Abstract

The global energy landscape has experienced a significant transformation over the last few decades, fuelled by population growth and economic expansion. This study investigates global energy consumption patterns from 1965 to 2019, with a predictive analysis extending to 2029. The goal is to understand the future energy consumption pattern while developing few energy consumption forecasting models.

Utilising data from "Our World in Data," this research explores key trends, focusing on the leading consumers of various energy sources. Advanced predictive analytics, including ARIMA and Long Short-Term Memory (LSTM) networks, were employed to forecast future energy consumption. The deep learning-powered LSTM model outperformed other tested machine learning models, such as random forest and XGBoost, achieving the lowest Root Mean Squared Error (RMSE) of 17.57% in performing non-linear forecasting. ARIMA was used for linear forecasting of specific energy forms with RMSE of 19.13%.

Results indicate a gradual shift towards renewable energy adoption. However, the pace is insufficient to surpass the consumption of primary energy sources (oil, gas, and coal) within the next couple of decades. This suggests that countries will not be able to meet the Paris Agreement's goal of limiting global warming to well below 2°C above pre-industrial levels by the 2030s. This research also indicates that China will be the leading consumers of both primary and renewable energy in most forms of energies. Wind and solar energy appear the most promising sources of renewable energy, with anticipated exponential growth in the coming decades.

Furthermore, this study proposes future research to integrate weighted values of country-specific energy policies, innovation, and renewable energy investment into the predictive models. This approach could improve the accuracy of energy forecasting and help evaluate whether individual countries are on track to meet their sustainable energy goals within the targeted timeframes.

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Abbreviations

ACF - Autocorrelation Function

ADF - Augmented Dickey-Fuller (test)

AIC - Akaike Information Criterion

ARIMA - Autoregressive Integrated Moving Average

CNNs - Convolutional Neural Networks

CO2 - Carbon Dioxide

EJ - Exajoules

LSTM - Long Short-Term Memory

MAE - Mean Absolute Error

MAPE - Mean Absolute Percentage Error

MSE - Mean Squared Error

Mtoe - Million Tonnes of Oil Equivalent

PACF - Partial Autocorrelation Function

RMSE - Root Mean Squared Error

SED - Sustainable Economic Development

XGBoost - Extreme Gradient Boosting

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1. Introduction & Background

As the global population boom and economies grow the usage of energy consumption has increased exponentially over the time ranging from 8,588.9 million tonnes (Mtoe) in 1995 to 13,147.3 Mtoe in 2015. (Dong, et al., 2020). Energy is a key driver of sustainable economic development (Iddrisu & Bhattacharyya, 2015), influences geopolitics (Högselius, 2008; Vakulchuk, et al., 2020), and is directly and indirectly responsible for global warming when derived from fossil fuels such as coal, oil, and natural gas (Kona, et al., 2018).

In discussing sustainable economic development (SED) with a focus on sustainable energy, Iddrisu & Bhattacharyya (2015) define SED as achieving economic growth while ensuring the well-being of current and future generations. This necessitates developing cost-effective, affordable energy supplies with the potential for reinvestment. However, an over-dependence on fossil fuels is not compatible with sustainable energy goals as it is not affordable. For instance, countries that import oil and natural gas has to spend a large share of their annual budget on energy purchases. India's Petroleum Planning & Analysis Cell (PPAC) reported that the country spent $119.2 billion on crude oil imports in 2021-22, a substantial increase from $62.2 billion in the previous fiscal year (PTI, 2022). Hence, countries are shifting their policies toward sustainable renewable energy.

Countries with economies based on hydrocarbon production (oil, gas, coal) play a significant role in global geopolitics. Traditionally, oil-rich nations have wielded economic power, influence oil prices and always be at the centre of geopolitical tensions (Högselius, 2008). Various articles and reports suggest that Russia use oil and gas as geopolitical weapon to overcome western sanction and fund the illegal invasion of Ukraine (Zhang, et al., 2024; Ilas, et al., 2023). Hence achieving energy freedom by investing on renewable and safe energy is not an option but a critical imperative for all nations.

Fossil fuels are also responsible for global warming due to CO2 emissions. Recent global warming events include bushfires, extremely hot summers in Europe and Asia, melting ice in Antarctica, and many other unusual and unpredictable environmental disasters. To tackle global warming, countries have joined together to reach the Paris Agreement target of limiting the global average temperature increase to below 2 °C above pre-industrial levels (Kona, et al., 2018).

This study aims to analyse energy consumption patterns from 1965 to 2019 and forecast energy usage from 2020 to 2029, specifically focusing on the following research questions:

i. Which country is the highest user of global energy, and who will be the potential champion of using renewable energy in the future?
ii. What are the top 5 nations for each type of energy consumption?

iii. Which source(s) of energy will be the most promising renewable energy source in the future?
iv. Will the usage of renewable energy surpass the usage of primary energy within the next couple of decades?

To achieve these aims, the following research objectives were established:

- To examine the trends in energy consumption across various sources such as oil, gas, coal, and renewables.
- To apply advanced predictive analytics, including machine learning and deep learning techniques, to forecast future energy demands.
- To evaluate the efficacy of different predictive models in the context of energy forecasting.

