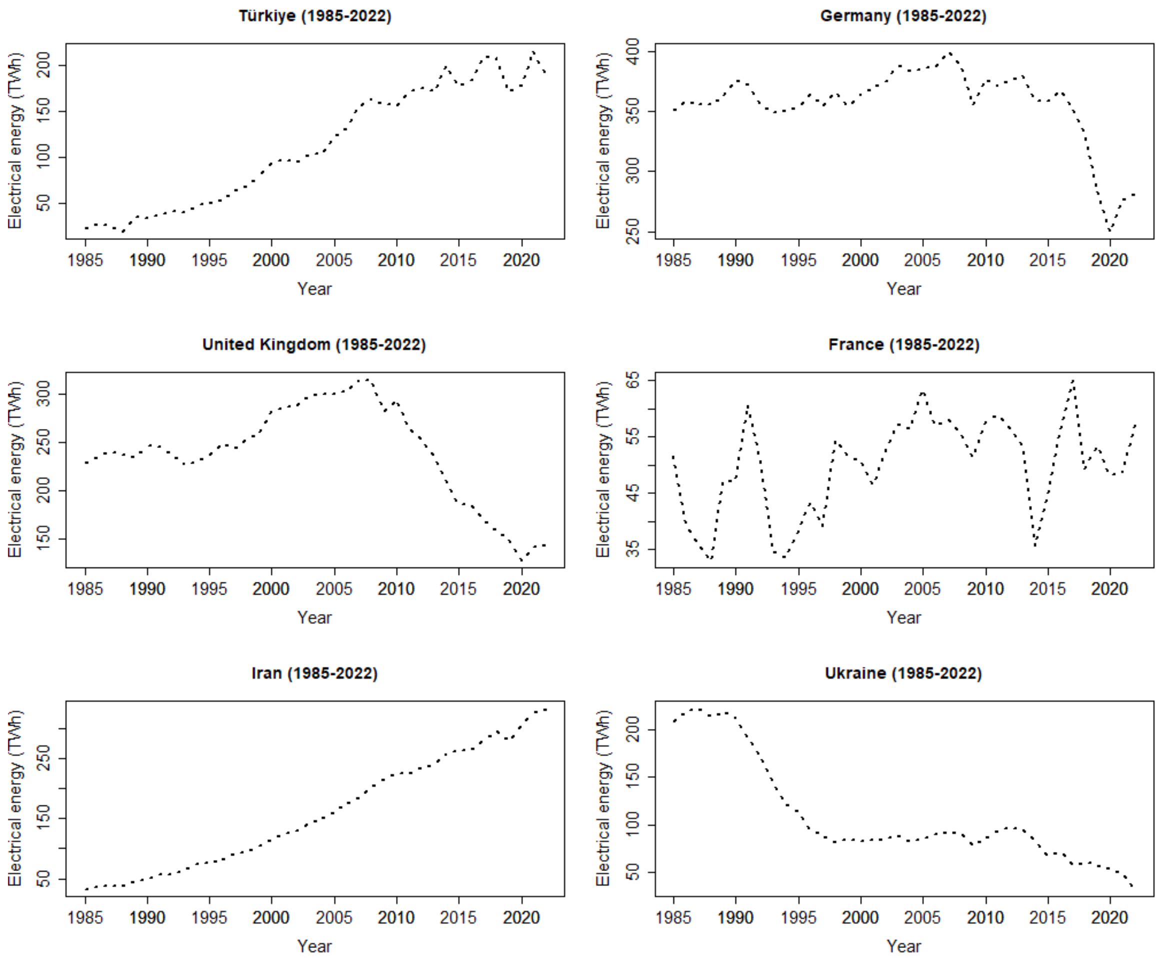

Figure 2. Time series of electrical energy (TWh) produced from fossil sources in Türkiye, Germany, the United Kingdom, France, Iran and Ukraine between 1985-2022.

France's electrical energy production from fossil resources has generally been fluctuating. Electricity production, which started with 51.65 TWh in 1985, reached the highest value of 65.09 TWh in 2017. Since 1921, electricity production has been on the rise again.

Iran started producing electricity from fossil resources with 33.01TWh in 1985 and continued to increase its production with a general upward trend. It reached the highest value of 332.11TWh in 2022. Unlike Iran, Ukraine's production from fossil resources started in 1985 with 207.98 TWh, reached its highest value in 1987 with 221.48 TWh, and has started to decline since then. In 2022, it dropped to 32.94 TWh, the lowest value in its own production process.

2.2. Model Selection and Configuration

Çalışmada her proje konsepti, plan organizasyonu ve fonksiyonel dağılım, donatıların organik yerleştirilmesi, erişilebilirlik ve sirkülasyon, bitkilendirme ve mikroiklim başlıklarında analiz edilmiştir.

Models were chosen based on their established efficacy in time series forecasting literature:

NAİVE: The Naive prediction model offers a straightforward approach to forecasting, assuming that upcoming values in a time series will mirror the most recent observation [23]. Essentially, it suggests that the next data point will match the last one recorded. Although simplistic, this model serves as a reference for comparing against more intricate forecasting methods. It proves handy for rapid and uncomplicated accuracy assessments but may falter when faced with time series data featuring intricate patterns or trends. Despite its constraints, the Naive model offers a foundational basis for gauging the efficacy of more sophisticated forecasting techniques in capturing the underlying data patterns. The NAÏVE model was included as a baseline approach to provide a simple benchmark for comparison with more advanced techniques. Its simplicity allows for rapid evaluation, but its limitations in capturing trends and seasonality are well-documented.

AUTO.ARIMA: AUTO.ARIMA, or automatic ARIMA, is a forecasting model that utilizes an automated algorithm to determine the optimal parameters for an ARIMA (AutoRegressive Integrated Moving Average) time series model. The auto.arima function has the ability to automatically identify and adapt Auto Regressive Integrated Moving Average (ARIMA) models [24], [25], [26]. ARIMA models are widely used to model trends and seasonal patterns in time series.

For a dependent time series$\{X_t : 1 \leq t \leq N\}$, ARIMA can be modeled mathematically as follows:

$$\emptyset(B)\nabla^d X_t = \theta(B)\varepsilon_t$$
(1)

Where B is the backshift operator, $BX_t = X_{t-1}$ and $\emptyset(B)$ is the autoregressive operator represented as a polynomial in the backshift operator:

$$\emptyset(B) = 1 - \emptyset_1(B) - \cdots - \emptyset_p B^p$$
(2)

$\theta(B)$ is the autoregressive operator, represented as a polynomial in the backshift operator:

$$\theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$$
(3)

ε_t is the independent disturbance, also called the random t error [27]. AUTO.ARIMA was selected for its ability to automatically identify and model linear trends and seasonal components in time series data. It is particularly effective for datasets with consistent patterns but struggles with highly non-linear dynamics.

