Time Series Analysis of Electricity Consumption in the UK

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Introduction

Electricity demand forecasting is a critical component of power system planning and operations, enabling the efficient allocation of resources and ensuring grid stability. This project focuses on forecasting the *National Demand (ND)* for electricity in the United Kingdom, spanning the years 2009 to 2024.

The National Demand variable represents the total metered electricity generation required to meet consumer needs. It is a vital metric measured in megawatts (MW) by the National Grid ESO. Accurate forecasting of ND supports energy policymakers, grid operators, and utility companies in maintaining reliable and cost-effective electricity supply.

In this project, we utilise a time series analysis approach to identify patterns, trends, and seasonal components in the data, allowing for accurate forecasting of future values. We implemented three models - **SARIMA (Seasonal AutoRegressive Integrated Moving Average)**, **Holt-Winters Exponential Smoothing**, and **Long Short-Term Memory (LSTM)** - to forecast electricity consumption. By comparing the performance of these models, the project aims to identify the most effective approach for forecasting the UK's electricity demand.

Motivation

The motivation behind this project arises from the growing importance of sustainable and reliable energy systems. Electricity demand fluctuates significantly based on various factors, such as time of year, economic activity, and consumer behaviour. Inaccurate demand forecasting can lead to either energy deficits, risking outages, or overproduction, leading to increased operational costs and wastage.

By forecasting the National Demand, this project contributes to:

- *Operational Efficiency*: Enabling grid operators to prepare for demand fluctuations and reduce operational inefficiencies.
- *Cost Optimization*: Helping utilities minimise costs by aligning generation with consumption patterns.
- *Energy Sustainability*: Supporting the integration of renewable energy sources by improving demand predictability.
- *Policy and Planning*: Providing insights that assist in long-term energy policy formulation and infrastructure investment decisions.

Through this work, we aim to demonstrate the utility of time series analysis in addressing a real-world problem while contributing to the growing body of research in energy forecasting. The project serves as an academic exercise in applying theoretical knowledge to a domain with significant practical relevance.

Objective

The main objective of this project is to develop predictive models for forecasting the National Demand (ND) for electricity in the United Kingdom using time series analysis. Specifically, we aim to:

- Analyse historical electricity consumption data to identify trends, seasonality, and other patterns.
- Build robust forecasting models using *SARIMA, Holt-Winters Exponential Smoothing,* and *Long Short-Term Memory (LSTM)* to capture the underlying structure of the time series data.
- Conduct a comparative analysis of these models to determine their strengths, weaknesses, and suitability for electricity demand forecasting.
- Evaluate the models' performance in predicting future National Demand and provide insights for grid operators and policymakers.

Methodology

The Dataset

The dataset, sourced from Kaggle and provided by National Grid ESO, contains electricity demand data for Great Britain spanning from 2009 to 2024. Updated twice per hour, it provides 48 entries per day, making it ideal for time series forecasting tasks. The primary variable of interest, *National Demand (ND)*, represents the total metered electricity generation required to meet consumer demand, excluding station load, pump storage pumping, and interconnector exports.

Data Preprocessing

Effective data preprocessing is a crucial step in time series forecasting. The following steps were undertaken to prepare the dataset for modelling:

1. *Aggregating the Data*: The original dataset contained twice-hourly electricity demand data, with 48 entries per day. To reduce the computational complexity and focus on broader trends, the data was aggregated into weekly intervals by calculating the average *National Demand (ND)* for each week. This transformation helps capture long-term patterns and seasonal variations while smoothing short-term fluctuations.

2. *Feature Selection*: Out of the available variables in the dataset, only the *National Demand (ND)* was considered for forecasting. This variable serves as the target feature, as it represents the total electricity demand required to meet consumer needs.

3. *Data Transformation*:
    - *Log transformation*: The *National Demand* data was converted to its logarithmic scale. This transformation reduces variance and stabilises the time series, making it easier for the models to capture trends and seasonality.
    - *LSTM Model*: For the deep learning model, the data was normalised to a range of 0 to 1. We used the Min-max normalisation which is given by the formula $x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$. It ensures that all input values are scaled proportionately, improving the efficiency and stability of the LSTM model during training.

4. *Train-Test Split*: The dataset was split into training and testing sets to evaluate model performance. The last three years of data (2022–2024) were reserved for testing, while the remaining data (2009–2021) was used for training the models. This approach ensures that the models are trained on historical data and evaluated on their ability to forecast future demand.

