A COMPREHENSIVE TIME SERIES ANALYSIS OF ANNUAL FOSSIL-BASED ELECTRICAL ENERGY PRODUCTION ACROSS KEY NATIONS (1985-2022)

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Abstract

This study addresses the critical challenge of accurately predicting annual electrical energy production derived from fossil sources across diverse nations, including Türkiye, Germany, England, France, Iran, and Ukraine spanning the years 1985 to 2022. Employing a combination of advanced deep learning techniques and traditional statistical models, the research aims to enhance forecasting precision and contribute to a deeper understanding of global energy consumption dynamics.

By leveraging time series analysis, the study captures the intricate temporal patterns inherent in fossil-based energy production data, enabling robust predictions over an extended historical timeframe. Performance evaluation metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) are utilized to rigorously assess the accuracy and reliability of the developed forecasting models.

The scientific significance of this study lies in its ability to provide valuable insights into the complex interplay between socio-economic factors, technological advancements, and environmental considerations shaping fossil-based energy production trends. By conducting a comparative analysis across multiple countries with distinct energy landscapes, the research not only elucidates regional variations but also underscores the need for tailored forecasting approaches to address unique contextual challenges.

The findings of this study hold significant implications for energy policymakers, industry stakeholders, and researchers striving to optimize resource allocation, mitigate environmental impacts, and transition towards sustainable energy systems. By advancing the state-of-the-art in energy forecasting methodologies, this research contributes to the broader goal of achieving a more resilient, equitable, and environmentally sustainable energy future.

Key words: Fossil-based energy production, Global energy sustainability, Forecasting methodologies, Policy implications

1. INTRODUCTION

Electric power generation holds profound significance for developing countries, serving as a linchpin for overall socio-economic development. The access to reliable electricity not only improves the standard of living but also contributes to environmental sustainability and resilience in the face of natural disasters. By addressing the energy needs of developing nations, electric power generation becomes a catalyst for inclusive growth, job creation, and improved quality of life, thereby laying the foundation for a sustainable and prosperous future.

This study delves into the economic considerations of electrical energy production through fossil sources, namely coal, oil and gas. It examines the economic viability of each by assessing factors such as initial investment costs, operational expenses, and externalities. While fossil resources often have lower initial costs, the analysis explores how the long-term benefits of renewable sources, such as hydropower, solar, and wind energy, contribute to their economic competitiveness. The abstract sheds light on the evolving landscape of energy economics, emphasizing the sustainable and cost-effective attributes of renewable technologies in contrast to the traditionally dominant fossil resources.

Türkiye relies on a mix of fossil fuels, renewable energy, and hydropower. Fossil resources, including natural gas and coal, play a significant role in the energy mix. Additionally, Türkiye harnesses its abundant renewable resources, particularly solar and wind energy, to diversify its energy portfolio. Hydropower, drawing upon the country's ample water resources, also contributes significantly. This abstract highlights Türkiye's multifaceted approach to electrical energy production, reflecting efforts to balance energy security, environmental sustainability, and economic considerations.

Renowned for its commitment to renewable energy, Germany has made significant strides in transitioning away from traditional fossil fuels. A leader in wind and solar power, Germany leverages these renewable sources to bolster its energy grid. Additionally, the country utilizes biomass, hydropower, and a decreasing share of nuclear energy in its diverse energy mix. This abstract underscores Germany's strategic pursuit of sustainable and low-carbon energy solutions, marking its position as a global pioneer in the transition to a more environmentally friendly electricity generation system.

The United Kingdom (UK) has undergone a notable shift toward renewable energy, with wind power emerging as a major contributor. Offshore and onshore wind farms play a crucial role in the nation's energy landscape. Additionally, nuclear power remains a significant component, contributing to the low-carbon mix. The UK is also diversifying its sources, incorporating solar energy, natural gas, and interconnectors to enhance energy security. This abstract highlights the UK's commitment to a well-balanced and sustainable energy portfolio, aligning with global efforts to combat climate change and ensure a resilient energy future.