HOLT-WINTERS: The Holt-Winters technique, also termed triple exponential smoothing, stands as a method for forecasting time series data, engineered to grasp and foresee patterns within data that possess seasonality and trend. By employing smoothing parameters (alpha, beta, and gamma), the model finely tunes the impact of past data on these elements. Particularly adept for data featuring both trend and seasonality, the Holt-Winters model offers adaptability in forecasting by accommodating diverse data patterns. With its trio of smoothing parameters, users gain control over recent observations' influence and can fine-tune the model's responsiveness to shifts in level, trend, and seasonality. Consequently, it emerges as a versatile instrument for projecting future values within time series data [28]. The HOLT-WINTERS model, also known as triple exponential smoothing, was chosen for its proficiency in capturing trends and seasonality in data with relatively stable patterns over time.

ETS: The ETS model, short for error, trend, seasonality, serves as a valuable tool in time series analysis for forecasting purposes [29]. It dissects time series data into three fundamental elements: error, trend, and seasonality.

These components elucidate the random fluctuations, long-term movements, and repeating patterns within the data, respectively. ETS models are adaptable, catering to diverse time series patterns by adjusting smoothing parameters for each component. They manifest in three principal variations: ETS (AAA) encompasses all three components, ETS (AAN) comprises error and trend, while ETS (ANN) involves error and seasonality. This adaptability renders ETS models apt for forecasting across a spectrum of scenarios characterized by varying levels of seasonality and trend complexities. The ETS model was employed to decompose the data into error, trend, and seasonality components, offering a flexible approach to datasets with varying degrees of complexity.

THETAF: The THETAF model, known for its robustness in handling seasonal and non-linear trends, was included as a versatile option for forecasting diverse time series data.

Advanced machine learning models, including NNETAR, MLP, and ELM, were chosen for their capability to capture intricate and non-linear relationships in the data. These models excel in scenarios where traditional statistical methods may fail to account for complex temporal dependencies.

TBATS: The TBATS model, short for Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend, and Seasonal components, represents a sophisticated approach to time series forecasting, specifically tailored to handle datasets exhibiting multiple seasonal patterns and intricate temporal structures [30], [31]. Devised by De Livera, Hyndman, and Snyder, this model integrates trigonometric functions to capture diverse seasonal variations, applies a Box-Cox transformation to stabilize variance, incorporates an ARMA errors component for autocorrelation modeling, and includes distinct components to capture trend and multiple seasonal patterns [23]. This adaptable and resilient framework equips TBATS to effectively analyze and predict time series data marked by irregularities, rendering it invaluable for scenarios where conventional models falter, such as those involving daily or weekly seasonality, holidays, and other temporal intricacies. The TBATS model was selected for its ability to handle complex seasonality and irregular patterns, making it particularly suitable for data with multiple seasonal cycles or sudden fluctuations.

NNTAR: It is a function included in the forecast package in the R language and creates a time series forecast model using neural networks. This function is designed to address complexities in time series data and improve predictive performance [20].

NNTAR utilizes a sophisticated artificial neural network for forecasting time series[32][33][34][35]. This ensures adeptness in managing intricate and non-linear correlations within the data. Predictions are derived by autonomously identifying significant data features and adjusting their importance through learning. The model accommodates diverse time series frequencies, facilitating analysis across hourly, daily, monthly, quarterly, and annual intervals. NNTAR autonomously configures the neural network architecture and other crucial parameters, fostering the acquisition of intricate structures and enhancing generalization capabilities. It proficiently addresses seasonal and trend components, effectively capturing the essence of the time series data.

MLP: The Multilayer Perceptron (MLP) stands as a pivotal tool in the realm of artificial neural networks, specifically tailored for tasks demanding supervised learning such as regression and classification. Structured with layers of interconnected nodes, an MLP comprises an input layer, one or more hidden layers, and an output layer. Each node connection carries a weighted significance, while activation functions embedded within layers introduce crucial nonlinearities. The training process of an MLP revolves around fine-tuning these weights through backpropagation, a mechanism minimizing the disparity between predicted and actual outputs via iterative optimization methods like gradient descent. Renowned for their adeptness in grasping intricate data relationships, MLPs find widespread utility across diverse applications. Nonetheless, their effective deployment often necessitates meticulous hyperparameter tuning to forestall overfitting and attain peak performance [36].

In the MLP model, the relationship between y_t output and $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ inputs can be expressed as follows:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j . g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}\right) + \varepsilon_t, \tag{4}$$

Where α and β are the weights; p is the number of inputs, q is the number of hideen nodes, and g is the transfer function [37].

ELM: Extreme Learning Machine (ELM) is a model crafted for regression and classification tasks within machine learning. Originally devised by Huang, Zhu, and Siew in the early 2000s, ELM distinguishes itself as a single-layer feedforward neural network. What sets it apart is its utilization of randomly assigned and fixed input weights and biases, facilitating swift training. Its efficiency and simplicity arise from its capacity to determine output weights analytically in a single step, often employing Moore-Penrose pseudoinversion or similar optimization techniques. ELM boasts rapid learning and commendable generalization capabilities, rendering it highly suitable for real-time and large-scale applications. However, its susceptibility to outliers and the potential impact of random weight initialization on reproducibility necessitate careful consideration of data characteristics and preprocessing [38].

Suppose there is an ELM with k hidden layer neurons and an activation function g. In this case, modeling $\{X_i, y_i\}_{i=1}^{N}, x_i \in R^s$ data samples can be represented mathematically as follows:

$$\sum_{j=1}^{k} g_i\left(w_j, b_j, x_i\right)\beta_j = t_{i,}\, i = 1,2, \dots, N \tag{5}$$

Here w_j is the vector of input weights connecting the jth hidden neuron and the inputs. β_j is the output weight connecting the jth hidden neuron and the output and represents the bias of the jth hidden node [39].

Although neural-network-based approaches are commonly associated with large datasets, the models employed in this study (NNETAR, MLP, and ELM) represent relatively lightweight learning architectures. Their inclusion aims to evaluate whether simple nonlinear learners can capture long-term energy generation dynamics more effectively than traditional statistical methods. Nevertheless, the limited sample size of 38 annual observations may restrict generalization capability and increase the risk of overfitting. Therefore, the forecasting results should be interpreted as comparative evidence rather than definitive proof of deep learning superiority.

2.3. Training and Validation

To address temporal dependencies:

Data partitioning: A rolling-origin validation was adopted:

Phase 1: 30 years (1985–2014) training, 8 years (2015–2022) testing (79:21 split).

Phase 2: 28 years (1985–2013) training, 10 years (2014–2022) testing (74:26 split).

Hyperparameter tuning: Grid search optimized key parameters (e.g., TBATS: Box-Cox λ; MLP: hidden nodes).

Hyperparameter Optimization and Reproducibility

The primary objective of this study was to conduct a comparative evaluation of widely used statistical and machine-learning forecasting approaches under a common experimental setting. Therefore, all models were implemented using the default parameter configurations provided by their respective R packages. No extensive hyperparameter optimization or model-specific tuning procedures were performed.

This decision was motivated by two considerations. First, the available dataset for each country consisted of only 38 annual observations, which limits the reliability of extensive hyperparameter search procedures and increases the risk of overfitting. Second, using default configurations facilitates reproducibility and allows a more transparent comparison of model behavior under standard implementation conditions.