2. Related Literature

2.1 Historical Energy Consumption Patterns

Over the years, global energy consumption increases gradually with economic and technological advancement. From the ancient age of food and fire, early humans consumed roughly 2000 kilocalories daily, which increase to 70,000 kcal by 1875 during the industrial revaluation. By the mid-20th century, this number peaked at around 230,000 kcal per day in the United States only (Mattick, et al., 2010), which is globally surged by 580 EJ in 2018. Fossil fuels (coal, oil, and gas) have accounted for a significant 85% of this energy. Consequently, global energy-related CO2 emissions increased by 87%, from 18.0 billion tonnes to 33.7 billion tonnes during this period. The limited utilization of fundamental energies such as geothermal, hydro, and nuclear stands at only 13%. Since 2000, developed countries have begun utilizing fundamental energy, particularly nuclear. However, the percentage usage remains low compared to primary energy, with the United States being the highest consumer of global energy (Kober, et al., 2020).

2.2 Global Energy Usage Prediction

Ahmad & Zhang (2020) offered a comprehensive forecast of the global energy outlook until 2040 using economactics based recursive dynamic modeling, that includes insights into evolving demand patterns and the transition toward sustainable energy. They predict a significant increase in global primary energy demand, with Africa and Asia leading the growth at 2.7% and 1.9% annually, respectively. The transition towards renewable sources of electricity generation is evident, with Europe, the Pacific, and the Americas aiming to reach an average of 37% renewables in their electricity mix by 2040. Natural gas consumption is also predicted to rise, especially in the developing nations of Africa and Asia, where it could double by 2040. While energy consumption increases, the analysis suggests a concerted effort to reduce CO2 emissions. The carbon intensity of power generation is expected to fall by over 30% globally between 2015 and 2040, and a general decline in the CO2 intensity of GDP is also predicted. Hence their prediction summarise only the developed nation of Europe and North America will try to oblige the guideline to keep the temperature increase target of below 2 °C above pre-industrial levels.

2.3 Using Predictive Analysis in Energy Forecasting

Researchers used various models for forecasting the energy consumption to improve accuracy and efficiency. Xiao, et al. (2018) introduced a hybrid forecasting model combining AdaBoost ensemble methods with the Group Method of Data Handling (GMDH). Enhancing traditional models like Back Propagation Neural Network, Support Vector Regression, Genetic Programming, and Radial Basis Function Neural Network with AdaBoost, the model significantly improves forecasting accuracy, with RMSE values of 0.4672 for total energy consumption and 0.2341 for total oil consumption.

Liu, et al. (2020) evaluated Deep Reinforcement Learning (DRL) techniques such as Asynchronous Advantage Actor-Critic (A3C), Deep Deterministic Policy Gradient (DDPG), and Recurrent Deterministic Policy Gradient (RDPG). These models outperform traditional supervised models like MLR, BPNN, and RF, with DDPG and RDPG showing notable RMSE improvements ranging from 16% to 32%. Specifically, RMSE for DDPG was 17.390 and for RDPG was 16.668 in single-step forecasting, improving further to 28.787 in multi-step scenarios.

Similarly, Somu, et al., (2021) explored the application of CNNs and RNNs in various configurations across different datasets and settings. Their study demonstrated deep learning to effectively manage complex non-linear patterns in energy consumption data, with some RNN configurations LSTM in reducing prediction error by up to 15% compared to conventional methods. Their kCNN – LSTM model showed deep learning model's robust performance and highlights its practical applications in enhancing predictive accuracy and managing high-dimensional data in the energy sector.

3. Methodology

3.1 About the data

The dataset for this study was sourced from the "Our World in Data" repository. It contains global energy consumption data from 1900 to 2019, categorized by sources: oil, gas, coal, solar, hydro, nuclear, wind, and biomass. The pre-processing was done by imputing missing values (approximately 1305-1311 per energy source) by zeros, as they represented unrecorded data, primarily before 1965. For analysis and modelling, data from 1965 to 2019 was used. Aggregated global energy records were removed for normalization. To simplify the analysis, records labelled as "USSR" were relabelled as "Russia."

3.2 Exploratory Data Analysis (EDA)

The EDA aimed to uncover the global energy trends which examined overall energy usage patterns and the adoption of fundamental energies (solar, hydro, nuclear, wind, biomass). It also identified the highest global energy consumers over time. It explored energy use trends in these major economies (G7, Russia, China, India) compared to the rest of the world. The EDA also uncovered the top 5 consumers for each energy source. It specifically analysed individual counties like United States, China, Japan, Germany, India, the United Kingdom, Russia, and Brazil due to their frequent representation among top energy consumers.

3.3 Predictive Analysis

In forecasting the energy use of 2020 – 2029 various predictive modelling techniques were used. In model development United Kingdom and Oil Consumption were initially used for experiments and fine-tuned the models. Several statistics and machine learning techniques including ARIMA (Auto-Regressive Integrated Moving Average), Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks were used.

ARIMA, a traditional model for time series forecasting, was first tested to establish a baseline by analysing historical consumption patterns used for analysing the linear relationships in stationary data. It required confirming that the data did not change in its mean or variance over time—a precondition verified through the Augmented Dickey-Fuller test, which checks for stationarity in the dataset.

ARIMA(p, d, q) models are used for forecasting time series data. It looks at past trends, adjusts for any overall changes, and considers some randomness to predict future values. The general equation is:

$$(1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_p L^p)(1 - L)^d y_t = (1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_q L^q)\,\varepsilon_t$$

Equation 1: Basic ARIMA Equation

Where y_t: The value of the time series at time t. L: The lag operator ($Ly_t = y_{t-1}$, $L^2 y_t = y_{t-2}$, and so on). $\phi_1 \ldots \phi_p$: Autoregressive (AR) coefficients. $\theta_1 \ldots \theta_q$: Moving average (MA) coefficients. ε_t : Error term (white noise) at time t (Hyndman & Athanasopoulos, 2018).

