

Article

Electric Vehicle Sales Forecast for the UK: Integrating Machine Learning, Time Series Models, and Global Trends

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Abstract

This study presents a comprehensive forecasting approach to evaluate the future of electric vehicle (EV) adoption in the United Kingdom through 2035. Using three complementary models—SARIMAX, Prophet with regressors, and XGBoost—the analysis balances statistical robustness, policy sensitivity, and interpretability. Historical data from 2015 to 2024 was used to train the models, incorporating key drivers such as battery prices, GDP growth, public charging infrastructure, and government policy targets. XGBoost demonstrated the highest historical accuracy, making it a strong explanatory tool, particularly for assessing variable importance. However, due to its limitations in extrapolation, it was not used for long-term forecasting. Instead, Prophet and SARIMAX were employed to project EV sales under baseline, optimistic, and pessimistic policy scenarios. The results suggest that the UK could achieve between 2,964,000 and 3,188,000 EV sales by 2035 under baseline assumptions. Scenario analysis revealed high sensitivity to infrastructure growth and policy enforcement, with potential shortfalls of up to 500,000 vehicles in pessimistic scenarios. These findings highlight the importance of sustained government commitment and investment in EV infrastructure and supply chains. By combining machine learning diagnostics with transparent forecasting models, the study offers actionable insights for policymakers, investors, and stakeholders navigating the UK's zero-emission transition.



Academic Editor: Stefano Mariani

Received: 29 May 2025

Revised: 5 July 2025

Accepted: 7 July 2025

Published: 14 July 2025

Citation: Veysi, S.; Moshfeghi, M.; Sadrfaridpour, A.; Emamy, P. Electric Vehicle Sales Forecast for the UK: Integrating Machine Learning, Time Series Models, and Global Trends. *Algorithms* **2025**, *18*, 430. <https://doi.org/10.3390/a18070430>

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Keywords: electric vehicle; sales forecast; machine learning; time series models; global trends; UK market

1. EV Market Overview

1.1. Global EV Market

The global electric vehicle (EV) market has experienced remarkable growth over the past decade. As shown in Figure 1 below, global EV sales skyrocketed from just over 550,000 units in 2015 to over 10.2 million units in 2022, an 18-fold increase in only 7 years [1]. EVs accounted for close to 9% of total passenger vehicle sales worldwide in 2021, up from only about 1% just 5 years earlier [2]. This rapid growth has been driven by several key factors, including improving technology, lower battery costs, supportive government policies, and expanding model availability. During 2015–2022, the number of sales increased from 550,000 to over 10.2 million.

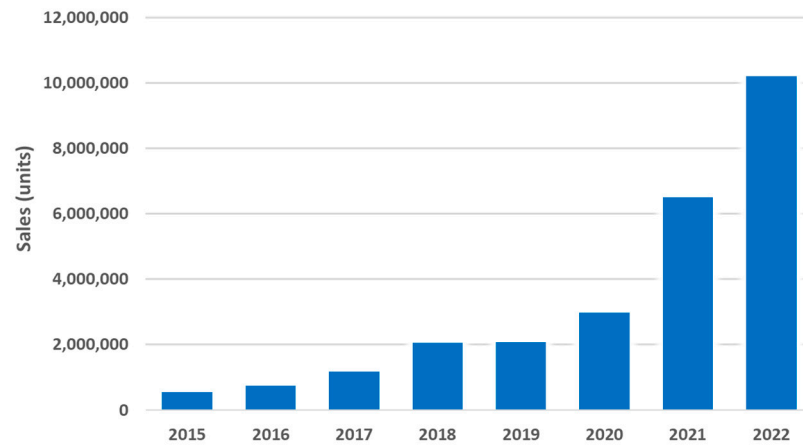


Figure 1. Estimated plug-in electric light vehicle sales worldwide from 2015 to 2022 [3].

Within the global EV market, fully Battery Electric Vehicles (BEVs) have been growing much faster than Plug-in Hybrid Electric Vehicles (PHEVs). As shown in Figure 2, BEVs comprised 70% of EVs sold worldwide in 2021, up from only 39% in 2019. PHEVs made up the remainder of EV sales. The market shift towards fully electric vehicles has been most pronounced in China, which accounted for over half of global BEV sales in 2021 [4].