These preprocessing steps ensured that the data was properly structured and transformed for accurate and reliable forecasting across all three models used in this project.

Exploratory Data Analysis

Exploratory Data Analysis (EDA) was conducted to uncover the underlying patterns in the electricity demand data for Great Britain, specifically focusing on National Demand (ND). The goal was to identify trends, seasonal patterns, and potential outliers in the time series data, which could inform the forecasting models.

Visualisation of Weekly National Demand

The first step in the analysis was to plot the weekly National Demand (ND) from 2009 to 2024 (Fig. 1). This visualisation provided an overview of the electricity consumption patterns over time, helping to identify visible trends, cycles, and any unusual variations.

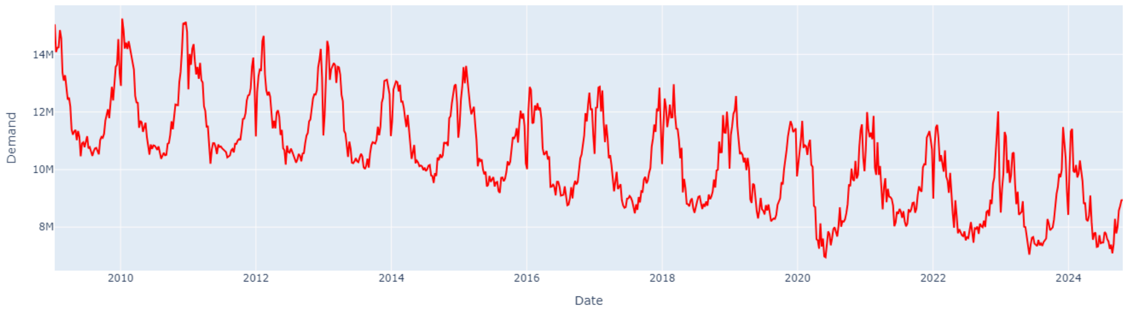

Fig. 1. Date vs Demand

Key Observations from the Plot:

- There is a general *downward trend* in *National Demand* over the years, which may be attributed to factors such as improvements in energy efficiency, changes in the energy mix, or shifts in consumer behaviour and industrial activity.
- Clear seasonal fluctuations are evident, with National Demand generally peaking in colder months due to higher heating requirements and dropping in warmer months when electricity consumption typically decreases.
- No significant presence of outliers/noise in the data.

Moving Average Analysis

After performing the initial exploratory data analysis (EDA), we applied moving average techniques to further understand the underlying patterns and smooth out short-term fluctuations in the *National Demand (ND)* data.

We calculated moving averages for both *monthly* and *3-month (quarterly)* periods to capture the trends in electricity demand over different time horizons. The moving averages help smooth the data by averaging out fluctuations, making it easier to identify longer-term trends and seasonal patterns (Fig. 2).

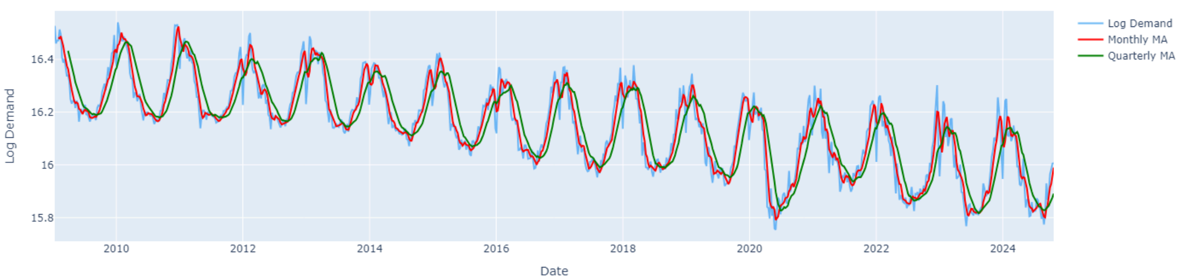

Fig. 2. Moving Average Smoothing

- *Monthly Moving Average*: The monthly moving average was used to capture short-term fluctuations and trends. It effectively smooths out weekly variations in the data while retaining more responsive changes in demand.
- *3-month Moving Average*: The quarterly moving average, with a larger time window, is better at identifying long-term trends by smoothing out more of the short-term fluctuations.

Seasonal Decomposition

Seasonal decomposition is a technique that breaks down a time series into its constituent components: trend, seasonality, and residuals. This decomposition helps in understanding the underlying patterns in the data and aids in improving forecasting accuracy. In our analysis, we applied seasonal decomposition to the *National Demand (ND)* data to identify and separate these components (Fig. 3).