All forecasting analyses were conducted in the RStudio environment using publicly available forecasting libraries. Consequently, the reported results reflect the baseline performance of each forecasting approach rather than the maximum performance achievable through extensive model tuning. All models were implemented using the default parameter settings of their corresponding R packages. No additional hyperparameter optimization procedure was performed.

2.4. Performance Evaluation

The Root Mean Squared Error (RMSE) serves as a widely accepted measure to assess the accuracy of prediction models, notably in regression analysis and time series forecasting. It quantifies the average magnitude of variances between predicted and actual values by computing the square root of the mean of squared differences. RMSE offers a concise numerical representation of the model's typical prediction error, with decreased values indicating superior predictive capability. Notably, RMSE is attuned to outliers, as it gives more weight to larger errors through the squaring process, rendering it a prevalent tool for evaluating the overall adequacy of predictive models [40], [41], [42].

$$\boldsymbol{RMSE} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}}\sum_{i=1}^{N}(\boldsymbol{y_t} - \boldsymbol{\hat{y}_t})^2} \quad (6)$$

Here, N represents the total number of observations, y_t represents the actual value, $\boldsymbol{\hat{y}_t}$ represents the predicted value. Mean Absolute Error (MAE) is a useful metric utilized in evaluating the accuracy of predictive models, often applied within regression analysis or when forecasting time series data. It quantifies the average absolute disparities between predicted and actual values. By averaging these absolute disparities, MAE furnishes a gauge of the typical magnitude of the model's discrepancies irrespective of their direction. Unlike metrics such as Root Mean Squared Error (RMSE), MAE demonstrates lesser sensitivity to outliers, as it doesn't involve squaring the disparities. A diminished MAE signifies enhanced predictive precision, rendering it a straightforward and easily interpretable measure for assessing regression model performance [43].

$$\boldsymbol{MAE} = \frac{\mathbf{1}}{\boldsymbol{N}}\sum_{i=1}^{N}|\boldsymbol{y_t} - \boldsymbol{\hat{y}_t}| \quad (7)$$

In contrast, MAPE presents errors in relation to the actual values, providing a scale-free assessment. It furnishes a percentage metric, facilitating the conveyance of accuracy within a relative framework. However, MAPE may encounter issues when actual values approach zero, potentially resulting in infinite or undefined values in the denominator [44].

$$\boldsymbol{MAPE} = \frac{\mathbf{1}}{\boldsymbol{N}}\sum_{t=1}^{N}\frac{|\boldsymbol{y_t}-\hat{\boldsymbol{y}}_t|}{|\boldsymbol{y_t}|}x100\ (\%) \tag{8}$$

2.5. Time Series Analysis

Time series are data sets that show the change of an event or value over time. This type of data has a variety of applications in many different fields and industries. Some areas where time series are used: These can be listed as weather [11], health [12], speech recognition [13], energy consumption [14], [15], radiation predictions [16], [17], sunspot prediction [18], [19], natural gas production prediction [20], [21], sensor data analysis [22].

Time series analysis provides a valuable tool for predicting future events by combining a number of functions. However, successful time series forecasting model selection and implementation includes factors such as correct parameter tuning and regular model updates.

3. RESULTS and DISCUSSION

The performance of each model was assessed using RMSE, MAE, and MAPE metrics. These metrics were selected to provide a comprehensive evaluation of predictive accuracy, with an emphasis on penalizing large errors (via RMSE) and measuring relative error percentages (via MAPE). Each model was tailored to the specific characteristics of the dataset, such as seasonality, trend components, and data granularity. This ensured that the strengths of each approach were maximized while minimizing their limitations.

In this section, nine different analyzes were made for each country's electrical energy production estimates from fossil resources. RMSE, MAE and MAPE metric values of NAÏVE, AUTO.ARIMA, HOLT-WINTERS, ETS, THETAF, TBATS, NNETAR, MLP and ELM prediction models are given in Table 2.

In the first stage of the analysis, the training length was taken as 30-years (79%) and the validation length was taken as 8-years (21%), while in the second stage, the training length was taken as 28-years (74%) and the validation length was taken as 10-years (26%).

In the table, the metrics of the best prediction model for each country are shown in bold. While the smaller RMSE and MAE metric values used here indicate that the predictions made are better, the MAPE metric values show the error made as a percentage.

As seen in Table 2, depending on the validation data length, the best results from the prediction analyzes regarding Türkiye's electrical energy production from fossil resources were obtained with the help of NAÏVE model in the first one and THETAF model in the second one. With these models, when the ratio of the validation data length to the entire data was taken as 21% and 26%, the MAPE metric values were obtained as 8.79% and 7.52%, respectively. This shows that the models have an accuracy of 91.21% and 92.48%, respectively. In the same table, the results of MAPE are also supported by the RMSE and MAE metrics, as they appear at smaller values.

For the Türkiye data set, the second best prediction was made with the NNETAR model for both 8-year and 10-year data lengths. In the first and second stages of the predictions for Türkiye, the prediction average of the deep learning models was obtained as 15.08% and 9.65%, respectively, depending on the MAPE metric values. Similarly, the MAPE metric averages of statistical-based models in both analyzes are 17.61% and 11.04%, respectively. When the validation data length is set to 21%, the graphical representation of the prediction results obtained for Türkiye is given in Figure 3. The blue lines in the prediction part of each model chart show the prediction average, the red dots show the actual values and the dark shaded regions show the 80% prediction interval. That is, each future value is expected to be in the dark shaded region with an 80% probability. The lighter shaded region shows the 95% prediction interval. These forecast ranges are a useful way to illustrate the uncertainty in forecasts.

For Türkiye, forecasting performance appears to be influenced by the sustained upward growth observed throughout most of the study period. The relatively successful performance of THETAF and NNETAR suggests that models capable of adapting to long-term trend behaviour can effectively represent the evolution of fossil fuel-based generation in the country. The results also indicate that abrupt nonlinear fluctuations are relatively limited compared to some of the other countries included in the analysis.

Table 2. Metric values of the prediction results of the countries studied here depending on two different validation data lengths