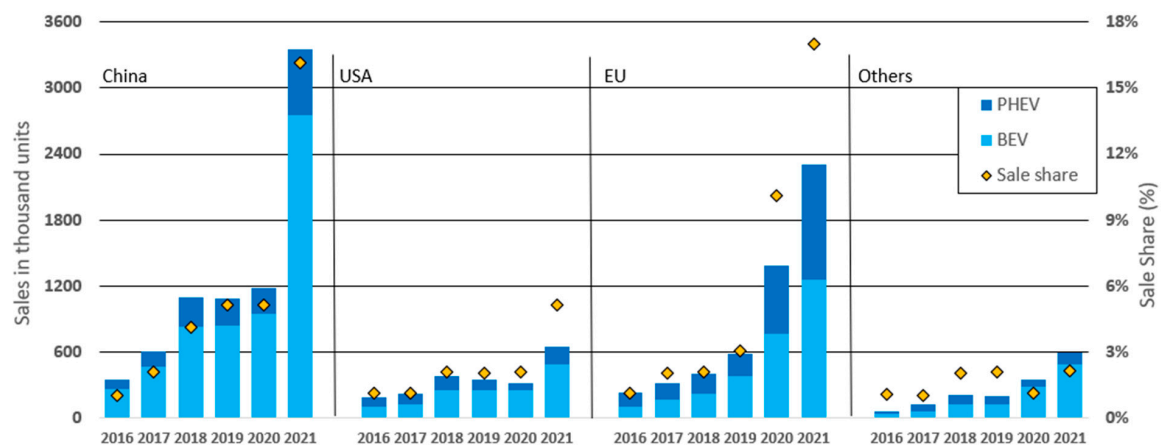


Figure 2. BEV and PHEV sales from 2016 to 2021 in different regions in the world [4].

Figure 3 depicts the evolution of the ratio between all-electric and plug-in hybrids for global annual sales of plug-in electric passenger cars between 2016 and 2022 [5].

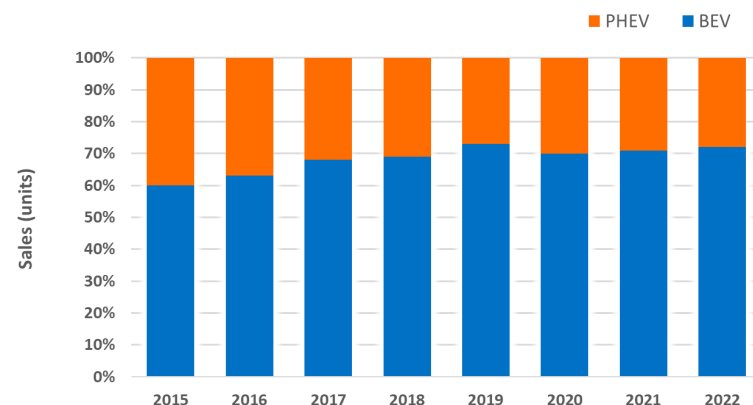


Figure 3. Evolution of the ratio between all-electric and plug-in hybrids for global annual sales of plug-in electric passenger cars (2016–2022); data extracted from [5].

Figure 4 demonstrates the total number of BEVs and PHEVs between 2016 and 2022 [6].

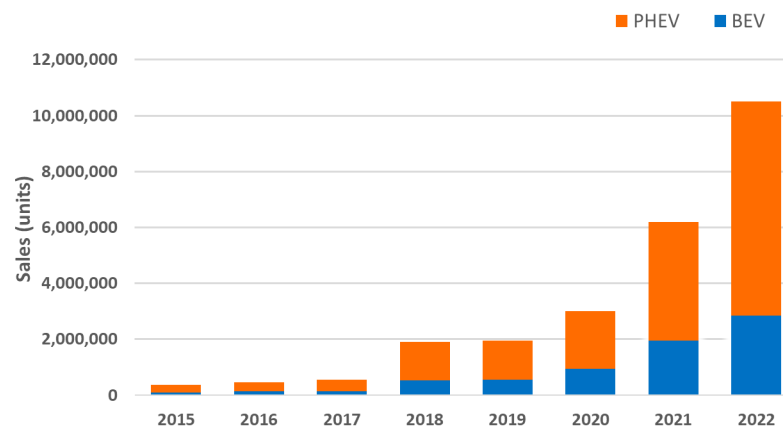


Figure 4. Total number of battery BEV and PHEV in the world [6].