To decompose the data, we used the seasonal_decompose function from the statsmodels library with an *additive* model, since our seasonality is constant with the trend. A multiplicative model assumes that the seasonal effect scales with the trend, which is suitable when the magnitude of the seasonal fluctuations increases with the trend. The decomposition was performed over a period of 52 weeks, corresponding to the annual seasonality, as electricity demand typically follows yearly cycles (e.g., higher demand in winter, lower demand in summer).

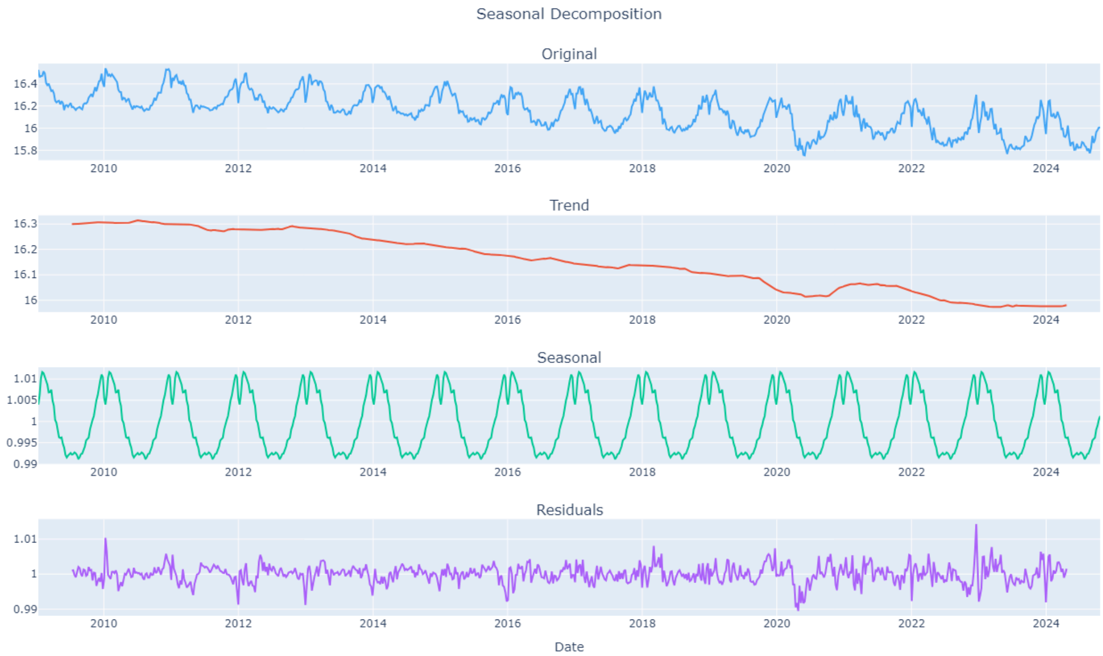

Fig. 3. Seasonal Decomposition (Additive)

Key Components from the Decomposition Plot

1. *Trend Component*: The trend component captures the long-term movement in the data. In our case, the plot clearly shows a downward trend in *National Demand* over the years. This could be due to factors like improved energy efficiency, changes in the energy mix, and a shift toward more sustainable energy sources.
2. *Seasonal Component*: The seasonal component reveals periodic fluctuations in demand that repeat every year. These fluctuations are more pronounced in the colder months due to heating demands and decrease in the warmer months.
3. *Residual Component*: The residual component represents the random noise or residuals after removing the trend and seasonality from the data. Ideally, this component should resemble white noise with no clear patterns or structure. In our decomposition plot, the residuals appear to fluctuate around 1 with no visible trends, indicating that the model effectively captured the seasonal and trend components.

Testing for Stationarity

Testing for stationarity is a crucial step in time series analysis, as many forecasting models, such as ARIMA and SARIMA, require the data to be stationary. A stationary series has constant mean, variance, and autocovariance over time, making it predictable and suitable for modelling.

From the initial plots of the *National Demand (ND)* data, we observed clear trends and seasonal patterns, which suggest that the series might not be stationary. To verify this, we conducted two stationarity tests: the *Augmented Dickey-Fuller (ADF)* test and the *Kwiatkowski-Phillips-Schmidt-Shin (KPSS)* test.