A pioneer in nuclear power, France relies heavily on nuclear energy to generate a substantial portion of its electricity. This commitment to nuclear energy has positioned France as one of the lowest carbon-emitting nations in terms of electricity production globally. Despite the dominance of nuclear power, France has been actively increasing its share of renewable energy, particularly through investments in hydroelectric power, wind energy, and solar power.

Iran's electric energy production primarily relies on a mix of fossil fuels and hydroelectric power. The country possesses significant oil and natural gas reserves, making these conventional energy sources major contributors to its electricity generation. Additionally, Iran has been investing in hydroelectric power plants, utilizing its abundant water resources to diversify its energy mix.

Ukraine has traditionally relied on fossil fuels, particularly natural gas and coal, for power generation. Natural gas-fired power plants contribute substantially to Ukraine's electricity production, providing a reliable source of energy. Additionally, coal-fired power plants have historically played a crucial role in the country's energy infrastructure. However, it's important to note that Ukraine, like many nations, has been working towards diversifying its energy sources and increasing the share of renewables in its energy mix to enhance sustainability and reduce environmental impact

Forecasting electricity generation is a critical aspect of efficient energy management, and time series models offer valuable tools for this purpose. Time series analysis enables the identification of patterns, trends, and seasonality in historical electricity data, facilitating accurate predictions of future generation. The ability to capture temporal dependencies allows for precise short-term and long-term forecasting, aiding in optimal resource allocation, grid planning, and energy market operations. The uses of time series models extend beyond electricity generation to various fields, including finance, economics, climate science, weather (Hossain, Rekabdar, Louis, & Dascalu, 2015), health (Yaldız & Pala, 2019), speech recognition (Srivastava, Hinton, Krizhevsky, Sutskever, & Salakhutdinov, 2014), energy consumption (Hwang & Yoo, 2014; Mohsin, Naseem, Sarfraz, & Azam, 2022), radiation predictions (Etem, Pala, & Bozkurt, 2017; Z. Pala, Ünlük, & Yaldız, 2019), sunspot prediction (C. Chen et al., 2010; Zeydin Pala & Atici, 2019), natural gas production prediction (N. Li, Wang, Wu,

& Bentley, 2021; Zeydin Pala, 2023), and sensor data analysis (Dhillon, Madhu, Kaur, & Singh, 2020) 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.

The biggest challenge in time series forecasting lies in capturing the complexity and variability of real-world data, including non-stationarity, complex dependencies, outliers, seasonality, trends, data quality issues, and dynamic external factors. Accurate forecasting is vital for informed decision-making, resource optimization, risk management, cost savings, and maintaining a competitive advantage. It enables organizations to anticipate future trends, allocate resources efficiently, mitigate risks, and respond proactively to market dynamics, ultimately leading to better strategic outcomes.
This study makes several significant contributions to the existing literature on energy forecasting and analysis:

1. It advances the methodology by integrating deep learning techniques with traditional statistical models, potentially improving the accuracy of energy production forecasts.
2. It contributes to a deeper understanding of the factors influencing fossil-based energy production trends, including socio-economic, technological, and environmental factors.
3. It highlights the importance of tailored forecasting approaches that account for regional variations in energy landscapes, thereby informing more effective energy policy and decision-making.
4. By combining innovative methodologies, comprehensive data analysis, and a nuanced understanding of energy dynamics, this study provides valuable insights that can inform future research efforts and guide energy policy development on both national and global scales.

2. MATERIALS AND METHODS

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 Prediction models

The description of the models used in the forecasting process and their working methods are briefly summarized below.