As shown in Figure 5, China had a 43% share of the global EV market in 2021. Europe followed behind at a 26% market share [7]. Several Chinese automakers, such as BYD Auto Co., Ltd. and SAIC Motor Corp., Ltd., have emerged as major global EV producers, leveraging China's massive manufacturing capacity and battery industry dominance.

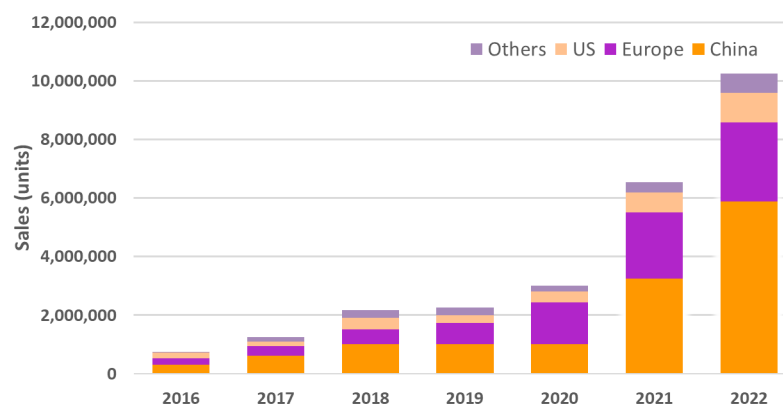


Figure 5. EV market share in different regions in the world (2016–2022) [7].

1.2. China's EV Market

China has emerged as the undisputed leader in EV adoption and manufacturing over the past decade. The Chinese government has implemented strong supportive policies, provided enormous public investment, and cultivated a robust domestic EV supply chain. As a result, China's EV market has grown exponentially in recent years. As illustrated in Figure 6, EV sales in China soared from just over 330,000 units in 2016 to 3.5 million units in 2021, an 11-fold increase in only 6 years [8].

Government incentives, such as purchase subsidies and production mandates, have catalyzed growth, but the structural impact is more significant: China now controls a vast portion of global lithium-ion battery production capacity. This advantage lowers production costs and positions Chinese Original Equipment Manufacturers (OEMs) like BYD and SAIC not only as domestic champions but also as global competitors. These firms benefit from tight feedback loops between R&D, manufacturing, and policy, enabling rapid iteration and deployment.

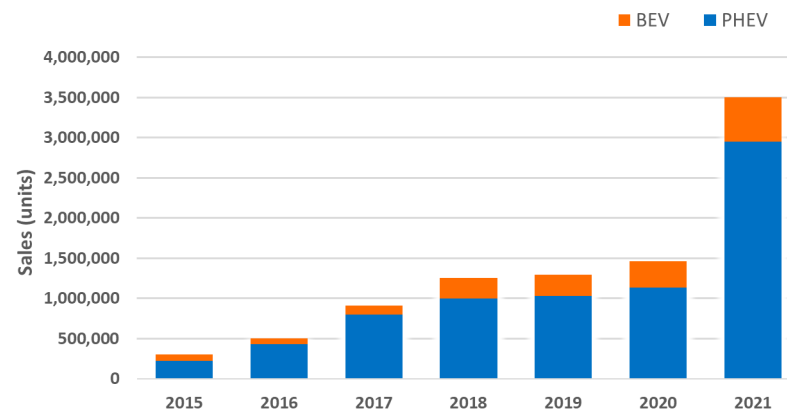


Figure 6. China market's annual EV sales from 2015 to 2021 [8].