Augmented Dickey-Fuller (ADF) Test

The ADF test is a widely used test for stationarity, which tests the null hypothesis that a time series has a unit root, implying that the series is *non-stationary*. When a time series has a unit root, it typically exhibits random walk behaviour where past values have a persistent effect on future values. If the p-value is below a chosen significance level (typically 0.05), we reject the null hypothesis and conclude that the series is stationary.

For our data, we performed the ADF test and obtained the following results:

- *ADF Statistic*: -4.129
- *p-value*: 0.00086

Given the p-value is less than 0.05, the ADF test suggests that the series is *stationary*. However, this test can sometimes give false results, especially for series with strong seasonal components. Seasonal patterns tend to repeat over fixed intervals (e.g., yearly, quarterly), while a unit root indicates a random walk that lacks this periodic structure. The ADF test focuses on detecting the presence of such random walk behaviour (i.e., unit roots) but does not test for the more regular, repeating fluctuations that characterise seasonality. This limitation can lead to incorrect conclusions, especially when there is underlying seasonality, as in our case.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The KPSS test, on the other hand, tests the null hypothesis that a time series is *stationary* around a deterministic trend, and the alternative hypothesis is that the series is non-stationary. If the p-value is low (below 0.05), it suggests the series is non-stationary.

For our data, we performed the KPSS test and obtained the following results:

- *KPSS Statistic*: 2.924
- *p-value*: 0.01

The p-value is below 0.05, indicating that the series is non-stationary, which aligns with our visual observation of a downward trend and seasonality. The KPSS test performs better in this case because it is specifically designed to account for deterministic trends (such as the downward trend in *National Demand*) and does not assume stationarity in the presence of such trends.

Differencing the Data

To address non-stationarity, we performed differencing on the series to remove the trend and make the series stationary (Fig. 4.). After differencing, we applied the KPSS test again to check for stationarity in the differenced series:

- *KPSS Statistic (after differencing)*: 0.112
- *p-value (after differencing)*: 0.1

The p-value is now above 0.05, indicating that the differenced series is stationary, confirming that the differencing process successfully removed the trend and made the series suitable for forecasting.

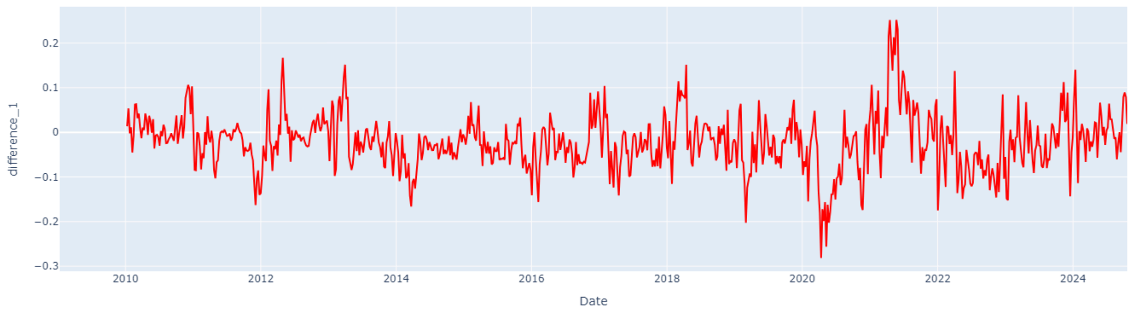

Fig. 4. Time Series after differencing

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Plots

The ACF and PACF are important diagnostic tools for identifying the nature of a time series and determining the appropriate model for time series forecasting.

These functions help identify:

- *AR (Auto-Regressive) processes*: Identified by significant lags in the PACF.
- *MA (Moving Average) processes*: Identified by significant lags in the ACF.
- *Stationarity*: ACF and PACF plots can also help determine whether differencing is necessary to make the series stationary.