TBATS: Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal components (TBATS) model is a time series forecasting model designed to handle data with multiple seasonal patterns and complex temporal structures (Munim, 2022; Zeydin Pala, 2021). Developed by De Livera, Hyndman, and Snyder, TBATS incorporates trigonometric functions to capture various seasonalities, a Box-Cox transformation for stabilizing variance, an ARMA errors component to model autocorrelation, and separate components for capturing trend and multiple seasonal patterns (Hyndman & Athanasopoulos, 2018). This flexible and robust approach enables TBATS to effectively model and forecast time series data with irregularities, making it particularly useful for applications where traditional models may struggle, such as those involving daily or weekly seasonality, holidays, and other temporal complexities.

ETS: Error, Trend, Seasonality (ETS) model is a forecasting model used for time series analysis. ETS models try to explain time series by focusing on the error, trend and seasonal components contained in the data (Dong et al., 2021). ETS decomposes a time series into three components: error, trend, and seasonality. The error component captures random fluctuations, the trend component represents the long-term movement, and the seasonal component accounts for repeating patterns. ETS models come in three main variations: ETS(AAA), where all three components are present; ETS(AAN), where only error and trend are included; and ETS(ANN), where only error and seasonality are considered. By adjusting the smoothing parameters for each component, ETS adapts to various time series patterns, making it suitable for forecasting in situations with different levels of seasonality and trend complexities.

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 (Basha, Zhenning, Rajput, Caytiles, & Iyengar, 2017; Zeydin Pala & Pala, 2021; Petropoulos & Svetunkov, 2020). 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:

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

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:

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

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

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

ε_t is the independent disturbance, also called the random t error (Yang, Gao, & Guo, 2018).

HOLT-WINTERS: The Holt-Winters method, also known as Triple Exponential Smoothing, is a time series forecasting model designed to capture and predict data patterns with seasonality and trend. The model applies smoothing parameters (alpha, beta, and gamma) to adjust the influence of historical data on these components. The Holt-Winters model is particularly useful for time series data that exhibit both trend and seasonality, providing a flexible approach to forecasting by adapting to various patterns in the data. The three smoothing parameters allow users to control the weight given to recent observations and adjust the sensitivity of the model to changes in level, trend, and seasonality, making it a versatile tool for predicting future values in time series data (Gelper, Fried, & Croux, 2010).

NAİVE: The Naive prediction model is a simple and intuitive forecasting approach that assumes the future values of a time series will be the same as the most recent observed value (Hyndman & Athanasopoulos, 2018). In other words, it predicts that the next data point will be equal to the last known value in the time series. While extremely basic, the Naive model serves as a baseline for comparison with more sophisticated forecasting methods. It is particularly useful for quick and straightforward assessments of prediction accuracy, but it may perform poorly when dealing with time series data that exhibit complex patterns or trends. Despite its limitations, the Naive model provides a starting point for evaluating the effectiveness of more advanced forecasting techniques in capturing the inherent patterns within the data.

ELM: Extreme Learning Machine (ELM) is a machine learning model designed for regression and classification tasks. Developed by Huang, Zhu, and Siew in the early 2000s, ELM is a type of single-layer feedforward neural network where the input weights and biases are randomly assigned and fixed, allowing for a fast training process. The model's simplicity and efficiency stem from its ability to analytically determine the output weights in a single step, typically through Moore-Penrose pseudoinversion or other optimization techniques. ELM exhibits a fast learning speed and good generalization performance, making it particularly useful for large-scale and real-time applications. However, it may be sensitive to outliers, and its random weight initialization can affect reproducibility, requiring careful consideration of data characteristics and preprocessing (Park & Yang, 2019).

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:

$$\sum_{j=1}^{k} g_i(w_j, b_j, x_i)\beta_j = t_{i,}\, i = 1,2, \ldots, N \quad (4)$$

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 (X. Chen et al., 2012).

MLP: The Multilayer Perceptron (MLP) is a type of artificial neural network used for supervised learning tasks, such as regression and classification. Comprising multiple layers of interconnected nodes (neurons), MLPs consist of an input layer, one or more hidden layers, and an output layer. Each connection between nodes is associated with a weight, and the nodes within layers contain activation functions that introduce non-linearities. Training an MLP involves adjusting the weights using backpropagation, where the difference between predicted and actual outputs is minimized through iterative optimization algorithms like gradient descent. MLPs are known for their capability to learn complex relationships in data and are widely used in various applications, although they may require careful tuning of hyperparameters to prevent overfitting and achieve optimal performance (Liao & Liang, 2021).