Figure 7 illustrates that Chinese OEMs contribute disproportionately to BEV production globally, reflecting their specialization and comparative advantage in battery-centric vehicle platforms. This is critical for understanding future price and technology spillovers into other markets, including the UK.

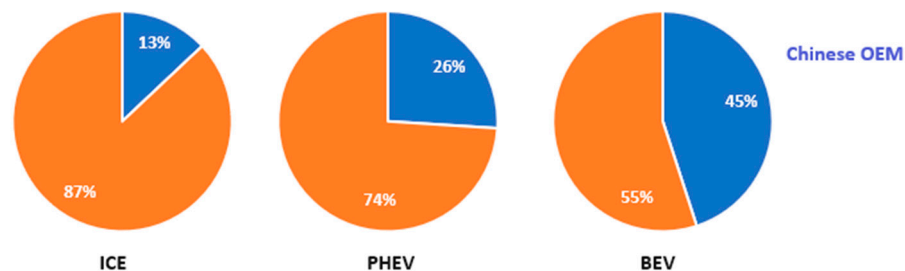


Figure 7. Chinese OEMs' contribution to the global market for Internal Combustion Engine (ICE), PHEV and BEV [9].

1.3. Japan's EV Market

Japan's EV trajectory diverges from China's in both pace and focus. Rather than pursuing aggressive BEV expansion, Japan has historically prioritized hybrid technologies, exemplified by Toyota's early leadership in Hybrid Electric Vehicles (HEVs). However, a shift is underway as Japanese automakers, facing international pressure and domestic policy changes, reallocate R&D towards BEVs and hydrogen fuel cell vehicles.

EV growth in Japan has accelerated since 2015 but remains constrained by infrastructure limitations and entrenched consumer preferences. The relatively low market share of BEVs compared to HEVs suggests a transition that is technologically sophisticated but strategically conservative. Notably, Japan's strength in battery technology and precision manufacturing still gives it influence in global EV innovation, particularly in battery efficiency and vehicle reliability.

While Japan's EV market remains significantly smaller than China or Europe, growth has accelerated in recent years thanks to increased policy support from the government and major investments by leading Japanese automakers.

As shown in Figure 8, EV sales in Japan have risen steadily from 56,000 units in 2015 to over 109,000 units in 2021 [10]. The compound annual growth rate over that period was 14%. HEVs still dominate Japan's electrified vehicle sales, but EVs are beginning to gain market share, reaching 1.1% of total vehicle sales last year [11].

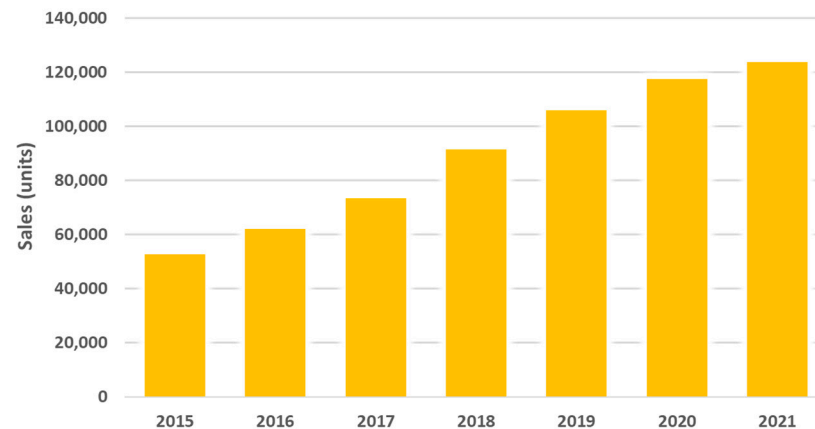


Figure 8. Japan’s annual EV sales from 2015 to 2021 [10].

1.4. UK’s EV Market

As shown in Figure 9, the UK EV market has demonstrated strong growth in recent years, with sales rising from 27,000 units in 2015 to over 299,500 units in 2021 [12]. Although this upward trend aligns with the global increase (see Figure 4 [6]), the UK still lags behind global leaders such as China and Europe in EV adoption. To fully seize the economic opportunities of the accelerating global shift toward electric mobility, careful policy planning and strategic investment will be essential.