After initial use of ARIMA model Random Forest and XGBoost algorithm were used to handle more complex datasets involving non-linear relationships without the requirement for data stationarity. Random Forest operates by constructing numerous decision trees during training and outputting the average prediction of the individual trees, thereby enhancing predictive accuracy, and controlling overfitting. XGBoost, or Extreme Gradient Boosting, builds on this by implementing gradient boosted decision trees designed for speed and performance. This study initiated both this machine leaning algorithm can potentially identify patterns beyond a simple linear trend that ARIMA might miss. However, after checking the overfitting issues this study found XGboost (Train RMSE: 0.00, Test RMSE: 123.45) exhibit extreme overfitting while Random Forest (Train RMSE: 27.16, Test RMSE: 105.96) also prone to overfitting, as train and testing RMSE had great difference.

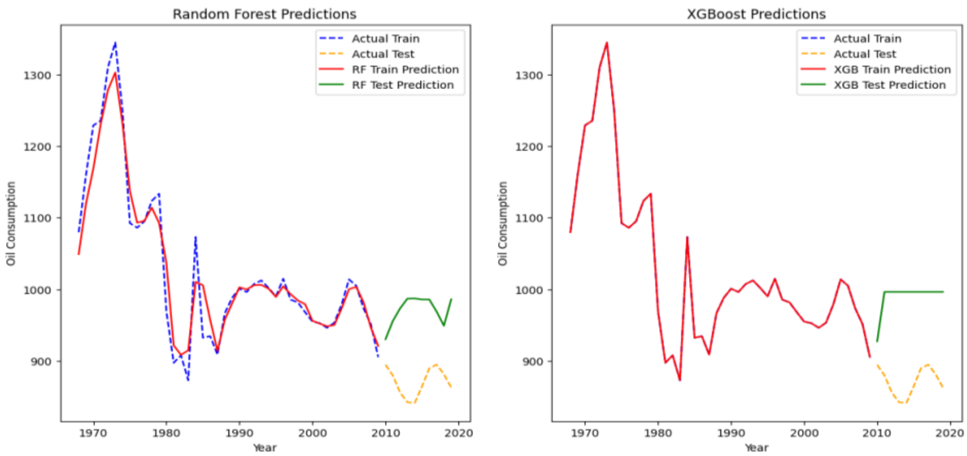


Figure 1: Overfit Random Forest & XGBoost Model

Since the Random Forest and XGBoost model exhibit the extreme overfitting issues this study used LSTM model to predict the energy use. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network suited for sequential data prediction. LSTMs are capable of learning order dependence in sequence prediction problems, which is crucial for accurate energy consumption forecasting (Somu, et al., 2021). The

LSTM models were used to predict future energy consumption in a specific country based on historical data. To achieve this, the dataset was first normalized and segmented into sequences. The LSTM model, with its ability to handle sequential data, was then trained using these sequences. Regularization and dropout techniques were used to prevent the model from overfitting on the training data. Time series cross-validation ensures the model's generalizability by training and evaluating on different chronological splits of the data. Finally, the best-performing model was used to forecast future consumption for the next decade, with predictions dynamically fed back into the model for further refinement. The overall goal was to leverage the LSTM model’s strengths in handling sequential data to create an accurate predictor of future energy consumption.

4 Result

4.1 Energy Consumption Trends

The dataset depicted that the primary energy (oil, coal, and gas) always remined the main source of the energy in all the countries, while Solar and Hydro energy started to get momentum from 1980s. Solar, Wind and Geo Biomass energy use always remained in lower side, only got some shift from 2010s. The United States was the highest user of global energy till 2007 when China surplus them in overall energy consumption. This data also showed an interesting fact that nuclear energy use getting reduced from 2010s, it may be caused due to several accident in the nuclear energy fields during those periods.