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

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j . g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}\right) + \varepsilon_t, \quad (5)$$

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 (Luis, Maia, De Carvalho, & Ludermir, 2008).

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 (Zeydin Pala, 2023).

NNTAR uses a multilayer artificial neural network in time series forecasting. This ensures that the model can handle complex and non-linear relationships. The model makes predictions by automatically selecting important features in the data and learning their weights. The model supports different time series frequencies, which enables it to work with data of various time intervals such as hourly, daily, monthly, quarterly and annual. The NNTAR function automatically determines the architecture of the neural network and other hyperparameters. This allows the model to learn complex structures and increase its generalization ability. The model can handle seasonal and trend components and thus model these features of the time series.

2.2 Evaluation metrics

Root Mean Squared Error (RMSE), and it's a commonly used metric for evaluating the accuracy of a prediction model, particularly in regression analysis and time series forecasting. RMSE measures the average magnitude of the differences between predicted values and actual values, taking the square root of the average of the squared differences. It provides a single numerical value that represents the typical error of the model's predictions, with lower RMSE indicating better predictive performance. RMSE is sensitive to outliers and penalizes larger errors more heavily due to the squaring operation, making it a widely used measure for assessing the overall goodness-of-fit of predictive models (Kim & Kim, 2016; Zeydin Pala, Atıcı, & Yaldız, 2023; Zeydin Pala & Ünlük, 2022).

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

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 metric used for assessing the accuracy of a predictive model, commonly in the context of regression analysis or time series forecasting. It calculates the average absolute differences between the predicted values and the actual values. By taking the mean of these absolute errors, MAE provides a measure of the average magnitude of the model's errors without considering their direction. MAE is less sensitive to outliers compared to metrics like RMSE (Root Mean Squared Error), as it doesn't involve squaring the errors. A lower MAE indicates better predictive accuracy, and it is a straightforward and easily interpretable metric for evaluating the performance of regression models (Willmott & Matsuura, 2005).

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

MAPE, on the other hand, expresses errors as a percentage of the actual values, making it scale-independent. MAPE offers a percentage-based measure, making it easy to communicate the accuracy in a relative context. MAPE can be problematic when actual values are close to zero, leading to infinite or undefined values in the denominator (H. Li et al., 2020).

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

2.3 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 (Hossain et al., 2015), health (Yaldız & Pala, 2019), speech recognition (Srivastava et al., 2014), energy consumption (Hwang & Yoo, 2014; Mohsin et al., 2022), radiation predictions (Etem et al., 2017; Z. Pala et al., 2019), sunspot prediction (C. Chen et al., 2010; Zeydin Pala & Atici, 2019), natural gas production prediction (N. Li et al., 2021; Zeydin Pala, 2023), sensor data analysis (Dhillon et al., 2020).

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.

2.4 Data Description

All data used in this study was obtained from Our World in Data (https://ourworldindata.org/energy). The data obtained and used here is based on obtaining electrical energy from fossil sources. 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.