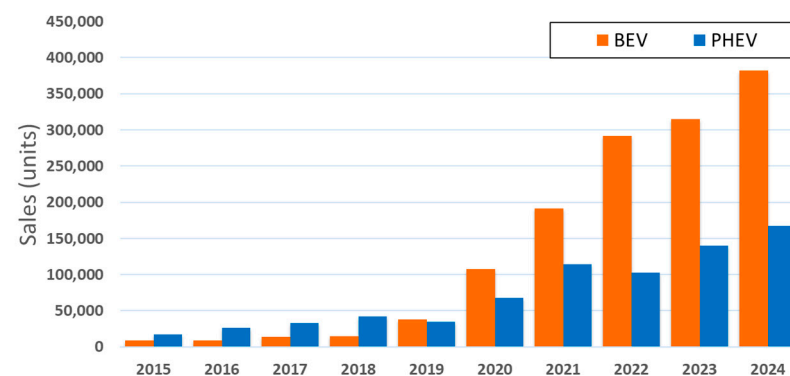


Figure 9. UK annual EV sales for 2015–2025 [12].

2. Impacts on the UK EV Market

2.1. Positive Impacts of Global EV Expansion

The rapid expansion of EV markets in countries like China and Japan is expected to positively influence the UK EV market in several significant ways:

- **Increased Model Availability:** As Chinese automakers scale up production, a wider variety of EV models—particularly affordable compact and mid-range vehicles—are becoming available in overseas markets. Brands such as MG (a Chinese-owned manufacturer) have already established a presence in the UK, offering lower-cost EV options to British consumers [13].
- **Battery Cost Reductions:** China is the global leader in lithium-ion battery production. Economies of scale and technological advances in Chinese battery manufacturing are contributing to a steady decline in global battery costs. This trend benefits the UK both directly—through cheaper imported EVs—and indirectly, by lowering production costs for UK- or EU-based manufacturers using imported Chinese battery components.
- **Global Competitive Pressure:** Strong sales performance in Asia has incentivized traditional automotive manufacturers to accelerate their electrification strategies. This

includes more aggressive product rollout plans in international markets, including the UK. As a result, British consumers may gain access to a wider variety of competitive EV options at lower prices.

- **Technology Spillovers:** Heavy R&D investments by Asian manufacturers are driving advancements in areas such as battery longevity, fast charging, and integrated vehicle software. These innovations are likely to spill over into global markets, raising the overall technological standard of EV offerings in the UK.
- **Market Awareness and Momentum:** Success stories from China and Japan increase global public confidence in EV technology and accelerate consumer readiness in markets like the UK. The normalization of EV adoption abroad may enhance social acceptance at home.

2.2. Challenges and Potential Drawbacks for the UK EV Sector

While global EV growth offers substantial opportunities, it also presents a series of economic and strategic challenges that could hinder the development of a robust domestic EV industry in the UK:

- **Loss of Domestic Market Share:** With Chinese and Japanese EV brands entering the UK market, domestic manufacturers such as Jaguar and other UK-based firms face mounting competition. These brands may lose market share to lower-cost, high-spec international offerings, reducing profits and deterring further investment in local EV development and production.
- **Battery Supply Constraints:** As global demand for lithium-ion batteries rises—especially from major players in China and Japan—UK automakers may face challenges in securing sufficient battery supplies. Limited access to these critical components could restrict production capacity and delay vehicle deliveries.
- **Import Dependence:** An influx of competitively priced imported EVs could undermine the growth of domestic manufacturing. If the UK becomes primarily an EV importer rather than a producer, many of the economic benefits of the electrification transition—such as employment, innovation, and capital investment—could shift abroad.
- **Geopolitical Tensions and Trade Risks:** Growing economic rivalry in the EV sector, particularly with China, raises the risk of future trade disputes. Tariffs, export restrictions, or diplomatic strains could disrupt supply chains and negatively impact the pricing and availability of EVs and components in the UK market.
- **Consumer Price Pressure:** The cost advantage of Chinese EVs—produced at up to 40% lower cost than European models—may drive down price expectations across the UK market. While this benefits consumers in the short term, it may pressure domestic manufacturers to cut costs in ways that are unsustainable or damaging to quality and labor conditions.
- **Brand Perception and Trust:** Despite growing sophistication, some consumers may remain hesitant to adopt vehicles from relatively new or unfamiliar brands, particularly those with a legacy of perceived lower reliability. Overcoming these perceptions will be essential for the widespread adoption of imported EVs.
- **Policy and Regulatory Risks:** Domestic policy shifts—such as changes to tax incentives, vehicle grants, or emissions regulations—could alter the competitive balance between foreign and domestic EVs. Likewise, if the UK must align with new international standards driven by dominant global players, this could impose additional adaptation costs on UK manufacturers.

