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Evaluating Socio-Economic and Geopolitical Events Impact on UK Electricity Demand using Explainable AI

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***Abstract*—This paper examines how socio-economic and geopolitical events affect electricity consumption in the United Kingdom from 2009 to 2024 using a multi-source, event-aware dataset. The study integrates electricity demand, climate, economic, COVID-19, holiday, renewable generation, and geopolitical indicators, and evaluates Random Forest, XGBoost, and LightGBM models with time-aware validation. LightGBM achieved the best performance, with an RMSE of 1,590 MW and an R^2 of 0.920 on the holdout test set, outperforming XGBoost by 137 MW in RMSE. SHAP analysis further revealed that temporal, weather, and event-based features were key demand drivers. The framework improves forecasting accuracy while providing interpretable, policy-relevant insights for resilient energy planning.**

Keywords: Electricity, Demand, Explainable, Forecasting, machine learning, LightGBM, Random Forest, SHAP.

I. Introduction

Energy consumption is one of the important indicators of socio-economic development, technological advancement and quality of life of nations [1]. It is related to the size of industrial production, transport infrastructure, housing characteristics, and the general character of an economy. Global electricity demand increased by nearly 2.2% in 2023, according to the International Energy Agency [2], driven by continued population growth, digitalisation, and the accelerating electrification of industries and mobility. However, energy demand trends over the last decade have been extremely volatile because a series of disruptive events has called into question long-held expectations of how demand will behave. [3] noted that while total electricity demand in the UK fell relatively steadily between 2009 and 2019 as a result of improvements in energy efficiency, continued shift away from heavy industry, and there were anomalies during the pandemic (2020-2021) and as a result of the geopolitical tension affecting energy markets. Additionally, the continued policy reforms toward the promotion of renewable energy adoption and energy efficiency improvement and structural eliciting have further changed the temporal and structural attributes of electricity consumption [4]. These dynamic patterns show that progress in pricing, technologies and behaviours, as well as larger socio-economic shocks and international forces, play a role in shaping the demand for electricity in the UK. Traditional time-series and econometric regression forecasting models have encountered difficulties to account for these complex, nonlinear and event-driven variations [5][6]. Although recent models of machine learning have shown better predictive performance by being able to capture hidden dynamics and seasonality [7][8], they are a "black box" so we lack easy understanding of how certain features affect predictions. [9] points out that this lack of interpretability makes it difficult to make decisions about policy, where it is needed not only to predict consumption but also to see what drives variations. This study aims to fill these gaps by incorporating heterogeneous event information into explainable machine learning models to analyse the pattern of the UK electricity consumption from 2009 to 2024. Also to analyse the effects of socio-economic and geopolitical occurrences on the UK electricity consumption trends and to prepare inferential and analysable data-driven models to facilitate proper energy prediction and policy consideration. The objectives include ranking important external events, which affect the UK electricity consumption patterns, to predict consumption in the presence of various possible external conditions through explainable machine learning models, gauge the magnitude

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and direction of effect of each category of events on electricity demand with feature attribution and counter-factual analysis, and offer practical strategic responses to policy-makers and energy operators in the light of the necessity of better energy planning and response to future disruptions. The research is limited to the UK and secondary data is used based on official sources of information.

II. Related Work

Statistics and econometric models as linear regression, ARIMA, SARIMA, exponential smoothing, and vector autoregression models have been traditionally used to predict electricity demand [10]. These techniques are appreciated due to their transparency and the capacity to model trends and seasonality, but do not consider the linearity and structural stability. Consequently, they do not do well in volatile environments that are brought about by external shocks like economic crises, pandemics, geopolitical tensions, and sudden changes in policies [11].

To address these shortcomings, recent research has used machine learning and hybrid modelling. Random Forest, XGBoost, artificial neural networks and long short term memory networks algorithms have been shown to have better predictive power as they are able to be used to model non-linear relationships and complex time dynamics in electricity consumption data [12]. Hybrid models incorporating both statistical and machine learning elements enhance the performance even further through the modelling of both linear and non-linear structures [13]. In spite of these benefits, the majority of machine learning models act like black boxes and are not very transparent and policy-relevant.