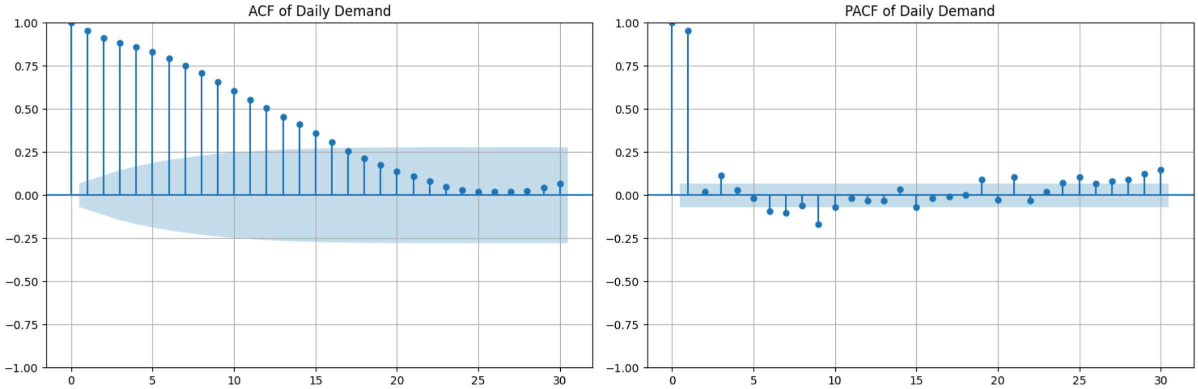

Fig. 5. ACF and PACF Plot Before Differencing

- *ACF*: The ACF plot shows slow decay, which is a typical characteristic of a non-stationary time series. This suggests that the series exhibits a long-term dependency (i.e., there is autocorrelation at long lags), which is often caused by trends or seasonality.
- *PACF*: The PACF plot shows a cyclic pattern, suggesting that the series may have a seasonal structure.

After Differencing (Fig. 6.)

- *ACF*: After differencing, the ACF plot shows rapid decay, which is a sign that the series is now stationary. The autocorrelation at higher lags diminishes quickly, suggesting that the long-term dependencies (trend or seasonality) have been removed, and the data no longer exhibits a trend.
- *PACF*: The PACF plot shows no significant spikes after lag 2, which suggests that the series is likely free of autoregressive structure beyond lag 2. This behaviour is typical after differencing because any autoregressive processes present before differencing have been removed or are now insignificant.

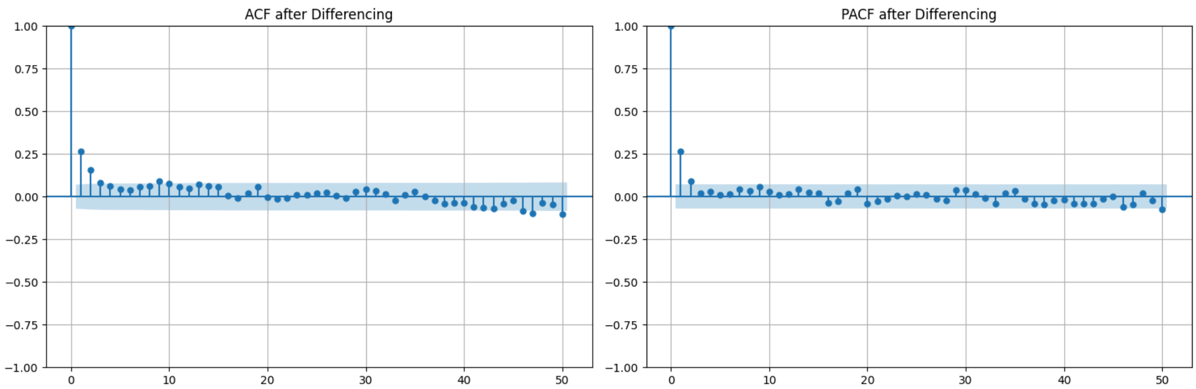

Fig. 6. ACF and PACF Plot After Differencing

Models

SARIMA

The SARIMA (Seasonal Autoregressive Integrated Moving Average) model is an extension of the ARIMA model that explicitly accounts for seasonality in time series data. SARIMA combines the autoregressive (AR), moving average (MA), and differencing components of the ARIMA model, with seasonal counterparts for each of these components, allowing it to model both trend and seasonality.

SARIMA Model Components:

A SARIMA model is typically represented as:

ARIMA(p, d, q)(P, D, Q)[S]

- *p*: The order of the autoregressive (AR) component.
- *d*: The degree of differencing.
- *q*: The order of the moving average (MA) component.
- *P*: The seasonal autoregressive order.
- *D*: The seasonal differencing order.
- *Q*: The seasonal moving average order.
- *S*: The length of the seasonal cycle (e.g., 52 for weekly data with annual seasonality).

SARIMA can be used effectively in cases where a time series has both trend and seasonal patterns, such as our electricity consumption.

Optimization Approach:

Minimising the AIC (Akaike Information Criterion) - AIC is a statistical measure used for model selection. It balances the goodness of fit of the model with the complexity (number of parameters). A lower AIC value suggests a better model.