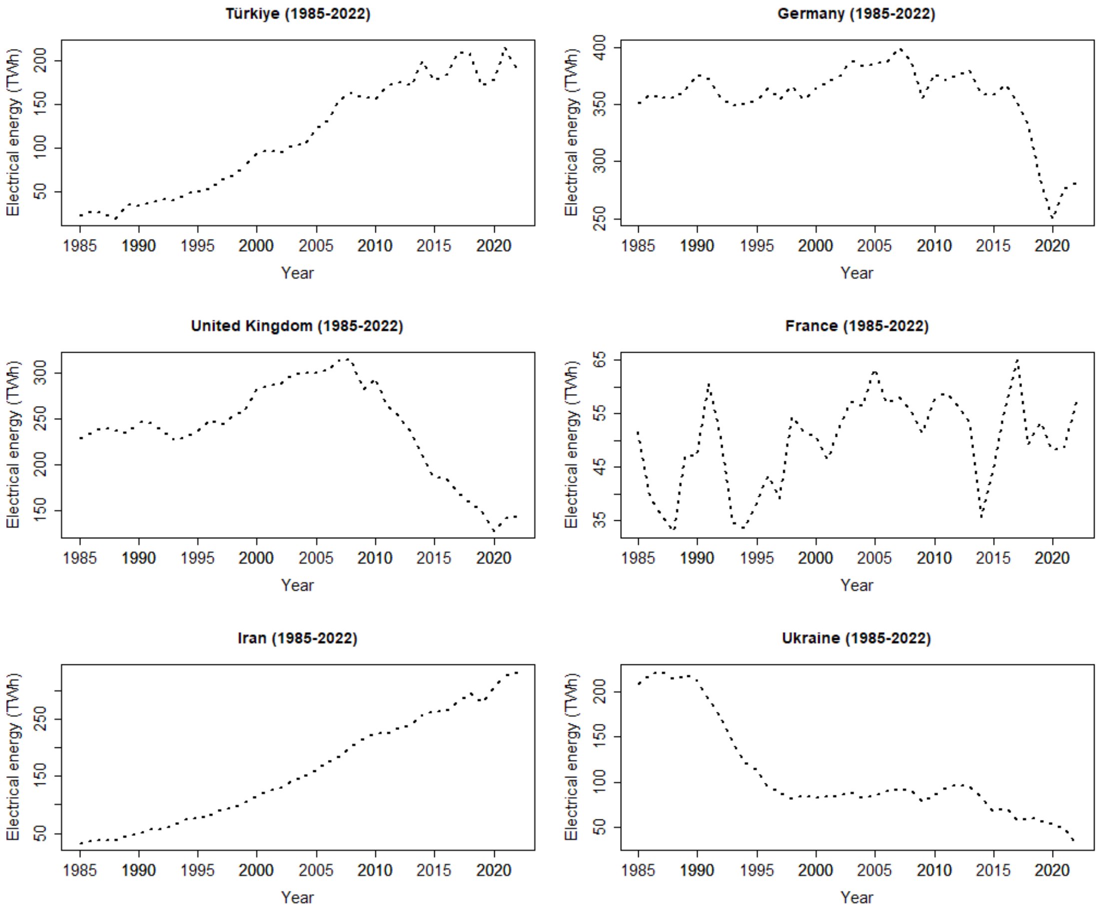

Figure 2. Time series of electrical energy (TWh) produced from fossil sources in Türkiye, Germany, the United Kingdom, France, Iran and Ukraine between 1985-2022.

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.

3. RESULTS AND DISCUSSION

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-months (79%) and the validation length was taken as 8-months (21%), while in the second stage, the training length was taken as 28-months (74%) and the validation length was taken as 10-months (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-month and 10-month 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.

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.

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.

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-month and 10-month 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.

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.

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-month and 10-month 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.