Issues of interpretability have resulted in the increasing popularity of explainable machine learning (XML). Methods like SHAP and LIME have been suggested to assign the significance of features and also offer local and global explanations regarding the predictions of the models [14]. Previous research indicates that XML improves trust, accountability and decision-making in energy forecasting, especially when it comes to households or buildings [15]. Regardless, the literature reports a significant gap on the national level. Not many studies combine the structured socio-economic and geopolitical events into forecast models, and even fewer use explainable machine learning models in the national electricity demand in the UK setting [9][16]. Such an inability to forecast events in an interpretable manner restricts the capability of policymakers and energy planners to learn and control demand volatility, which compels the development of explainable and event-sensitive modelling.

III. Methodology

The methodology is based on predictive accuracy and explainable machine learning that is based on secondary data analysis. The datasets used consist of UK electricity demand and renewable generation data on Kaggle [17], climate variables data on Copernicus ERA5 reanalysis [18], economic data available on UK Office for National Statistics [19], COVID-19 policy and health data available on Oxford COVID-19 Government Response Tracker [20], calendar and holiday data on WorldPop [21], and geopolitical events that were manually coded: Brexit milestones, the Ukrainian war and the energy price crisis.

A. Research Design

The research is structured as a supervised regression problem in which electricity demand is treated as the target variable and a set of external explanatory variables are used as predictors. Let y_t denote the observed electricity demand at time t, and let $\mathbf{X}_t$ represent the vector of associated explanatory features, including weather, calendar, economic, renewable generation, COVID-19, and geopolitical variables. The modelling objective is to learn a function $f(\cdot)$ such that:

$$y_t = f(\mathbf{X}_t) + \varepsilon_t \tag{1}$$

where ε_t captures unobserved variation and random noise.

In practical terms, the study does not aim only to forecast demand values; it also seeks to understand how specific classes of events and conditions shift consumption patterns over time. This makes the research both predictive and explanatory, with a strong emphasis on interpretability. The paper explicitly frames this as a secondary-data investigation using explainable machine learning to study UK electricity consumption over 2009–2024.

B. Data Preprocessing

Data cleaning was done to remove missing values and inconsistencies, time synchronisation of heterogeneous datasets, and variable normalisation to make them compatible with electricity demand time series. Exploratory data analysis was performed to investigate trends, anomalies and correlation of electricity demand and external events.

C. Model Development and Evaluation

Random Forest, XGBoost, and LightGBM types of ensemble-tree-based machine learning models were used because they can capture non-linear associations and use high-dimensional features. The records were divided into training (2009-2021) and testing (2022-2024) groups, cross-validation of the time-series was used. RMSE, MAE, MAPE and R^2 were used to determine model performance.

D. Train–Test Split and Validation Strategy

To preserve temporal ordering, the dataset was split sequentially (not randomly). Let

$$\mathcal{D} = \{(\mathbf{X}_t, y_t)\}_{t=1}^{T}, \tag{2}$$

where y_t is electricity demand and $\mathbf{X}_t$ is the feature vector at time t. The training set contains the earliest observations and the test set contains the most recent observations. In this study, $\approx 80\%$ of the data (2009–2021) was used for training, and 2022–2024 was held out for final testing.

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Model selection used forward-chaining (expanding-window) time-series cross-validation. For fold k, the training and validation sets are

$$\mathcal{D}_{\text{train}}^{(k)} = \{(\mathbf{X}_t, y_t)\}_{t=1}^{t_k}, \tag{3}$$

and

$$\mathcal{D}_{\text{val}}^{(k)} = \{(\mathbf{X}_t, y_t)\}_{t=t_k+1}^{t_k+h}, \tag{4}$$

where h is the validation horizon. This strategy respects temporal dependence and prevents look-ahead bias.