Results:

The table (Table 1) below summarises the performance of the SARIMA models using AIC:

Best Model: Based on the AIC values, the best model is *ARIMA(1,0,2)(1,1,1)[52]*, with the lowest AIC of *-2320.72*, which indicates the most efficient model in terms of fitting the data with the least complexity.

Model	AIC	MAE	MSE
ARIMA(1,0,1)(1,1,1)[52]	-2320.72	0.0425	0.0033
ARIMA(1,0,1)(2,1,1)[52]	-2320.57	0.0427	0.0033
ARIMA(1,0,1)(1,1,2)[52]	-2319.14	0.0424	0.0032

Table 1. SARIMA Performance

Forecast

After identifying the optimal parameters for the SARIMA model, we proceeded to use the model for generating forecasts on the test data. The forecasted values were obtained by applying the SARIMA model to the test dataset. These predicted values were then compared with the actual observed values in the test data to assess the model's forecasting performance (Fig. 7).

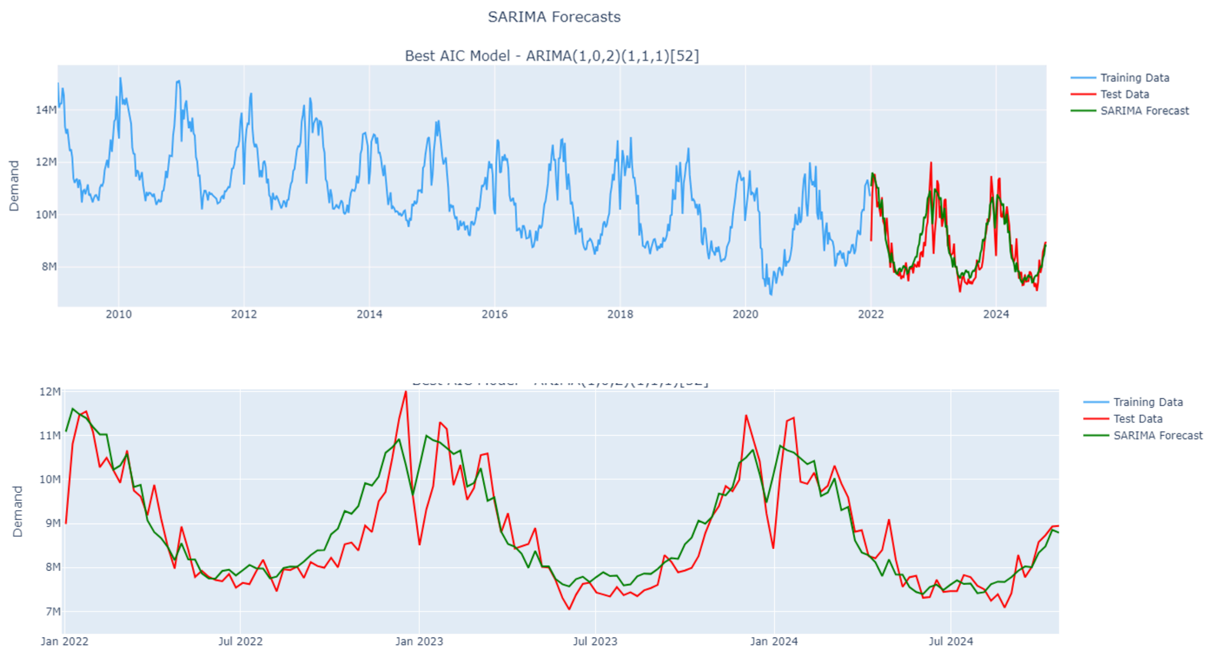

Fig. 7. SARIMA Forecasts

Holt-Winter's Model

The Holt-Winter's model is a popular time series forecasting method that extends exponential smoothing to capture trends and seasonality in the data. It is particularly useful for datasets that exhibit both trend and seasonality, which is the case with our electricity consumption data. The model consists of three components:

- *Level*: The average value of the series at each point in time.
- *Trend*: The direction in which the series is moving (either upward or downward).
- *Seasonality*: The repeating pattern or cycle in the data over a specified period (e.g., weekly, monthly).

The Holt-Winter's model can be applied in two forms:

- *Additive*: Suitable for time series with constant seasonal fluctuations.
- *Multiplicative*: Used for time series where the seasonal fluctuations are proportional to the level of the data.

In this project, we used the additive version of the Holt-Winter's model, as the seasonal effect is expected to vary with the level of electricity demand.