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**

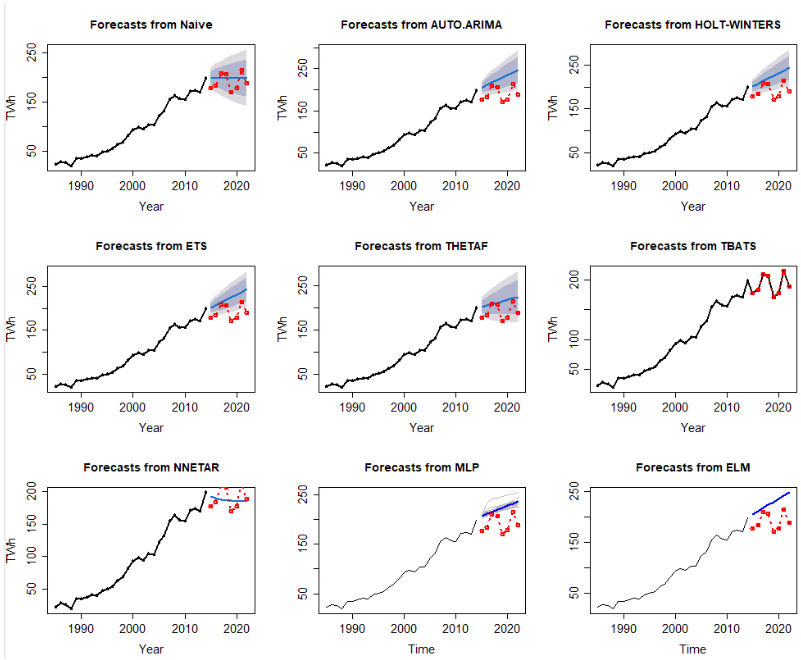

Figure 3 8-month electrical energy production forecast graphs from fossil resources in Türkiye between 2014 and 2022, with the help of nine different models

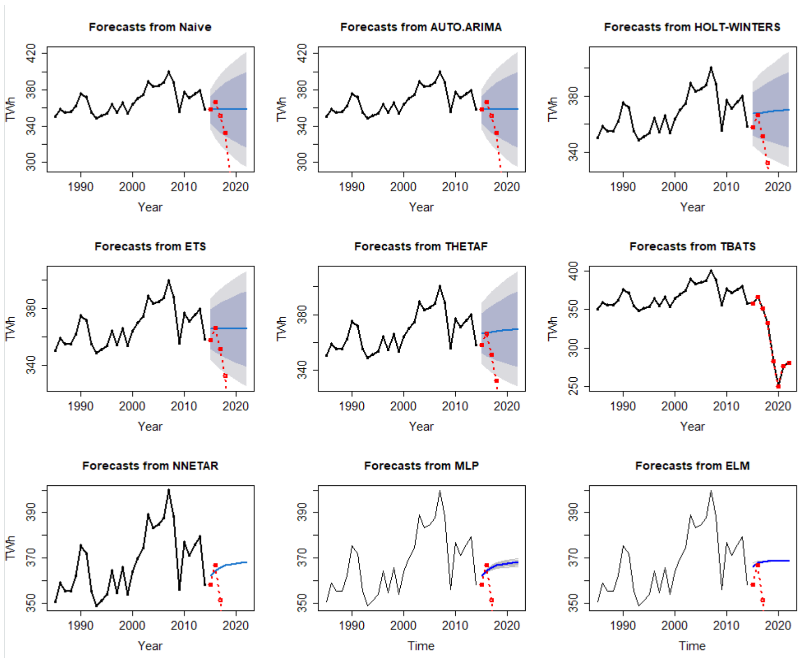

Figure 4 8-month electrical energy production forecast graphs from fossil resources in Germany between 2014 and 2022, with the help of nine different models