E. Explainability and Interpretability Analysis

To complement predictive accuracy with interpretability, the study employed SHAP (Shapley Additive exPlanations) and conventional feature-importance measures. SHAP explains an individual prediction by decomposing it into additive feature contributions:

$$\hat{y}(\mathbf{x}) = \phi_0 + \sum_{j=1}^{p} \phi_j(\mathbf{x}), \tag{5}$$

where $\phi_0 = \mathbb{E}[\hat{y}(\mathbf{X})]$ is the baseline prediction and $\phi_j(\mathbf{x})$ is the contribution of feature j.

The Shapley value for feature j is defined as

$$\phi_j(\mathbf{x}) = \sum_{S \subseteq \mathcal{F}\setminus\{j\}} \frac{|S|!\,(p-|S|-1)!}{p!}\Big(f_{S\cup\{j\}}(\mathbf{x}) - f_S(\mathbf{x})\Big), \tag{6}$$

where $\mathcal{F}$ is the set of p features and f_S denotes the model evaluated with only features in subset S.

Global importance was obtained by aggregating absolute attributions (e.g., $\frac{1}{N}\sum_{i=1}^{N}|\phi_j(\mathbf{x}_i)|$), while local explanations were inspected for disruption periods. Counterfactual analysis assessed sensitivity by perturbing selected drivers and re-estimating predictions:

$$\Delta\hat{y} = \hat{y}(\mathbf{x}') - \hat{y}(\mathbf{x}), \tag{7}$$

linking demand changes to specific socio-economic and geopolitical conditions.

F. Ethical Considerations

This study uses only secondary, publicly available, aggregate-level datasets and does not involve human subjects, clinical records, or personally identifiable information. The electricity-demand dataset, climate reanalysis data, economic statistics, COVID-19 policy indicators, and holiday variables were obtained from public sources and used strictly for academic analysis and forecasting purposes.

IV. ANALYSIS

This section presents a comprehensive analysis of electricity demand forecasting in the UK using machine learning techniques. The analysis aims to assess the predictive accuracy of the models, identify the key factors driving electricity demand, and quantify how major external shocks affect consumption patterns. The models were trained using practical, deployable input features and evaluated with a time-aware split, using earlier years for training and the most recent years for testing.

A. Temporal Patterns in Electricity Demand

Fig. 1 illustrates the temporal pattern of UK electricity demand from 2009 to 2024, with some of the major geopolitical events such as the Brexit referendum (June 2016), Covid-19 lockdowns (March 2020) and the Ukraine war (February 2022). The monthly average trend shows the evolution in demand over a long period and a general declining trend over the last years despite population growth.

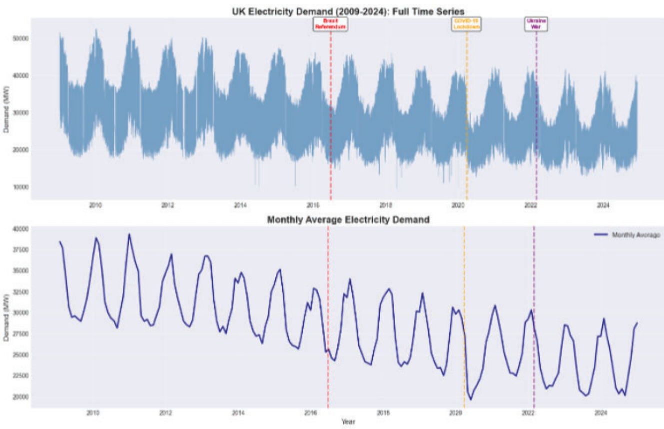

Fig. 1. UK Electricity Demand Pattern (2009 to 2024)

This indicates seasonal decomposition, revealing a pronounced annual cycle in electricity consumption. The observed series was decomposed into trend, seasonal, and residual components, showing that seasonal effects account for fluctuations of approximately ±4,000 MW around the underlying trend. Demand is consistently higher in winter than in summer, primarily due to increased heating requirements.

The hourly and weekly patterns (Fig. 2) shows strong daily cycles. Average demand showed two peaks: in the morning at 09:00 (31,344 MW) and in the evening at a higher level of consumption at 18:00 (34,395 MW), reflecting commercial and residential consumption patterns. The weekly assessment shows significant differences between weekdays and weekends, with average demand on weekdays 29,413 megawatts and average demand on weekends 25,748 MW, a reduction of 12.5% owing to reduced commercial and industrial activity.