Datasets	Electricity generation from fossil fuels (TWh)						
Country	Models	Validation dataset length %21			Validation dataset length %26		
		RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)
Türkiye (TR)	**NAÏVE**	**17.57**	**16.28**	**8.79**	22.21	17.18	8.51
	AUTO.ARIMA	40.03	35.24	19.11	24.57	19.29	10.57
	HOLT-WINTERS	36.40	31.14	16.96	24.55	19.28	10.56
	ETS	36.41	31.14	16.95	24.56	19.28	10.57
	THETAF	27.07	22.03	12.20	**15.83**	**14.26**	**7.52**
	TBATS	66.76	69.35	31.70	42.13	34.33	18.54
	NNETAR	17.01	15.01	9.45	23.89	18.64	9.24
	MLP	34.90	30.45	16.64	20.90	16.74	9.16
	ELM	40.11	35.31	19.15	24.57	19.30	10.57
Germany (DEU)	**NAÏVE**	**62.06**	**47.95**	**17.36**	68.17	52.85	18.61
	AUTO.ARIMA	**62.06**	**47.95**	**17.36**	68.17	52.84	18.60
	HOLT-WINTERS	70.84	56.53	20.31	72.45	56.60	19.88
	ETS	67.79	53.58	19.30	67.18	51.80	18.25
	THETAF	70.25	55.78	20.07	70.58	54.91	19.30
	TBATS	68.11	53.88	19.40	67.15	51.77	18.24
	NNETAR	69.10	54.33	19.59	**63.83**	**48.90**	**17.26**
	MLP	69.11	54.35	19.60	**64.19**	**48.79**	**17.26**
	ELM	69.86	54.35	20.00	**62.84**	**46.99**	**16.68**
United Kingdom (UK)	NAÏVE	56.42	52.87	35.80	88.22	82.23	53.37
	AUTO.ARIMA	51.89	41.93	28.82	88.22	82.23	53.37
	HOLT-WINTERS	54.01	43.79	30.10	**27.59**	**18.80**	**12.64**
	ETS	**51.25**	**41.38**	**28.44**	88.22	82.23	53.37
	THETAF	60.65	56.72	38.43	96.60	89.78	58.36
	TBATS	54.52	50.83	34.48	88.33	82.35	53.45
	NNETAR	79.06	76.00	50.93	102.66	94.54	61.71
	MLP	91.96	73.86	51.05	130.71	125.83	80.16
	ELM	51.36	48.24	32.64	103.77	95.97	62.52
France (FR)	NAÏVE	18.26	17.20	31.65	9.17	7.12	15.82
	AUTO.ARIMA	18.26	17.20	31.65	9.17	7.12	15.82
	HOLT-WINTERS	19.90	18.89	34.87	13.58	12.03	26.01
	ETS	17.54	16.43	30.19	9.33	7.28	16.18
	THETAF	16.48	15.28	27.99	10.47	8.78	19.26
	TBATS	16.60	15.42	28.25	9.40	7.35	16.33
	NNETAR	10.97	9.14	16.32	8.23	5.99	12.49
	MLP	10.29	8.30	14.72	8.03	5.99	12.56
	ELM	**7.42**	**5.12**	**8.75**	**7.79**	**5.80**	**11.71**
Iran (IRN)	NAÏVE	43.68	36.08	11.70	57.14	49.46	16.59
	AUTO.ARIMA	13.18	9.99	3.50	**8.55**	**6.95**	**2.40**
	HOLT-WINTERS	12.02	8.40	2.97	8.85	7.39	2.53
	ETS	**11.16**	**7.17**	**2.90**	11.73	9.89	3.32
	THETAF	24.18	18.10	5.78	33.07	27.75	9.25
	TBATS	39.84	35.59	11.88	49.08	43.00	14.60
	NNETAR	30.74	23.03	7.35	39.34	31.69	10.47
	MLP	10.44	8.94	3.46	8.79	6.68	2.42
	ELM	9.69	7.33	4.48	10.10	8.64	2.93
Ukraine (UKR)	NAÏVE	29.31	27.02	55.82	37.95	33.99	66.73
	AUTO.ARIMA	12.73	10.08	22.48	43.30	39.35	76.44
	HOLT-WINTERS	13.61	11.94	23.69	63.42	56.72	91.36
	ETS	13.61	11.94	23.70	63.42	56.72	91.36
	THETAF	17.13	15.80	32.54	21.00	18.89	36.87
	TBATS	26.65	24.12	50.40	38.52	34.63	67.83
	NNETAR	32.56	30.43	62.27	28.85	24.82	50.13
	MLP	7.95	6.60	13.42	25.36	23.00	44.64
	ELM	**6.44**	**7.13**	**9.45**	**14.54**	**13.5**	**25.07**

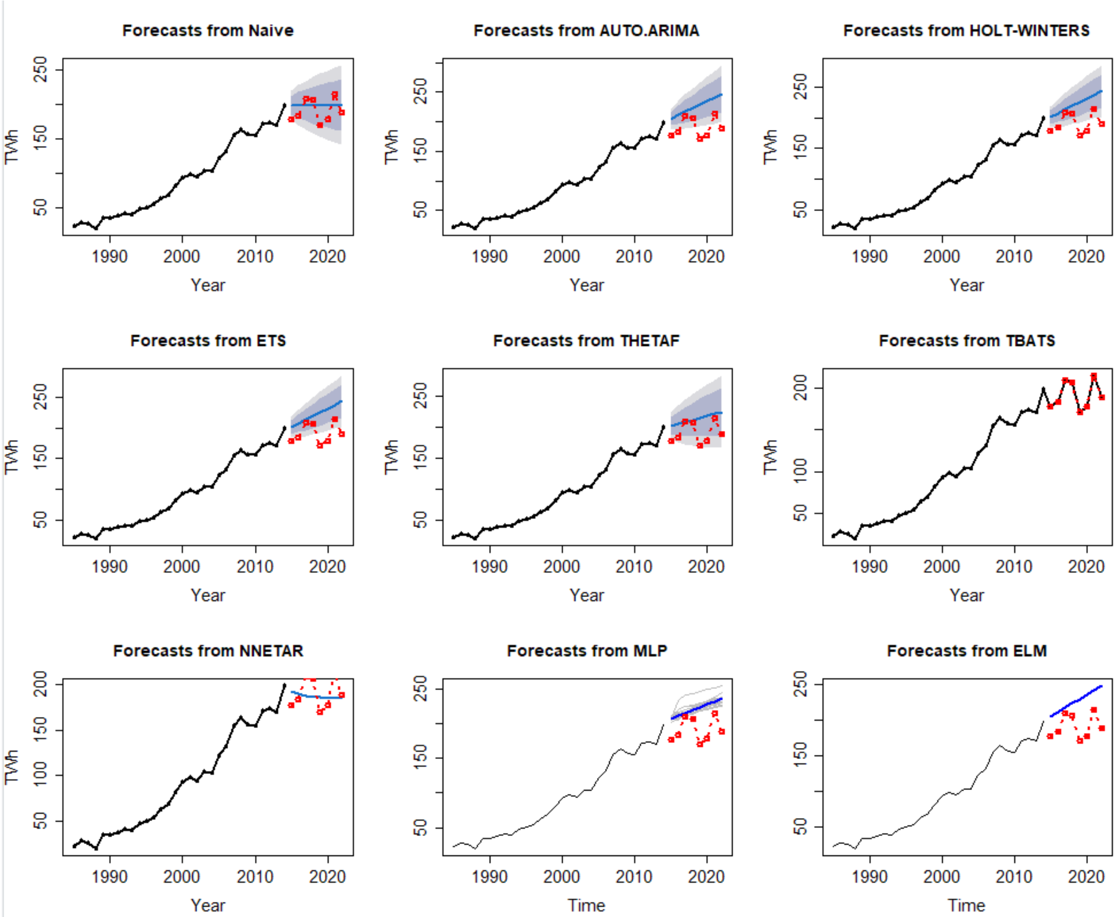

Figure 3. 8-year electrical energy production forecast graphs from fossil resources in Turkey between 2014 and 2022, with the help of nine different models

3.1. Comparative Performance Analysis

The forecasting results demonstrate that model performance varies substantially across countries and validation settings. No single model consistently achieved the best results for all datasets, indicating that forecasting accuracy is highly dependent on the structural characteristics of the underlying time series.