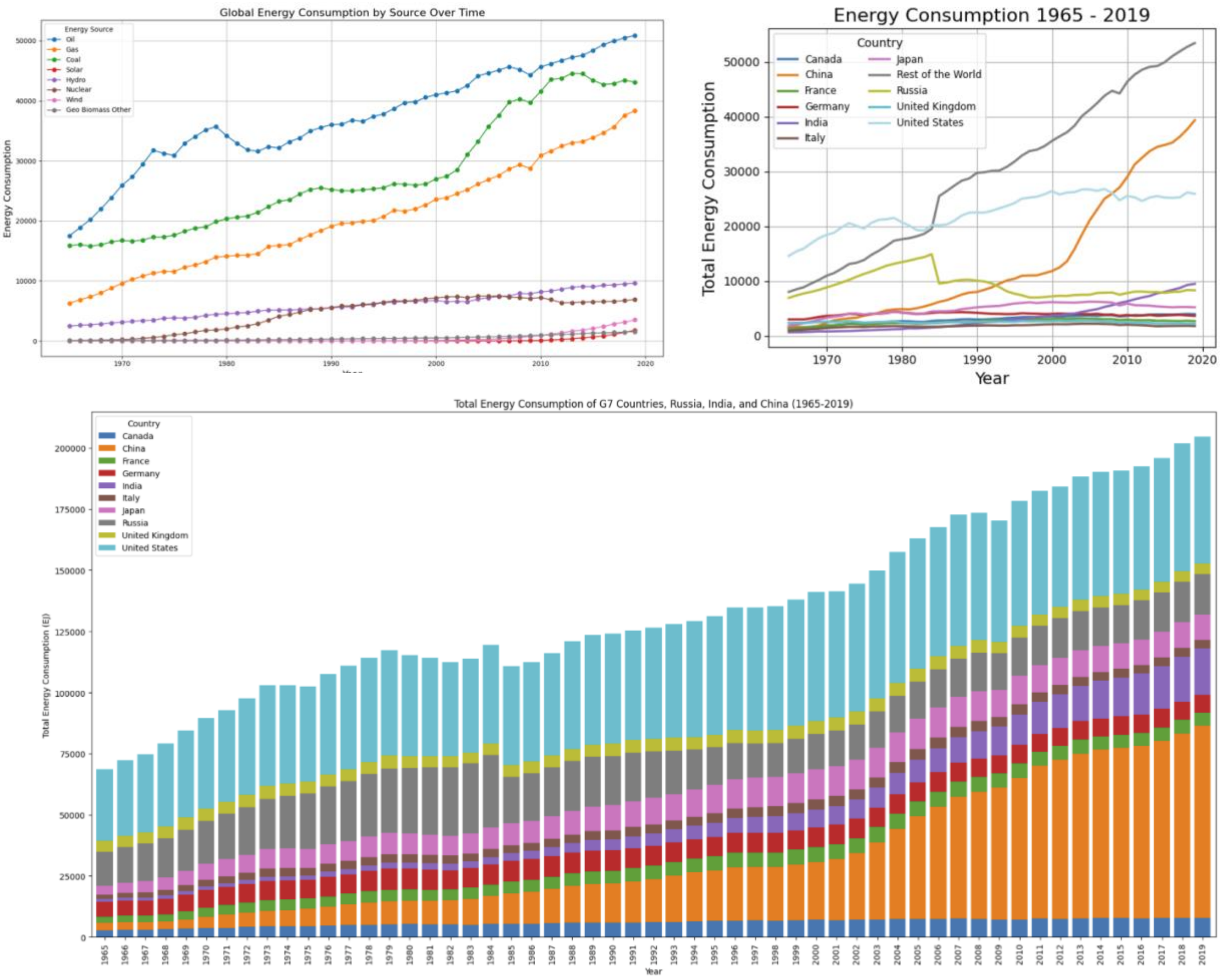


Figure 2: Global Energy Consumption from Various Sources with Yearly Growth By Country

A shift toward renewable energy sources became evident in the early 2000s and gained further traction from the 2010s onward. Among renewable energies, hydro has maintained the highest consumption over time, which is multiple times greater than that of other forms of renewable energy.

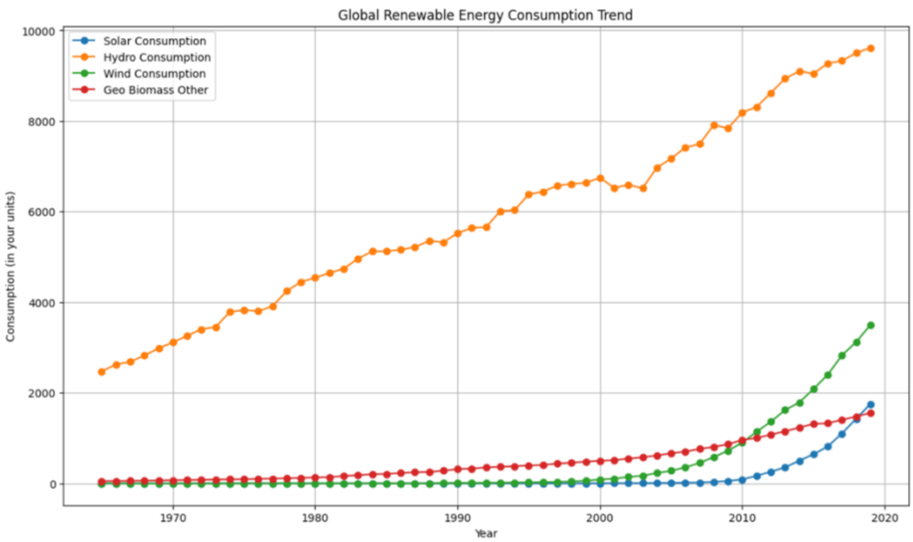


Figure 3:Global Renewable Energy Consumption Trend

4.2 Top Energy Consumers

The United States, China, Japan, Germany, India, the United Kingdom, Russia, and Brazil consistently ranked as top energy consumers across all sources. Italy, Spain, and France also frequently appeared on this list; for example, France ranked second to the United States in nuclear energy use. The United States and China maintained their positions as leading consumers in nearly every energy category.