Ukraine war and energy crisis (Fig. 3) shows continued suppression of demand. Pre-war average (January 2021 to February 2022) was 26,408 MW decreasing to 23,667 MW during the conflict and energy price crisis (February 2022 to December 2023), a 10.4% reduction. This significant decline was due to both price-driven conservation behaviour and industrial reductions in response to high energy costs, building on the Previous reductions driven by the pandemic.

Monthly and seasonal trends (Fig. 4) confirms winter-dominated demand profiles. December had the highest average demand and August the lowest, indicative of heating and cooling demands between seasons. Year-on-year boxplot comparisons showed a progressive decrease in demand between 2009-2024, with median demand decreasing despite economic

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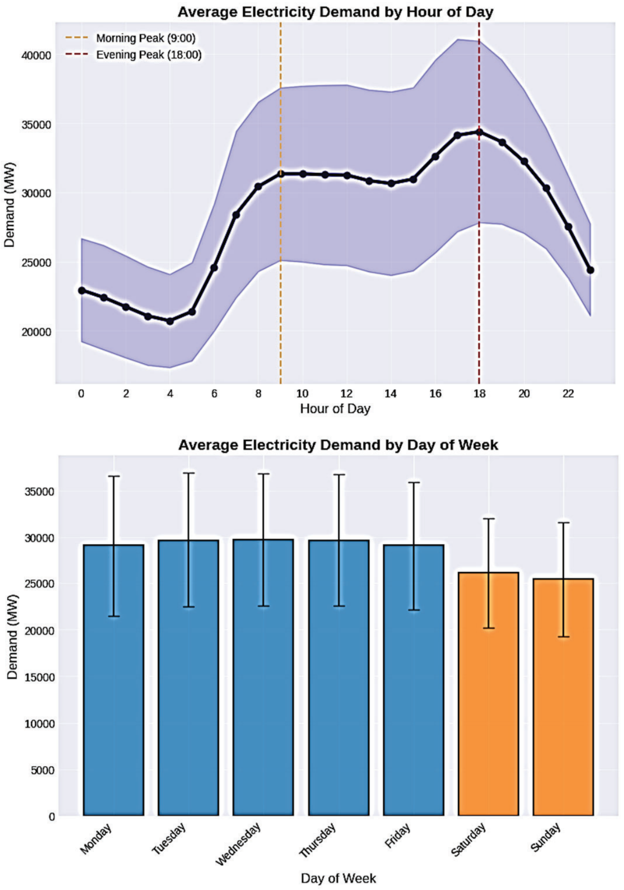

Fig. 2. Hourly and Weekly Pattern Analysis.