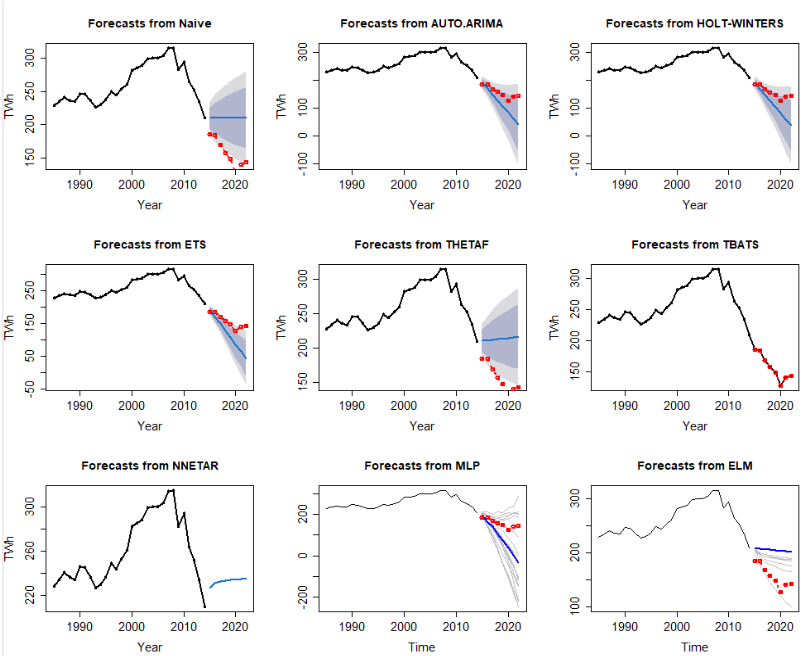

Figure 5 8-month electrical energy production forecast graphs from fossil resources in United Kingdom between 2014 and 2022, with the help of nine different models

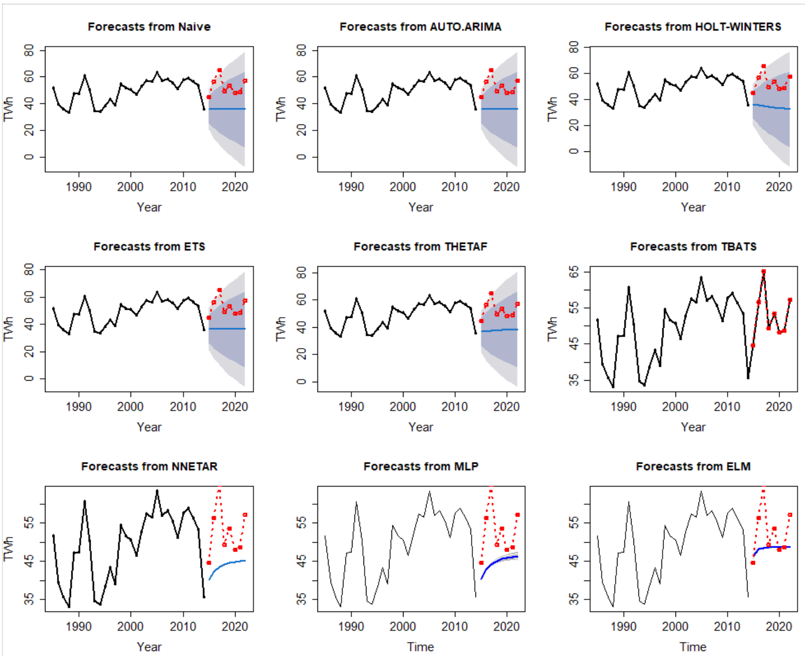

Figure 6 8-month electrical energy production forecast graphs from fossil resources in French between 2014 and 2022, with the help of nine different models