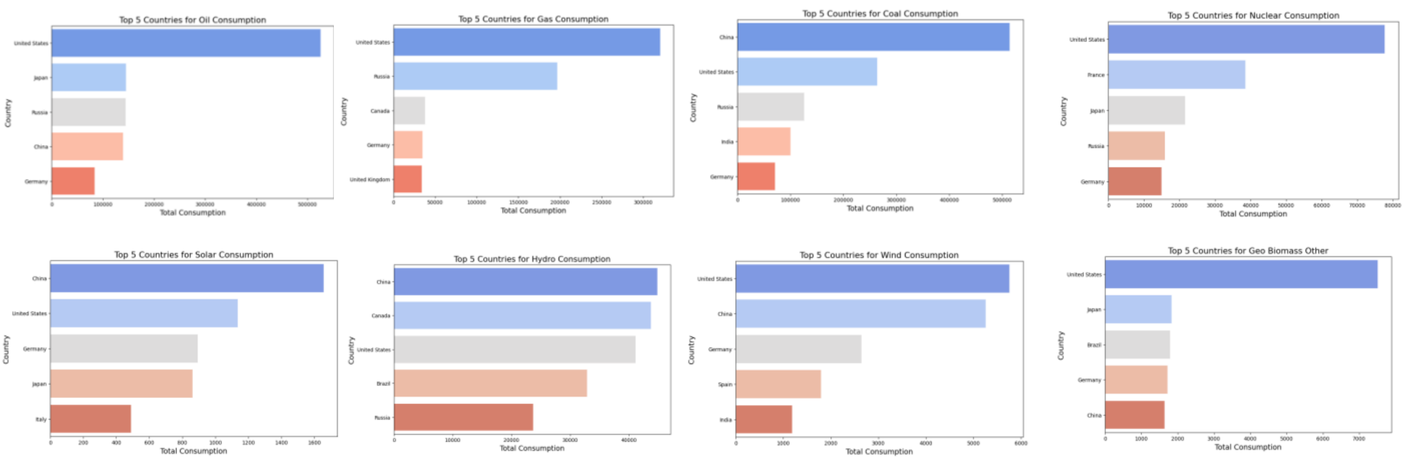


Figure 4: Top 5 Countries of Each form of Energy Consumption

4.3 Energy Use by Country and Source

This study unveiled distinct energy usage patterns by source for the United States, China, Japan, Germany, India, the United Kingdom, Russia, and Brazil. The United States heavily relied on oil, gas, and coal, although coal use decreased after 2010 alongside an increased focus on nuclear energy. In contrast, China's energy mix was dominated by coal, as was India's. The United Kingdom and Germany also exhibited an early over-dependence on coal, gradually transitioning towards oil and gas. Russia's energy consumption primarily consisted of natural gas.

Brazil's energy profile was unique, with a strong reliance on hydroelectricity (a renewable source). Hydro consumption steadily increased in China, the United States, Japan, India, Russia, and Brazil. Wind energy adoption became significant in the United Kingdom, Germany, and Brazil from 2010 onward. Japan and Germany shifted from nuclear to solar energy, with Japan appearing to cease nuclear energy use after 2011. This aligns with news articles suggesting that the Fukushima nuclear plant disaster led Japan to reduce its reliance on nuclear energy (BBC, 2023). The United States and the United Kingdom also generated a considerable share of energy from nuclear resources. Geo-biomass energy use was relatively low across countries, although Germany, the United Kingdom, and Brazil showed growing utilization in small portions.

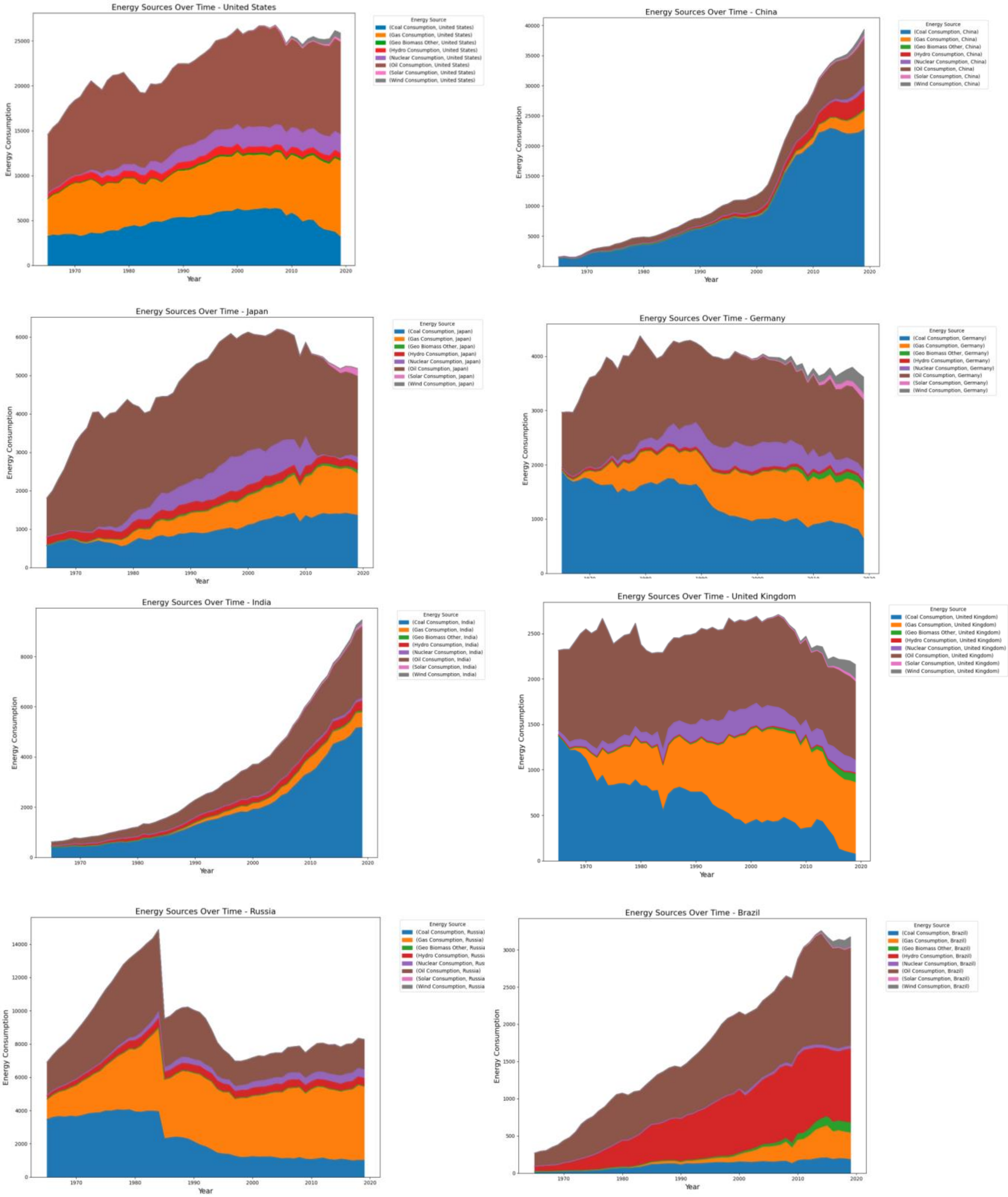
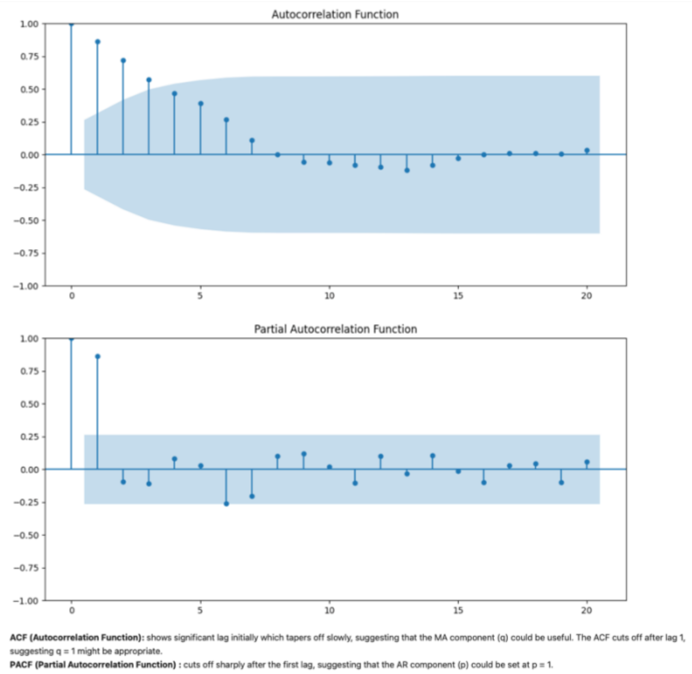