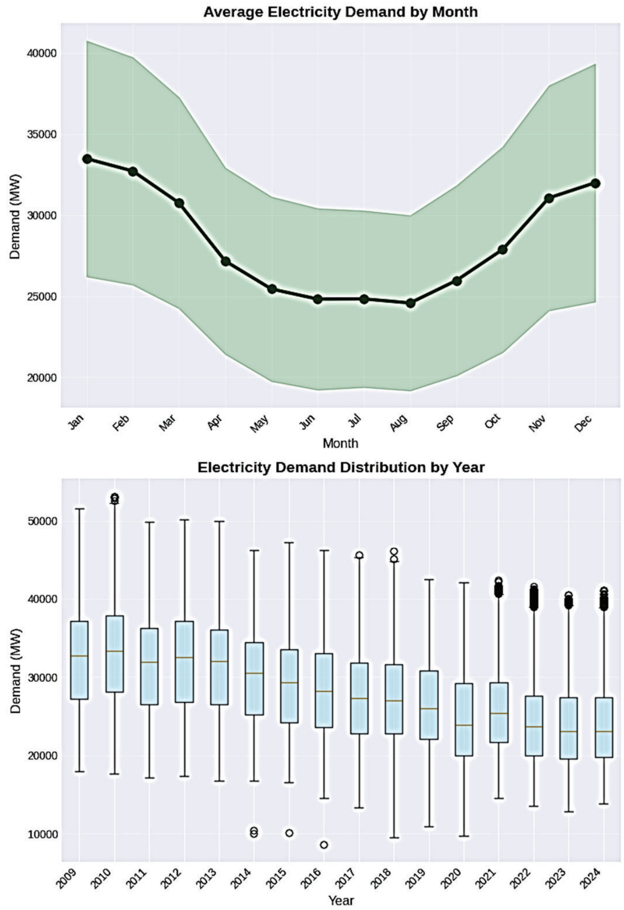

Fig. 4. Monthly and Seasonal Patterns.

growth and population growth, possibly due to improvements in energy efficiency and growth in renewable generation.

B. Climate and Energy Relationships

Temperature-demand correlation (Fig. 5) shows a non-linear U-shaped correlation. Demand rose at both ends of the temperature spectrum, low temperatures spurring the heating and high temperatures spurring cooling. The polynomial regression curve showed this pattern, with medium temperatures (15-20 degrees Celsius) showing the lowest demand levels. Binned temperature analysis supported this relationship with high demand below 5 degrees Celsius and above 25 degrees Celsius.

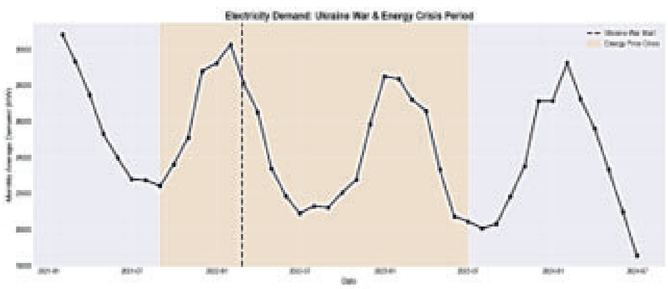

Fig. 3. Ukraine War Effect on Demand

The polynomial regression curve shows this pattern, with medium temperatures (15-20 degrees Celsius) showing the lowest demand levels. Binned temperature analysis supported this relationship with high demand below 5 degrees Celsius and above 25 degrees Celsius.

C. Economic and Calendar Effects

GDP sector correlations at monthly aggregation level with electricity demand shows moderate positive relationships. Total GVA was poorly correlated, and the production and manufacturing sectors were more highly correlated in line with their electricity intensive nature. Scatter plots showed linear trends, but there was a large amount of variance suggesting that other factors apart from economic activity affected demand. Population trends (Fig. 7) displays paradoxical trends. While UK population rose from 2009-24, per capita demand for electricity has fallen, indicating greater energy efficiency, technological progress and structural changes in the economy (energy intensive industries) counteracting the increased demand due to population growth.

D. Model Performance Results

This section introduces the performance of three tree-based machine learning models; Random Forest, XGBoost, and

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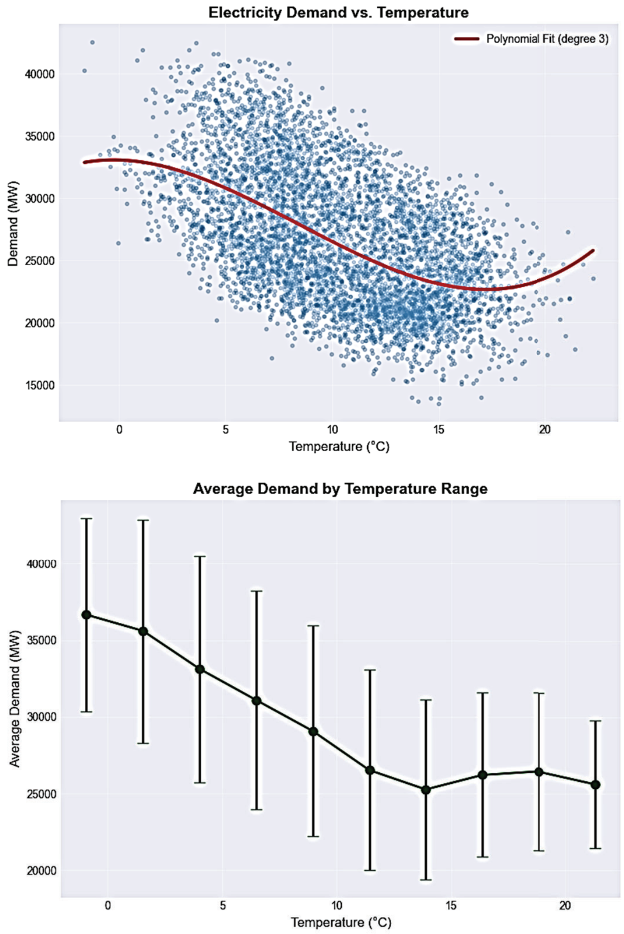