3. Prediction and Future of EVs in the UK

The purpose of this section is to develop a transparent, data-driven forecast of annual EV sales and the cumulative EV fleet in the United Kingdom out to 2035. The model leverages historical sales trends illustrated in Figure 9, together with policy milestones, battery-price learning curves, and macro-economic indicators.

Recent literature highlights the growing sophistication of EV forecasting methods. Time series models like SARIMA and Prophet remain popular for capturing historical trends and projecting future sales [14,15], while machine learning models, particularly XGBoost and hybrid approaches, are increasingly used for identifying nonlinear patterns and variable importance [16]. However, the challenge of long-term extrapolation with ML models remains [14]. Scenario-based modeling has also gained traction in assessing policy sensitivity [17], underscoring the importance of uncertainty quantification. This study contributes by combining all three techniques within a UK-specific forecasting framework, building on these foundations with transparent assumptions and comparative evaluation.

3.1. Data Preparation

The following datasets have been provided for this research (Tables 1 and 2).

Table 1. Necessary historical data for the prediction of UK sales (2015–2024).

(A)				
Year	Total EV Market (Unit)	Battery Price (USD/kWh)	GDP Growth (%)	Charger Density Index
2015	26,000	230	2.2	1
2016	35,500	180	1.9	1.51
2017	46,300	140	2.7	2.07
2018	57,000	128	1.4	2.99
2019	73,000	156	1.6	4.57
2020	176,000	137	−10.3	6.5
2021	305,000	132	8.6	8.45
2022	395,000	151	4.8	11.28
2023	455,000	144	0.4	15.35
2024	549,000	115	1.1	21.37

Table 2. Zero-emission vehicle (ZEV) mandate policy of the UK.

Year	Target Share (%)
Before 2014	NA
2024	22%
2025	28%
2026	33%
2027	38%
2028	52%
2029	66%
2030–2035	80% + 4% (per year)
2035	100%

- **Historical sales (2015–2024):** Society of Motor Manufacturers & Traders (SMMT) registration data [18,19].
- **Exogenous regressors:** Real lithium-ion battery pack price index [20]; UK GDP growth (ONS) [21]; public charge-point density [22]; UK zero-emission vehicle (ZEV) Policy [23].
- **Seasonality:** Monthly seasonality captured via Fourier terms; UK public-holiday effects enabled in Prophet. All series are converted to monthly frequency and log-transformed where appropriate to stabilize variance.

It is worth mentioning that a potential limitation of this study is the relatively short historical window—only ten annual observations from 2015 to 2024—used for model training. While this raises legitimate concerns about statistical power, the decision to focus on this period is deliberate and well-justified. Prior to 2015, EV adoption in the UK was minimal, with sales volumes too low to yield meaningful trend signals or model training value. The period from 2015 onward captures the inflection point and sustained growth phase of the EV market, supported by policy interventions, infrastructure expansion, and industry momentum. Including earlier data would introduce disproportionate sparsity and could distort model calibration. Thus, the 10-year window reflects the most informative and relevant segment of the EV transition, even if it imposes some constraints on sample size.