The evaluation results for the Holt-Winter's model are summarized in Table 2:

Model	AIC	MAE	MSE
Holt-Winter's (Additive)	-4420.09	0.1014	0.0130

Table 2. Holt-Winter's Performance

The relatively low MAE and MSE values indicate that Holt-Winter's model performed well in forecasting the national electricity demand. The AIC value, which is lower than other models, suggests that this model fits the data well without overfitting.

Forecasting Results

Finally, we used the Holt-Winter's model to forecast the national electricity demand for future periods. The forecasted values are compared to the actual values in the test set (Fig. 8), and we present the following forecast plots to visually assess the model's predictive accuracy.

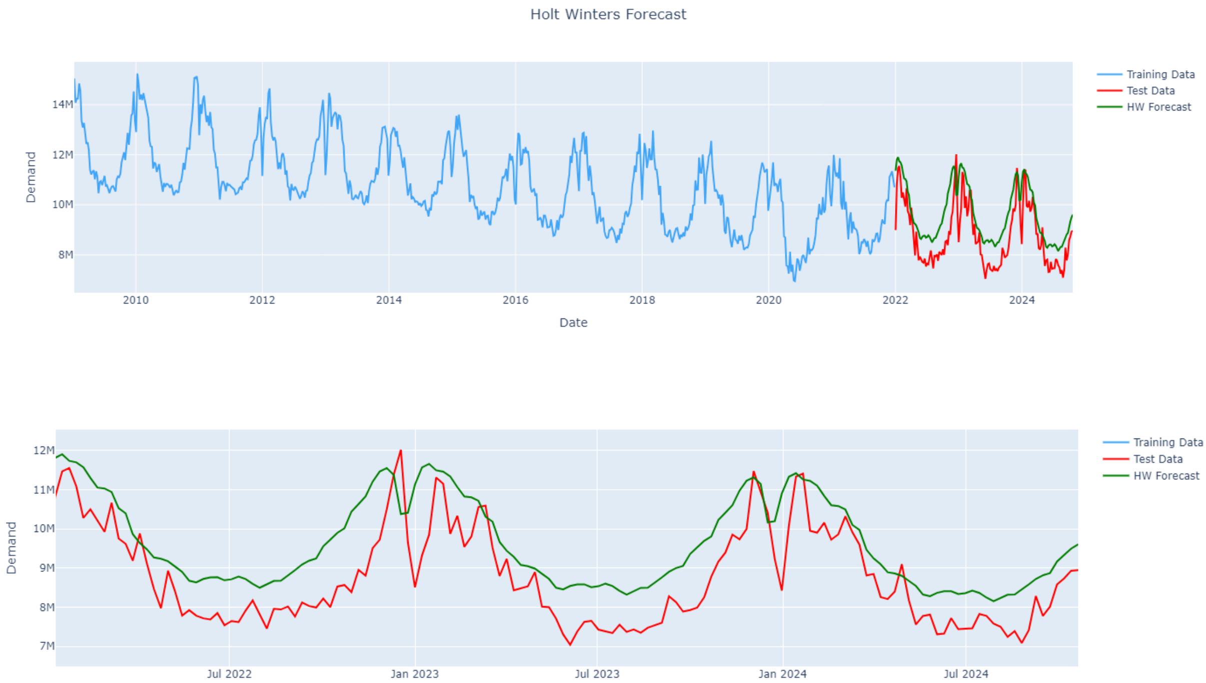

Fig. 8. Holt-Winter's Forecasts

LSTM Model

The Long Short-Term Memory (LSTM) model is a type of Recurrent Neural Network (RNN) designed to model sequences and time series data. Unlike traditional models like ARIMA and Holt-Winters, LSTM is a deep learning model that can capture complex, non-linear relationships in time series data, making it especially effective for forecasting when the data exhibits intricate patterns such as long-term dependencies, trends, and seasonality.

LSTMs are equipped with memory cells that help preserve information over long periods, enabling the model to learn patterns in the data that span over multiple time steps. This capability makes LSTM suitable for tasks like predicting national electricity demand, where past demand values can influence future consumption over extended periods.

Unlike SARIMA and Holt-Winters models, the LSTM model does not provide an AIC value, as it is a machine learning-based model and not a traditional statistical model. However, the MAE and MSE values can still provide a solid understanding of the model's predictive accuracy.

The evaluation results for the LSTM model are summarised in Table 3:

Model	**MAE**	**MSE**
LSTM	0.0258	0.0009

Table 3. LSTM Performance

The LSTM model demonstrated exceptionally low MAE and MSE values, indicating that the predictions closely matched the actual values in the test set. The very small MSE value suggests that the LSTM model was able to make precise predictions with minimal error, even for more complex patterns in the data.