Figure 5: Energy usage visualisation by different source over the time by Selected Countries

4.4 Predictive Model's Evaluation

The initial ARIMA model were performed setting the parameter using United Kingdom and Oil consumption as sample. The ARIMA(p, d, q = 1,0,1), indicating one autoregressive term and one moving average term as found from the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) function. Graph shows significant lag initially which tapers off slowly, suggesting that the moving average (MA) component (q) could be useful. The ACF cuts off after lag 1, suggesting q = 1 might be appropriate, while PACF cuts off sharply after the first lag, suggesting that the AR component (p) could be set at p = 1. Augmented Dickey-Fuller test was performed in confirming the stationarity of the data. The lower Akaike Information Criterion (AIC) of ARIMA model (611.47) over the SARIMA (612.93) model suggest that seasonal component may not improve the model.



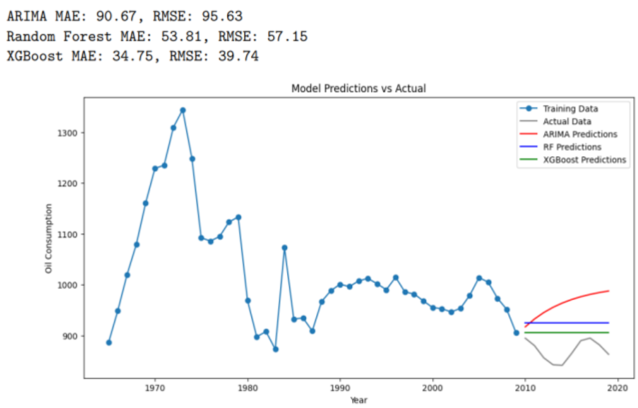


Figure 6: Augmented Dickey-Fuller test of Initial ARIMA Model (left), ARIMA vs Random Forest vs XGBoost RMSE Comparison (Right)

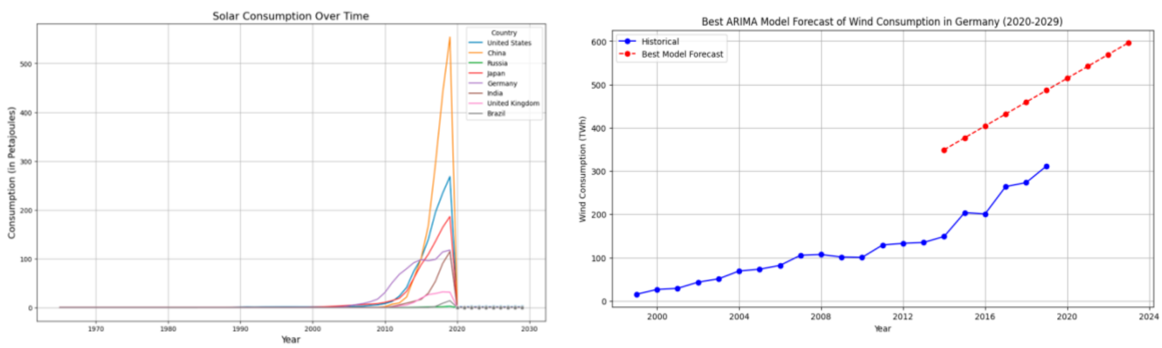
This ARIMA model was used to predict the energy use of 2011 – 2019 setting datapoint till 2010 as train data, which generate the Root Mean Squared Error (RMSE) of 95.63 which was in higher side, hence machine learning models Random Forest (RMSE – 57.15), XGBoost (RMSE – 39.74) were tested, however due to extreme overfitting issues in training set and higher RMSE (see figure 1) in the testing set both Random forest and XGBoost model were not use in the finalising the model.