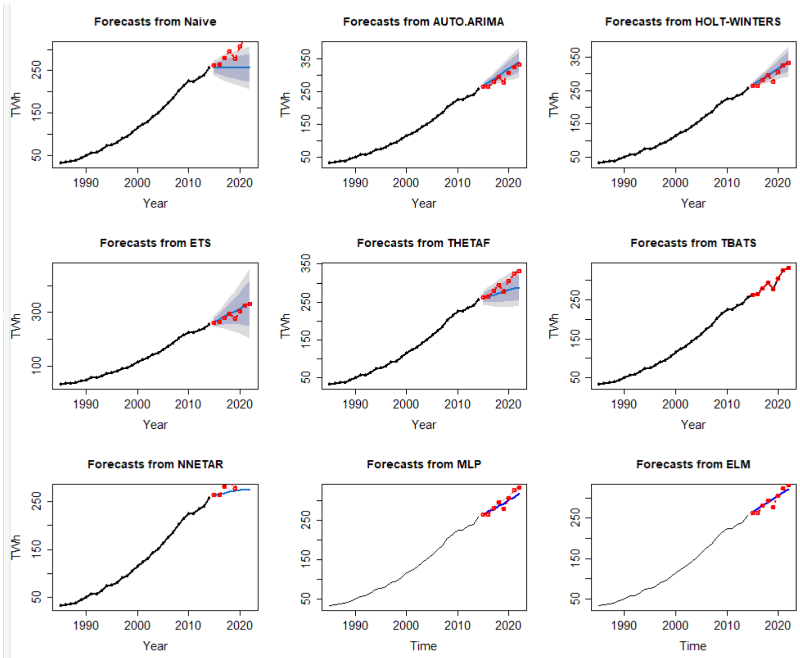

Figure 7 8-month electrical energy production forecast graphs from fossil resources in Iran between 2014 and 2022, with the help of nine different models

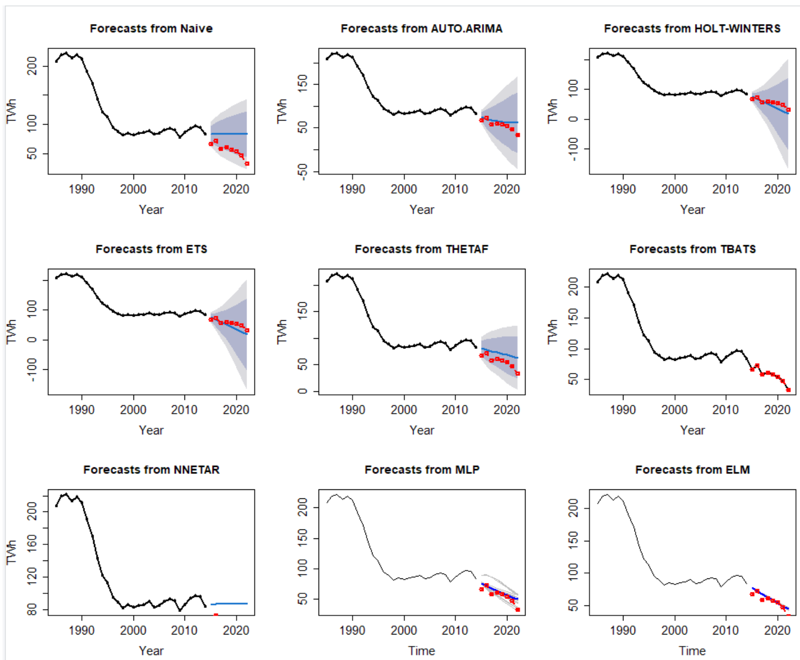

Figure 8 8-month electrical energy production forecast graphs from fossil resources in Ukraine between 2014 and 2022, with the help of nine different models

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.

CONCLUSIONS

In conclusion, this study has demonstrated the efficacy of a hybrid approach, combining advanced deep learning techniques with traditional statistical models, to accurately predict annual electrical energy production derived from fossil sources across diverse nations. By analyzing data spanning nearly four decades and encompassing countries such as Türkiye, Germany, England, France, Iran, and Ukraine, we have gained valuable insights into the temporal patterns inherent in fossil-based energy production.

Our rigorous evaluation using performance metrics such as mean MAPE, MAE, and RMSE has confirmed the reliability and precision of our forecasting models. Moreover, by leveraging time series analysis, we have been able to capture intricate temporal dynamics, enabling robust predictions over an extended historical timeframe. On the data sets used here, deep learning models demonstrated better performance than statistical-based models.

The scientific significance of our study lies in its ability to shed light on the complex interplay between socio-economic factors, technological advancements, and environmental considerations shaping fossil-based energy production trends. Through a comparative analysis across multiple countries with distinct energy landscapes, we have highlighted regional variations and underscored the importance of tailored forecasting approaches to address unique contextual challenges.

This article's global value lies in its demonstration of a hybrid approach combining deep learning and statistical models to accurately forecast fossil-based energy production across diverse nations, providing valuable insights for policymakers and researchers aiming to address energy sustainability challenges on both national and global scales.

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