Forecasting Results

After training the LSTM model, we generated forecasts for future national electricity demand. The forecasted values were plotted alongside the actual test data to visually compare the model's performance (Fig. 9).

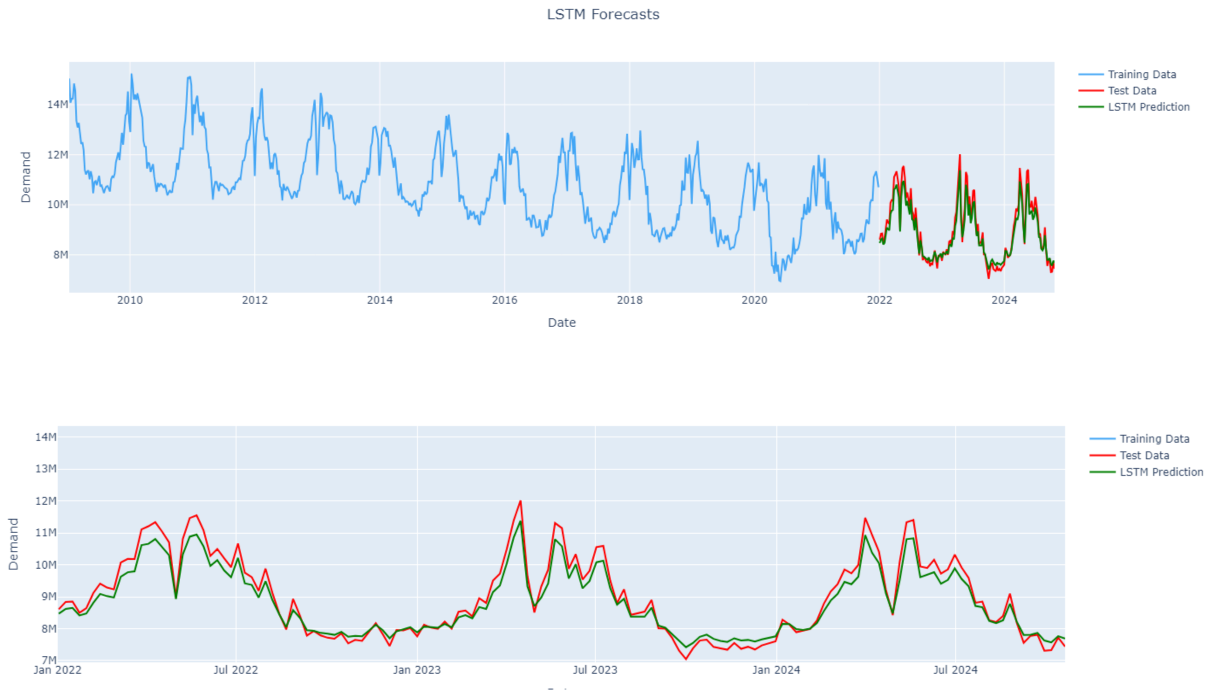

Fig. 9. LSTM Forecasts

The forecast plots for the LSTM model show that it was able to capture the underlying patterns in the time series data effectively. The forecasted values closely follow the trend and seasonal variations of the actual values, indicating that the model can predict future demand with high accuracy. The plots also reveal that the LSTM model handled long-term dependencies and seasonality well, outperforming traditional statistical models like SARIMA and Holt-Winters in terms of accuracy and precision.

Conclusion

The following Table 4 summarises the evaluation results for each model used.

Model	MAE	MSE
ARIMA(1,0,2)(1,1,1)[52]	0.0425	0.0032
Holt-Winter's	0.1013	0.013
LSTM	0.0258	0.0009

Table 4. Model Comparison

The results suggest that for forecasting national electricity demand, LSTM offers the best performance among the three models. It demonstrated the lowest error metrics, effectively handling the complex time series data with high precision. The SARIMA model followed closely, providing a solid, interpretable solution that fits the data well, though it is not as precise as the LSTM model. Finally, the Holt-Winter's model, while still valuable for capturing seasonality and trends, was less effective at predicting future values compared to the other two models.

Overall, while SARIMA and Holt-Winter's are more traditional and interpretable models for time series forecasting, the LSTM model's deep learning approach provided the most accurate predictions, especially when handling complex seasonal patterns and long-term dependencies in the data.