The LSTM model was developed performing various experiments starting from the simple model Various experiments were done inside the Jupiter notebook helps to improve the model performance by reducing the RMSE score. In various experiments this study employed early stopping, Reduce LR On Plateau, L2 regulations and few other techniques.

To find the optimise RMSE score this study also experimented setting the time frame from 1989 – 2019 as most the countries started to use the renewable energies from 2000 while some minor increase of usages observer from 2010s. Hence while performing various experiments this study found if the training period set till 2013, time steps set to 2 this model provide the lowest test RMSE score of 17.57. The cross validation also performed to improve the generatability of the model.

Figure 7: Model Performance by LSTM model

The model was then implemented to forecast all form energy consumptions of the United States, China, Japan, Germany, India, the United Kingdom, Russia, and Brazil. However, although the model fit the best when United Kingdom and Oil were set as sample, during prediction of other energy especially nuclear, solar and wind the trendline showed a sudden drop of usage as the energy use of sudden counties were found inconsistence every year, and insignificant data points prior to 2010 LSTM trend line predicted sudden drop of usage in few cases. As the model was trained till 2013 it failed to predict solar energy usage perfectly. To mitigate this, dataset from 1989 – 2019 were used to test if something improved, but the forecast line was note improved that much for these three energies. Hence this study adopted another ARIMA model using Germany and wind as sample for liner prediction. The best RMSE score of 19.13 were achieved using p,d,q score of 0, 2, 2. Based on this ARIMA model nuclear, solar and wind were predicted.



LSTM Model's poor forecasting of Solar consumption

ARIMA model to forecast Solar consumption with 19.13 RMSE

Figure 8: LSTM vs ARIMA forecast with Lower Training Data

4.5 Findings from the Predicting Models

Predictive LSTM models suggest that other than gas, China will remain the leading user of all form of energy China's dependence on oil will significantly increase in the next decade. Apart from China and India no other country will significantly increase the use of oil.

The United States, Russia, and China are expected to reduce their gas use. China and India will continue to rely heavily on coal, while the USA will decrease its use. China is projected to become the leader in hydro