Fig. 5. Temperature-demand correlation.

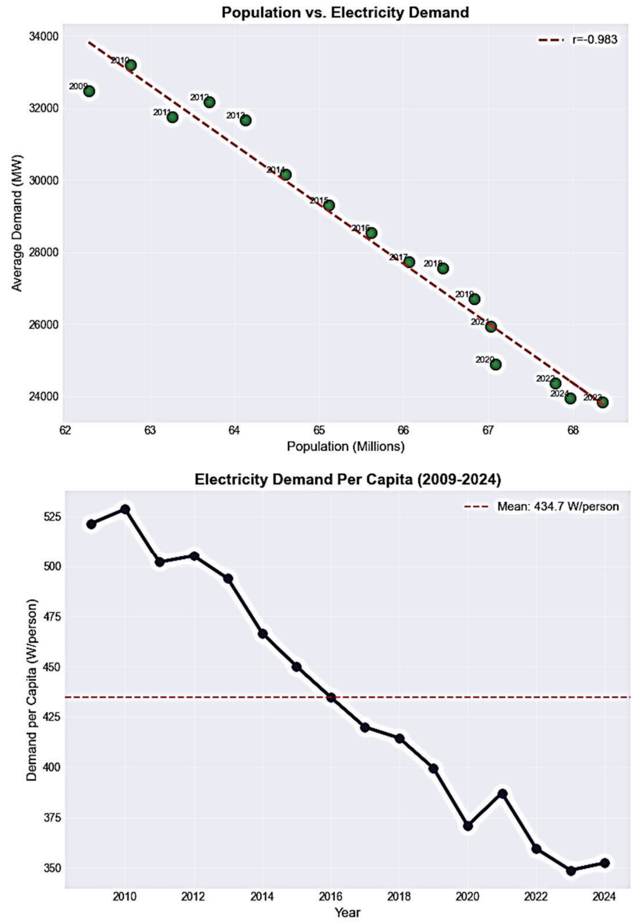

Fig. 6. Population Trends and Electricity Demand

LightGBM, using time series cross-validation, and holdout test data. LightGBM coutperforms the other models across all metrics, achieving RMSE of 1,590 MW, MAE of 1,243 MW, MAPE of 5.33%, and R² of 0.920. XGBoost ranked second with RMSE of 1,727 MW and R² of 0.906, while Random Forest shows RMSE of 1,745 MW and R² of 0.904.

Table 4 summarises the performance metrics on the holdout test set (2022–2024).

TABLE I
MODEL PERFORMANCE ON TEST SET (2022–2024)

Model	RMSE (MW)	MAE (MW)	R²	MAPE (%)	Training Time
Random Forest	1,745	1,331	0.904	5.75	563s
XGBoost	1,727	1,372	0.906	5.92	6s
LightGBM	1,590	1,243	0.920	5.33	22s

LightGBM's performance proves the efficacy of gradient boosting combined with the leaf-wise growth of the tree for learning complex temporal relationships in electricity demand forecasting.

E. Prediction Accuracy and Residual Behaviour

The predicted-versus-actual comparison in Fig. 10 shows that LightGBM predictions cluster closely around the 45-degree reference line, indicating high agreement between predicted and observed demand values. The scatter patterns for the other models are also strong, but LightGBM is visually the most concentrated around the ideal prediction line. The numerical performance results are confirmed by this, and the model is shown to generalise well to unseen data.