For countries characterized by relatively stable long-term growth patterns, such as Iran, conventional statistical approaches produced highly competitive results. In contrast, countries that experienced structural changes, policy-driven transitions, or abrupt fluctuations tended to benefit more from nonlinear learning-based approaches.

Another notable finding is that the performance gap between statistical and machine-learning methods was not uniform across all cases. While neural-network-based models frequently achieved lower forecasting errors, traditional methods remained strong competitors, particularly when the historical patterns exhibited relatively smooth trajectories.

These findings suggest that forecasting model selection should be guided by the characteristics of the dataset rather than assumptions regarding the superiority of a specific modeling family.

When looking at Germany's electrical energy production estimates from fossil resources in Table 2, in the 21% validation case, NAÏVE and AUTO.ARIMA models come to the fore, while in the 26% validation case, the ELM, MLP and NNETAR models come to the fore with their performances. In the first and second stages of the predictions for Germany, the prediction average of the deep learning models was obtained as 19.73% and 17.06%, respectively, depending on the MAPE metric values. Similarly, the MAPE metric averages of statistical-based models in both analyzes are 18.96% and 18.81%, respectively. When the validation data length is set to 21%, the graphical representation of the prediction results obtained for Germany is given in Figure 4.

Germany presents a more challenging forecasting environment due to the long-term effects of the Energiewende policy and the gradual reduction of fossil fuel dependency. These structural transitions introduce variability that is more difficult to capture using purely trend-based statistical models. The comparatively stronger performance of neural-network-based approaches under some validation settings may therefore be associated with their ability to adapt to nonlinear changes in generation behaviour.

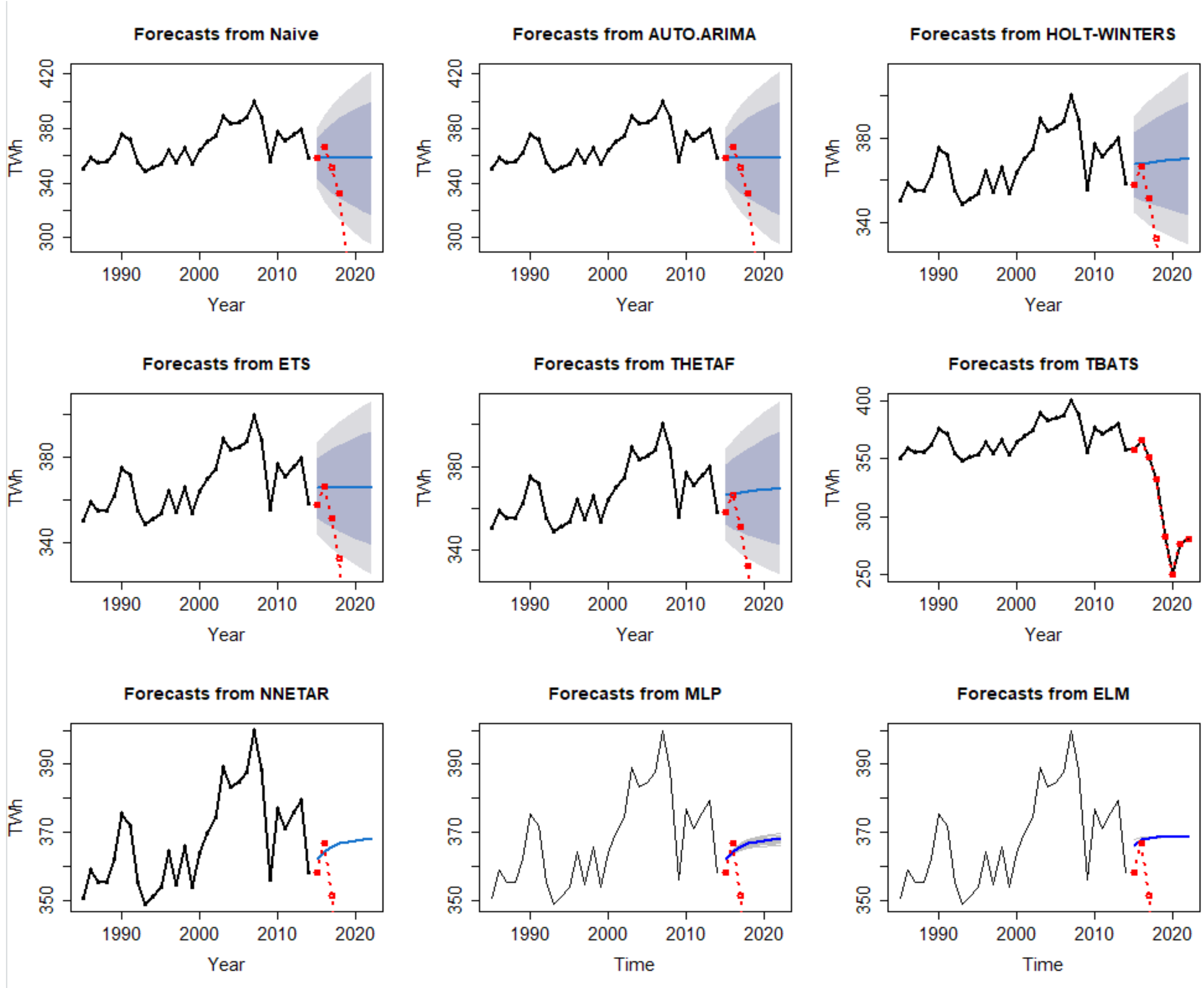

Figure 4. 8-year electrical energy production forecast graphs from fossil resources in Germany between 2014 and 2022, with the help of nine different models

In the case where the United Kingdom data set was used, the best predictions were made with the ETS model in the first analysis and the HOLT-WINTERS model in the second analysis. In the first and second stages of the predictions for United Kingdom, the prediction average of the deep learning models was obtained as 44.87% and 68.13%, respectively, depending on the MAPE metric values. Similarly, the MAPE metric averages of statistical-based models in both analyzes are 32.67% and 47.42%, respectively. Model graphics of the predictions are given in Figure 5.

The United Kingdom exhibited one of the most distinctive patterns among the examined countries. Following a prolonged increase, fossil fuel-based generation entered a period of rapid decline. This structural shift creates forecasting challenges because future observations are no longer governed by the same dynamics that characterized earlier periods. Such behaviour partly explains the relatively high forecasting errors observed across several models.