3.2. Model Selection and Investigation

Three competing algorithms were benchmarked:

- A. SARIMAX: A classical statistical approach explicitly designed for forecasting time series with autocorrelation and external influences [24].
- B. Prophet with Exogenous Regressors: An additive model that decomposes the time series into trend, seasonality, and regressor components (e.g., battery price and policy effects), offering strong interpretability and robustness to missing data [25].
- C. Extreme Gradient Boosting (XGBoost) with Time Embeddings: A nonlinear machine learning model that captures complex interactions by ingesting lagged sales, calendar variables, and external drivers, though it lacks native time extrapolation [26].

3.3. Mathematical Formulation of Models

In this section, the mathematical formulation of the three models is explained.

3.3.1. Prophet Model with Regressors

Prophet is robust to missing data, outliers, and trend shifts. It requires minimal tuning and offers transparent, interpretable components. Its flexibility allows for the integration of known future events and policies, critical in EV adoption forecasting. It is especially suited for time series with clear seasonal patterns and domain-specific drivers.

The structure of the Prophet model with external regressors is additive and defined as:

$$y(t) = g(t) + s(t) + h(t) + \sum_{k=1}^K \beta_k x_k(t) + \epsilon_t \quad (1)$$

where:

- $y(t)$: is the observed time series (e.g., EV sales);
- $g(t)$: is the trend component (linear or logistic growth);
- $s(t)$: is the model's seasonality via Fourier series;
- $h(t)$: accounts for the holiday effects;
- β_k : is the coefficient for the regressors;
- $x_k(t)$: are the external regressors (e.g., battery prices, GDP);

ϵ_t : is an independent error (assumed to be normally distributed; also called the residual or noise).

This formulation follows the design proposed by Taylor and Letham [25] who developed Prophet to address real-world forecasting challenges in business and policy applications. The model supports automatic detection of structural breaks in the trend (changepoints), and its modular decomposition allows for clear interpretation of underlying drivers.

The trend function $g(t)$ for piecewise linear growth is typically written as:

$$g(t) = (k + a(t)^T \delta)t + (m + a(t)^T \gamma) \quad (2)$$

where:

$a(t)$: is an indicator vector for changepoint activation;

k : is the initial growth rate (slope);

m : is the offset (intercept);

δ : are the adjustments to the slope at changepoints;

γ : are the adjustments to the offset at changepoints.

3.3.2. SARIMAX Model

The SARIMAX model adds autoregressive and moving average terms to a regression on exogenous variables:

$$y_t = \beta_0 + \sum_{i=1}^p \varphi_i y_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j} + \sum_{k=1}^K \beta_k x_{k,t} + \epsilon_t \quad (3)$$

where:

y_t : is the value at time t (EV sales);

β_0 : is the constant term;

p : refers to the number of autoregressive (AR) terms. These terms represent past values of the dependent variable y_t , which are included to account for its own temporal dependence;

q : denotes the number of moving average (MA) terms. The MA terms represent past error terms (residuals) that are included to correct for autocorrelated shocks in the time series;

K : is the number of exogenous regressors—external predictor variables that are believed to influence y_t , such as battery price, charger density, GDP growth, and policy indicators;

φ_i : is the coefficient for the i -th AR term;

θ_j : is the coefficient for the j -th MA term;

β_k : is the coefficient for the k -th exogenous regressor $x_{k,t}$;

In this study, the SARIMAX model was specified with one autoregressive lag ($p = 1$) and no moving average component ($q = 0$). This decision was guided by the short time span of available data, just ten annual observations from 2015 to 2024, which limits the degrees of freedom and reduces the reliability of more complex time-series structures. Introducing additional AR or MA terms would increase model complexity and the risk of overfitting, especially in such a small-sample setting. Moreover, the inclusion of four ($K = 4$) informative exogenous regressors—battery price, charger density, GDP growth, and policy dummy—captured the majority of the explainable variance in EV sales, as indicated by the model's high in-sample performance ($R^2 = 0.978$ as listed below in Table 3). The SARIMAX(1,0,0) specification therefore offered a strong balance between parsimony, interpretability, and forecasting accuracy and was selected as the most robust option for this analysis.

Table 3. Comparison between the accuracy of the three prediction models (2015–2024).