Slight underestimation at the extreme upper range, particularly above 50,000 MW, is also identified across all three models. Very high peak events continue to be difficult to capture perfectly, even with flexible ensemble methods. Such underestimation is not unusual in electricity forecasting, because the highest-demand periods are often associated with rare combinations of weather, behaviour, and system stress. Overall, the residual behaviour indicates that the proposed modelling framework is stable and suitably accurate for national-level forecasting applications.

F. Interpretability Insights

The interpretability analysis is shown to produce broadly consistent feature-importance rankings from tree-based meth-

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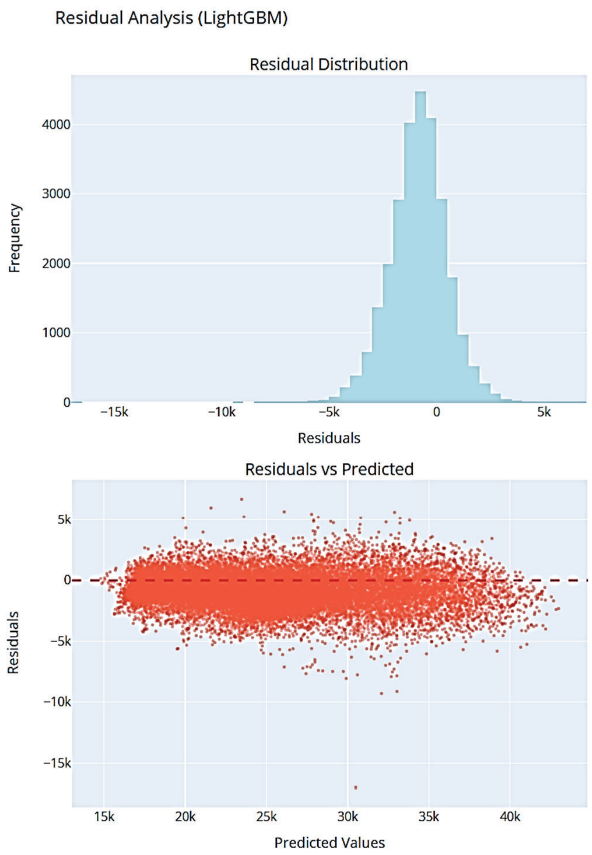

Fig. 7. Model Performance Metrics Comparison

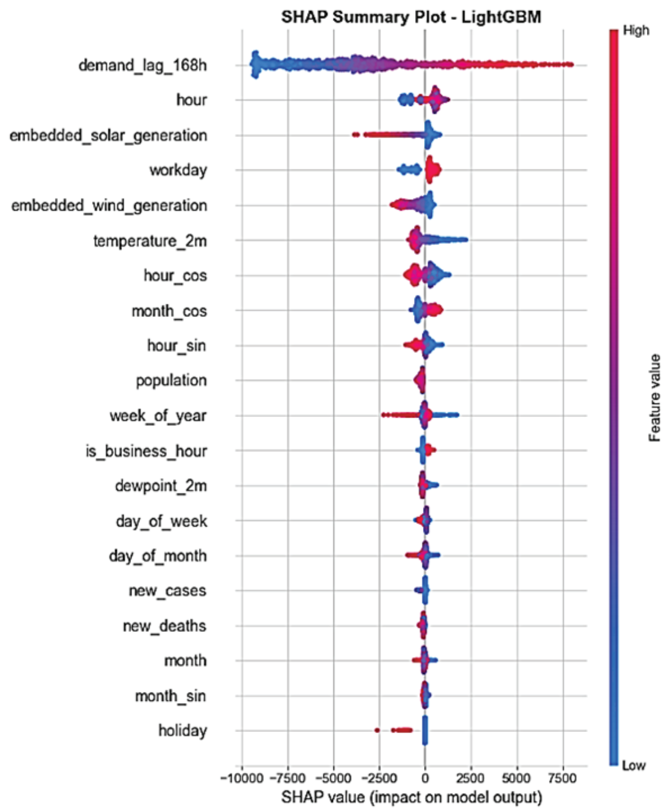

Fig. 8. SHAP Summary Plot

ods and SHAP values, strengthening confidence in the model conclusions. Temporal variables are brought forward as the most important predictors, providing confirmation of the dominant role of hourly, daily, weekly, and seasonal cycles in electricity demand. Additional explanatory power is provided by climate variables, while longer-term shifts and shock-related deviations are accounted for by economic and event-based features.