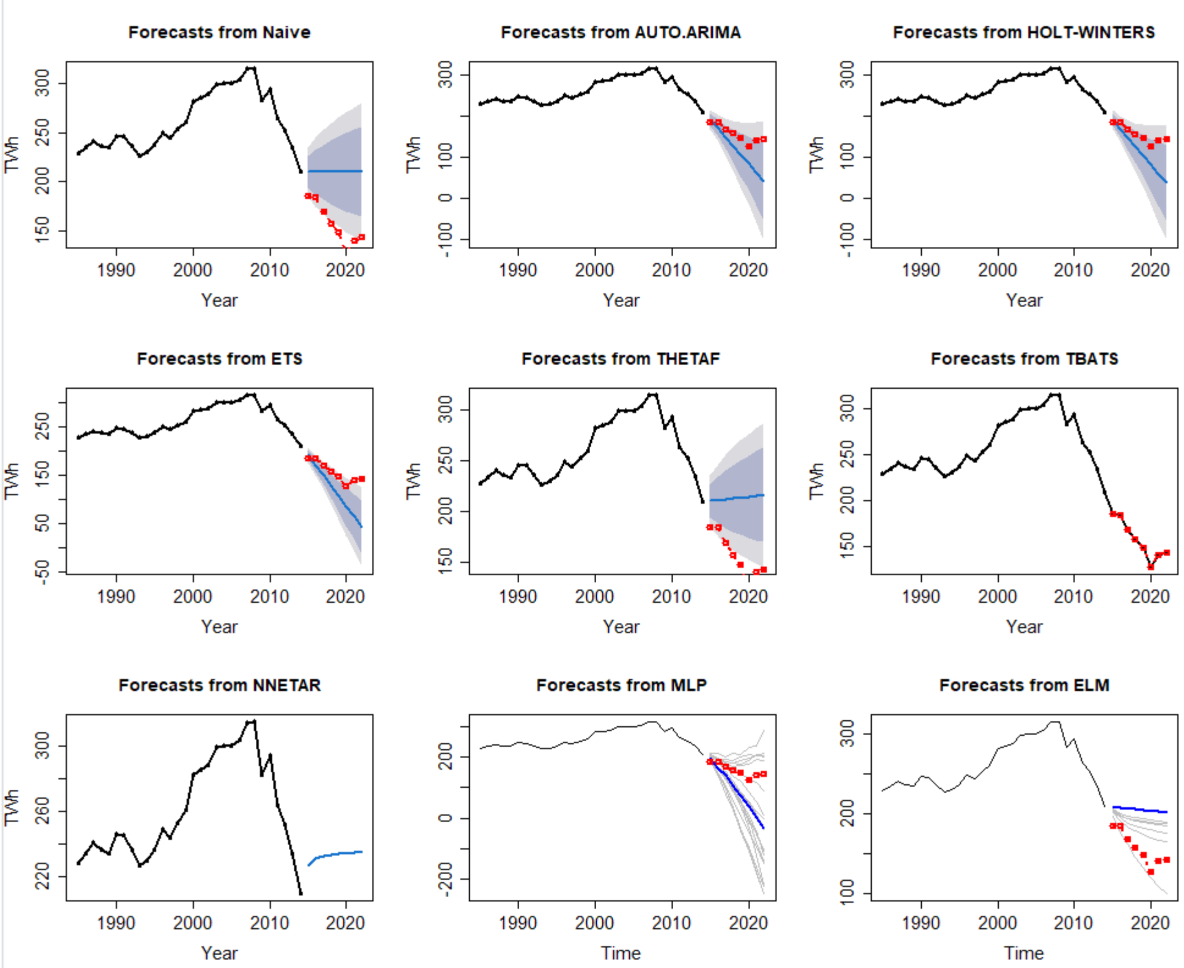

Figure 5. 8-year electrical energy production forecast graphs from fossil resources in United Kingdom between 2014 and 2022, with the help of nine different models

In the case where the French data set was used, the best predictions were made with the ELM model in both the first and second analysis. Error rates on the 8-year and 10-year validation data length of the ELM model were obtained as 8.75% and 11.71%, respectively, with the MAPE metric. In the first and second stages of the predictions for French, the prediction average of the deep learning models was obtained as 13.26% and 12.25%, respectively, depending on the MAPE metric values. Similarly, the MAPE metric averages of statistical-based models in both analyzes are 30.76% and 18.23%, respectively. Model graphics of the predictions are given in Figure 6.

The French dataset displays considerable fluctuations throughout the observation period. Despite these variations, the ELM model consistently achieved the lowest forecasting errors. This outcome suggests that lightweight nonlinear learning approaches may offer advantages when the data contain recurring but irregular movements that are difficult to represent using traditional trend-based forecasting methods.

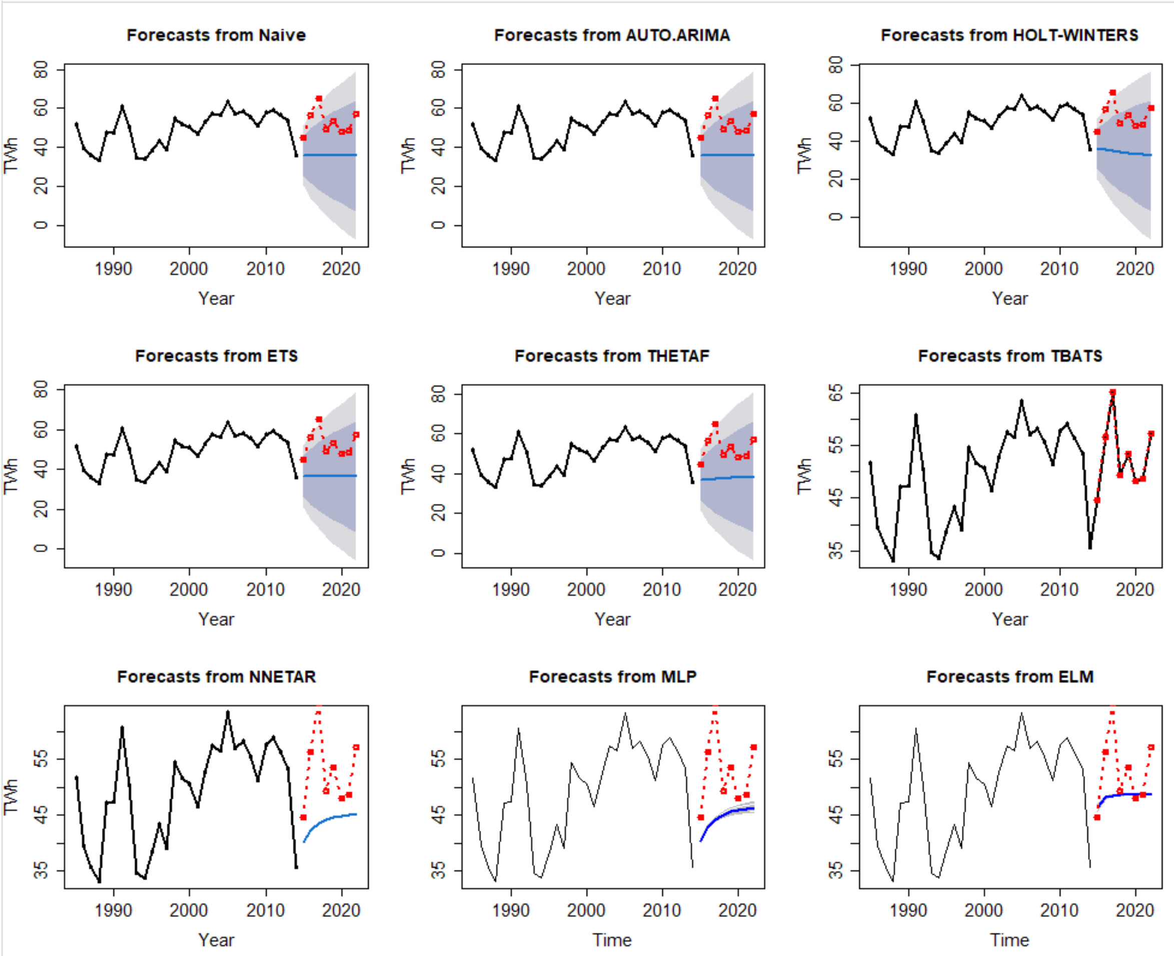

Figure 6. 8-year electrical energy production forecast graphs from fossil resources in French between 2014 and 2022, with the help of nine different models