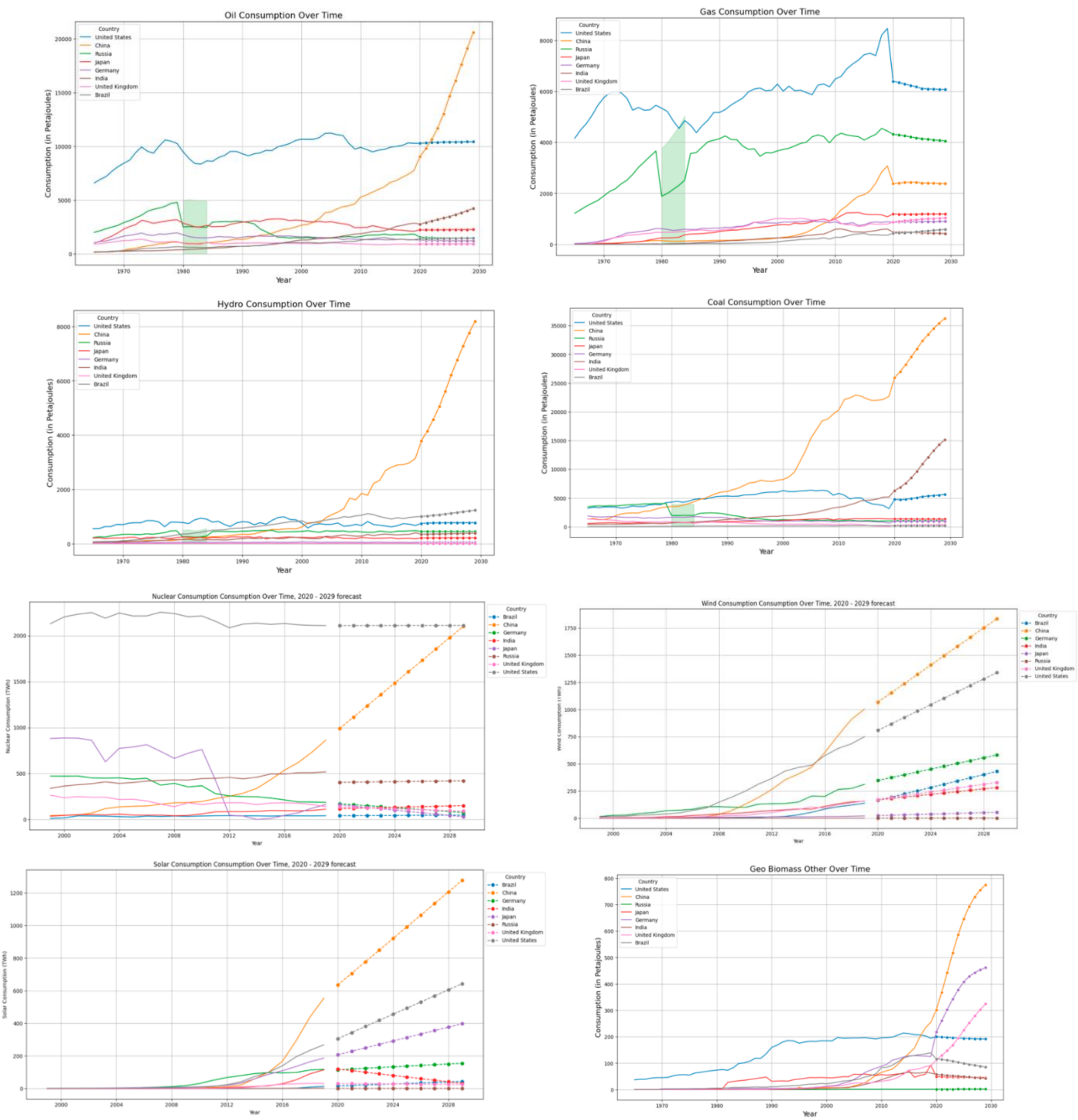


Figure 9: Energy Use Forecast of Different Source by Selected Countries

energy consumption as well. Additionally, China, Germany, and the United Kingdom are likely to significantly increase their use of geo-biomass in the coming decades.

The ARIMA models indicate an overall rise in wind energy use, with China becoming the top user. China is also projected to increase its nuclear energy usage, while other countries will reduce their reliance on this source. Solar energy consumption is expected to rise globally in the coming decades.

4.6 Renewable Energy Outlook

Based on the volume of consumption across all renewable energy sources, this study predicts that hydro energy will remain the most widely used. However, considering year-over-year growth, wind and solar energy appear to be the most promising renewable sources in the coming years. Predictive analysis suggests that China will lead in renewable energy use, followed by the United States. Figure 9 indicates that while countries are transitioning towards renewable energy, it's unlikely that renewable energy consumption will surpass conventional primary energy use in the near future.

5. Discussion

The results obtained for the predictive modelling conducted in this study – employing the LSTM and ARIMA models, shed light on numerous useful takeaways regarding the future trajectory of global energy consumption. The choice of each model was guided by the nature of the data and the unique aspects of each modelling technique, as outlined in the literature.

In summary, the LSTM model showed strong potential for modelling highly complex, non-linear time series data. Indeed, Somu et al. (2021) echoed the same in the literature, reporting that LSTM models tend to work well in handling non-linearities of larger data sets. The test RMSE score of the LSTM model in this study is 17.57. Unlike the RMSE of 0.4672 reported by Xiao et al. (2018) in forecasting total energy consumption. It may be due to the LSTM model's ability to capture the relevant information for the complex dataset. Yet, the LSTM model also presented some limitations. Like all other deep learning models LSTM models need to feed large, which was not the case in the prediction of solar and wind energy. In contrast, the ARIMA model, performed well in capturing simple, regular trends. While it lacked the LSTM's ability to incorporate complexities, its performance in predicting wind, nuclear, and solar energy consumption reaffirms the ARIMA model's value, as described by Hyndman and Athanasopoulos (2018).

Apart from the predictive modelling point of view this result resembled the econometric model's findings of Ahmad & Zhang, (2020) that the Asian countries will lead the use of global energy consumption because of emerging economy and population growth, this study also found China to be leading user of both primary and renewable energy in the future.

However, when comparing these models utilised in this study with Liu, et al. (2020), this model outperfomed by complexity and performance of Deep Reinforcement Learning (DRL) techniques. Liu, et al. (2020) deployed a combination of Asynchronous Advantage Actor-Critic (A3C), Deep Deterministic Policy Gradient (DDPG), and Recurrent Deterministic Policy Gradient (RDPG) in building the model with RMSE of 16%, which outshine both LSTM and ARIMA model adopted in this study. This singnifies that the current model has plenty of options for improvement. One the other hand all the predictive analysis this literatuer review only forecast the enrgy consumption based on the historical data. However for accurate prediction of each country's future usages of energy a conuntry specific weighted value of renewable energy policy, innovation and investment shall be integrated to the predictive model.

Thus the future reseach direction can be the integrate weighted values of country-specific energy policies, innovation, and renewable energy investment into a Deep Reinforcement Learning (DRL) based predictive models for improved accuracy of forecasting. The proposed research will help to evaluate whether individual countries are on track to meet their sustainable energy goals within targeted timeframes.

6. Conclusion

This study provides broad insights into the trends of global energy consumption and predicts future usage. The study has pointed to the continued dominance of fossil fuels with the observation of a slow but steady shift to renewable sources. The LSTM and ARIMA models predict the exponential growth of solar and wind energy in the next few decades will make them the most viable renewable energy sources. Meanwhile, hydro energy will be the leading source for at least a couple of years.

This study used LSTM and ARIMA models to predict the global energy consumption trend, which demonstrated the limitations and strengths of each method in varying situations. LSTM model performed well with non-linear and complex datasets as found in energy markets. However, LSTM needs more data points and more robust datasets to learn. ARIMA, on the other hand, is good for straight-lined situations with normal computational power, and predictive power was limited in the previous model.

The findings align with broader literature, such as Ahmad & Zhang (2020), who forecasted shifts towards Asian energy consumption due to economic and population growth. The potential enhancements through advanced Deep Reinforcement Learning techniques in addition to the LSTM model also suggest further avenues for increasing predictive accuracy.

This study therefore analyses the consumption pattern of various energy by leading energy consuming economics, develops few predictive models for forecasting energy consumption, and proposes the integration of country-specific energy policies, innovation and investments into a deep reinforcement learning based predictive models. This would improve accuracy and provide deeper insights for policymakers and industry stakeholders aiming for sustainable energy goals within a targeted timeframe.

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