Importantly, short-term lag features were deliberately excluded by the study, even though they would have improved predictive performance in a retrospective setting, because they would not be available in a realistic operational forecasting environment. As a result, practical explainability is given priority over maximum back-tested accuracy. This makes the findings more policy-relevant because the feature set reflects information that decision-makers can plausibly know in advance. As illustrated in Fig. 9, the SHAP results therefore support the central conclusion of the study: UK electricity demand is driven by a combination of predictable temporal structure and less predictable event-based shocks, and both must be represented in future forecasting frameworks.

V. CONCLUSION

This study set out to examine how socio-economic and geopolitical events influence electricity consumption in the United Kingdom over the period 2009 - 2024, and to determine whether explainable machine learning can provide both accurate forecasts and interpretable insights for energy planning. Using a multi-source dataset that combined electricity demand, renewable generation, climate variables, economic indicators, COVID-19 measures, holiday information, and manually coded geopolitical events, the research developed a national-scale framework for analysing demand dynamics under routine and disruptive conditions. The results show that UK electricity demand is shaped by a combination of stable temporal structure and irregular external shocks. The exploratory analysis revealed strong daily, weekly, monthly, and seasonal cycles, with higher demand in winter, clear morning and evening peaks, and lower consumption during weekends. The long-term series also indicated a gradual decline in electricity demand over time, despite population growth, suggesting that improvements in energy efficiency, industrial restructuring, and renewable expansion have altered the traditional relationship between economic growth and electricity use . In addition, major events such as the COVID-19 pandemic, Brexit-related uncertainty, and the Russia–Ukraine energy crisis produced visible changes in consumption behaviour, confirming that national electricity demand is highly responsive to external disruption. Tree-based ensemble learning methods were shown to be well suited to electricity-demand forecasting in a complex, nonlinear environment. Random Forest, XGBoost, and LightGBM were assessed using time-aware validation, and

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strong performance on unseen data was achieved by all three models. The best overall predictive accuracy was delivered by LightGBM, along with the lowest error and the highest explanatory power among the models considered. The interactions among climate, calendar, renewable, economic, and event-based features in the UK electricity system are therefore suggested to be captured especially effectively by gradient-boosting approaches. More importantly, transparent evidence of the variables shaping demand changes was provided by the SHAP-based interpretability analysis, moving the model beyond pure prediction and toward explanation relevant to policy.

The main contribution of this research is threefold. First, an event-sensitive forecasting framework is introduced, and heterogeneous datasets are brought together to examine electricity demand at the national scale. Second, evidence is provided that both the magnitude and direction of demand drivers can be represented by explainable machine learning, with transparency for decision-makers improved as a result. Third, support for energy policymakers and grid operators is generated through evidence that can inform planning for shocks, demand volatility, and long-term system transitions. Taken together, the findings show that UK electricity demand should not be viewed as a smooth time series alone, but rather as a system influenced by climate, behaviour, structural economic change, and geopolitical instability.

VI. LIMITATION AND FUTURE WORK

Despite its contributions, several limitations are acknowledged in the study. Reliance is placed on secondary data from multiple public sources, creating possible differences in temporal granularity, measurement standards, and documentation quality. Although careful preprocessing and time alignment were carried out, some residual inconsistency may still remain. In addition, a degree of subjectivity is created by the manual coding of geopolitical events. The model also omits some potentially influential variables, such as electricity prices, grid constraints, fuel costs, and real-time behavioural indicators, which could further enhance forecast performance if included in future work.

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