In the case where the Iran data set was used, the best predictions were made with the ETS model in the first analysis and the AUTO.ARIMA model in the second analysis. The low MAPE metric values obtained here were 2.90% for ETS and 2.40% for AUTO.ARIMA, respectively. In the first and second stages of the predictions for Iran, the prediction average of the deep learning models was obtained as 5.09% and 5.27%, respectively, depending on the MAPE metric values. Similarly, the MAPE metric averages of statistical-based models in both analyzes are 6.45% and 8.11%, respectively. Model graphics of the predictions are given in Figure 7.

The Iranian dataset differs from several of the other countries because it exhibits a relatively consistent long-term growth trajectory. As a result, conventional statistical models such as AUTO.ARIMA and ETS performed remarkably well. This finding highlights that increased model complexity does not necessarily translate into improved forecasting accuracy, particularly when the underlying temporal structure remains relatively stable.

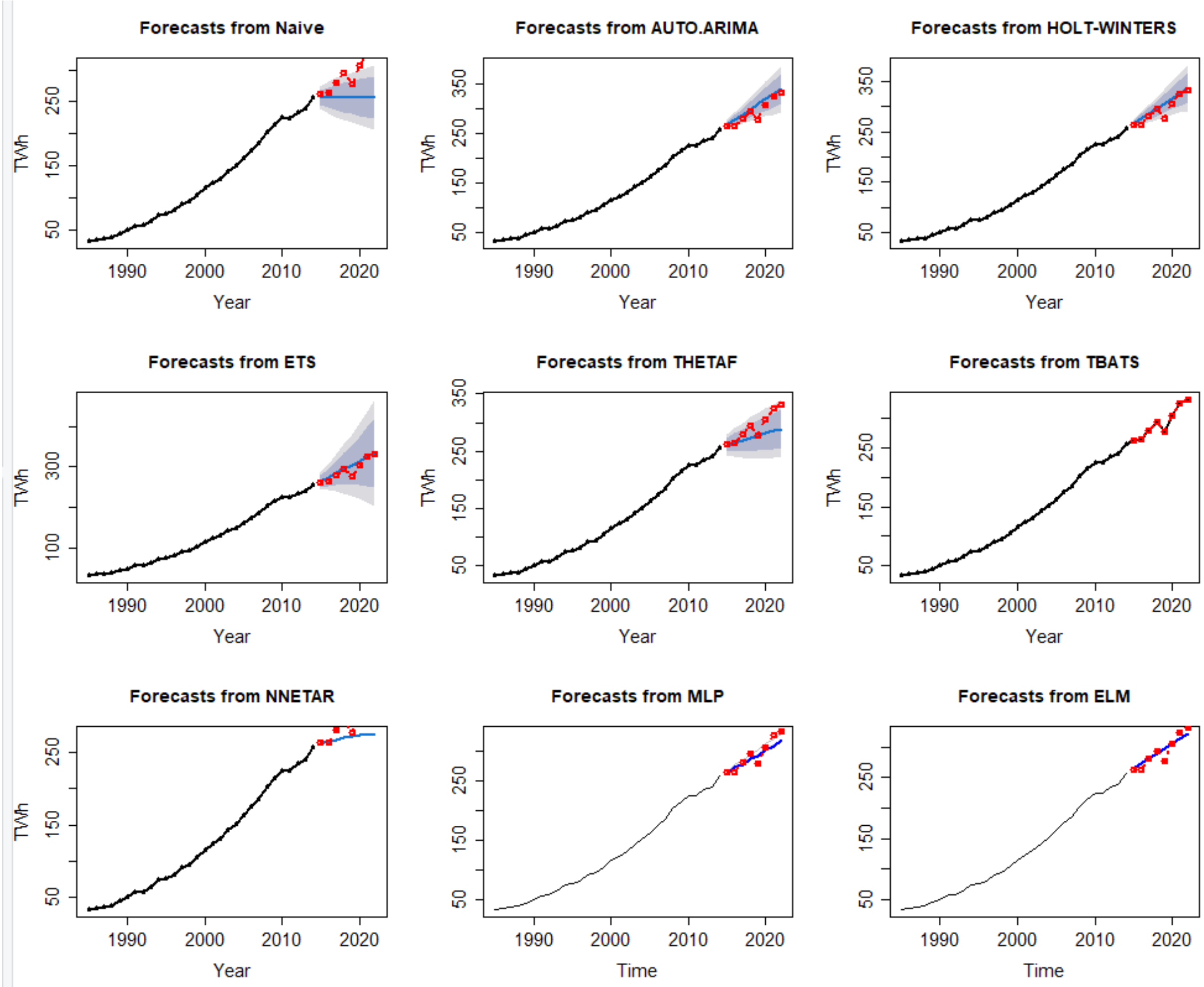

Figure 7. 8-year electrical energy production forecast graphs from fossil resources in Iran between 2014 and 2022, with the help of nine different models

Finally, when the Ukraine data set was used, the best predictions were made with the ELM model in both the first and second analysis. With the MAPE metric, the error rates of the ELM model in the 8-year and 10-year validation data length were obtained as 9.45% and 25.07%, respectively. In the first and second stages of the predictions for Ukraine, the prediction average of the deep learning models was obtained as 28.38% and 39.94%, respectively, depending on the MAPE metric values. Similarly, the MAPE metric averages of statistical-based models in both analyzes are 34.77% and 71.76%, respectively. The prediction graphs for the Ukraine dataset are given together in Figure 8.

Ukraine represents the most structurally dynamic case in the study. The long-term decline observed after the late 1980s introduces substantial forecasting complexity and challenges many conventional approaches. The comparatively stronger performance of ELM suggests that nonlinear learning mechanisms may be better suited to capturing the changing dynamics present in this dataset.

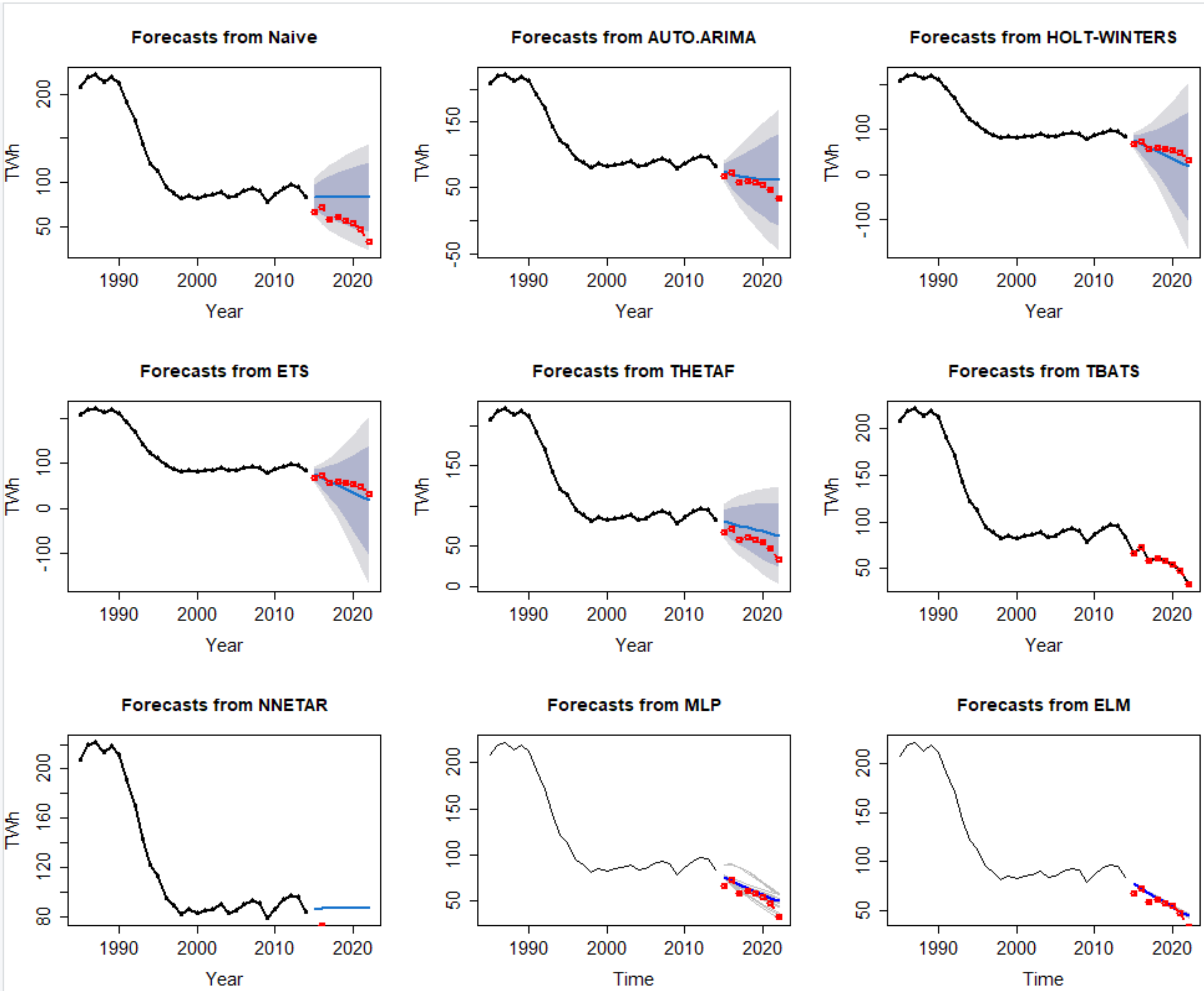

Figure 8. 8-year electrical energy production forecast graphs from fossil resources in Ukraine between 2014 and 2022, with the help of nine different models

When the average of the predictions made for the six countries whose data were used in this study is taken based on deep learning and statistics, in the first analysis, deep learning models come to the fore in four of the six countries, and in the second analysis, deep learning models come to the fore in five of the six countries.

3.3. Implications for Energy Forecasting

The findings indicate that forecasting performance is closely related to the maturity and transition characteristics of national energy systems. Countries undergoing substantial structural transformation may require forecasting approaches capable of representing nonlinear behaviour, whereas more stable systems can often be modeled effectively using conventional statistical techniques.

From a practical perspective, the results suggest that energy planners should avoid relying on a single forecasting methodology across different national contexts. Instead, model selection should be informed by the historical behaviour of the data and the anticipated evolution of the energy system.

4. CONCLUSIONS

This study examined the forecasting performance of nine different time-series models for fossil fuel-based electricity generation in six countries with distinct energy structures and transition pathways. The results show that forecasting accuracy is strongly influenced by the characteristics of the underlying time series and that no single model consistently outperforms all others across different national contexts.

The comparative analyses revealed that neural network-based approaches, particularly ELM, produced relatively accurate forecasts for countries with more irregular or rapidly changing generation patterns, such as France and Ukraine. In contrast, traditional statistical methods including AUTO.ARIMA and ETS remained highly effective for more stable series, as observed in the Iranian dataset. These findings suggest that model selection should be guided by the behaviour of the data rather than by a preference for a particular forecasting family.

Another noteworthy outcome is the variation in forecasting performance between countries. Nations undergoing substantial energy transformation tended to exhibit more complex temporal dynamics, which increased forecasting difficulty and affected model behaviour. This observation highlights the importance of considering national energy policies, market conditions, and structural changes when interpreting forecasting results.

The study has several limitations. First, the analysis is based on annual observations, which restricts the number of available data points and may conceal short-term fluctuations. Second, only historical generation values were used, while external factors such as fuel prices, renewable energy investments, policy interventions, and economic conditions were not explicitly incorporated. Finally, the relatively small sample size requires careful interpretation of neural-network-based forecasting results because of potential overfitting risks.

Future research could benefit from higher-frequency datasets, the inclusion of exogenous variables, and the development of ensemble forecasting approaches that combine the strengths of statistical and machine-learning methods. Such extensions may provide a more detailed understanding of energy system dynamics and improve forecasting performance under rapidly changing energy conditions.

Limitations and Future Research Directions

Several limitations should be acknowledged. First, the analysis relies on annual observations, resulting in relatively small datasets for each country. Although this design enables long-term comparison, it may conceal short-term fluctuations and seasonal dynamics. Second, the study evaluates forecasting models using historical generation data only. Exogenous factors such as carbon pricing mechanisms, renewable energy investments, fuel prices, geopolitical developments, and policy interventions were not incorporated. Third, neural-network-based models may be susceptible to overfitting when trained on small datasets. Consequently, the reported results should be interpreted as comparative forecasting outcomes rather than evidence of universal model superiority. Future research may benefit from higher-frequency datasets, additional explanatory variables, and ensemble forecasting frameworks that combine the strengths of statistical and machine-learning approaches.

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Data availability The datasets used to support the findings of this study are from the Our world in data archive which can be downloaded from https://ourworldindata.org/.

Declarations

Conflict of interest All authors declare that there are no conflicts of interest.

Ethical approval This study does not involve ethical issues.

Human participants and/or animals This article does not contain any studies with human participants or animals performed by any of the authors.

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