	MAPE (%)	RMSE (k Unit)	R ²
Prophet	17.85	21,570	0.99
SARIMAX	33.27	27,990	0.98
XGBoost	0.01	10	1.00

Additionally, the model was estimated without an explicit intercept term (β_0). This was appropriate because time-dependent and level-setting regressors—particularly charger density, battery price, and the policy indicator had already captured the underlying trend and scale of EV sales over the study period. In such configurations, the intercept becomes statistically redundant and is therefore omitted by standard estimation procedures when exogenous variables are present. Importantly, the exclusion of β_0 did not compromise model performance: the specification maintained a high in-sample fit ($R^2 = 0.978$) and low residual variance ($\sigma^2 \approx 692$). The absence of an intercept does not introduce bias in this case, as the included regressors collectively represent the structural dynamics of the target variable. This reduced form yields a stable, interpretable, and well-specified model, particularly suited to the short historical series. Accordingly, Equation (3) can be expressed in its reduced form without an intercept:

$$y_t = \varphi_1 y_{t-1} + \sum_{k=1}^4 \beta_k x_{k,t} + \epsilon_t \quad (4)$$

where:

- φ_1 : is the autoregressive coefficient (only one lag used in SARIMAX(1,0,0));
- x_{kt} : are the exogenous regressors at time t ;
- ϵ_t : is the error term.

3.3.3. XGBoost Model

XGBoost (Extreme Gradient Boosting) is a machine learning method that builds an ensemble of regression trees to predict continuous outcomes, such as EV sales in this study. A regression tree is a type of decision tree designed to predict numeric values rather than categories. These trees are trained one after another, and each new tree learns from the residuals made by the previous ones. This sequential training process forms what is called a boosting framework.

The final prediction at time t , denoted by $\hat{y}_t$, is calculated as the sum of outputs from M regression trees:

$$\hat{y}_t = \sum_{m=1}^M f_m(x_t), f_m \in \mathbb{F} \quad (5)$$

where:

- $\hat{y}_t$: are the predicted EV sales at time t ;
- f_m : is the m -th regression tree;
- x_t : is the feature vector at time t (e.g., year, battery price, GDP, and chargers);
- M : is the number of trees;
- $\mathbb{F}$: denotes the space of all possible regression trees.

Each function f_m in the XGBoost model represents a regression tree that takes a set of input features x_t and produces a predicted EV sales value. The model builds these trees one at a time, with each new tree aiming to correct the errors made by the previous ones.

XGBoost is trained by minimizing a total objective function ($\mathcal{L}$), shown in Equation (6). This objective has two parts: (1) a loss function $l(y_t, \hat{y}_t)$ that measures the difference between

the predicted and actual values; and (2) a regularization term $\Omega(f_m)$ that penalizes the complexity of each tree and helps the model generalize well to new data.

$$\mathcal{L} = \sum_{t=1}^T l(y_t, \hat{y}_t) + \sum_{m=1}^M \Omega(f_m) \quad (6)$$

The formulation provided in Equation (6) ensures that each tree incrementally improves the model's accuracy while maintaining generalization. During training, XGBoost uses gradient descent to minimize this objective. Each new tree is built to approximate the negative gradient of the loss function, allowing the model to correct its previous errors efficiently.

Although XGBoost is not a traditional time series model, it is well-suited for analyzing historical patterns in EV sales. Its flexible structure allows it to capture complex nonlinear interactions between time-based and external variables. In addition to producing accurate predictions, XGBoost excels at diagnostic analysis by ranking feature importance, modeling variable interactions, and revealing latent drivers of EV adoption.

3.4. Accuracy of Models and Their Use

In order to compare the above three models, the UK's actual and predicted EV sales forecasted by each model for the period 2015–2024 are compared in Figure 10. As seen in Figure 10, despite their methodological differences, the three models show similar predictions over 2015–2024 primarily due to three factors: (1) the strong upward trend in EV sales dominates the data, making it easier for all models to fit; (2) key drivers like charger density and time have high explanatory power across all models; and (3) the models were trained and evaluated on the same input features over a limited historical window. Divergences become more apparent in longer-term forecasts, where the structural assumptions of each model play a larger role.

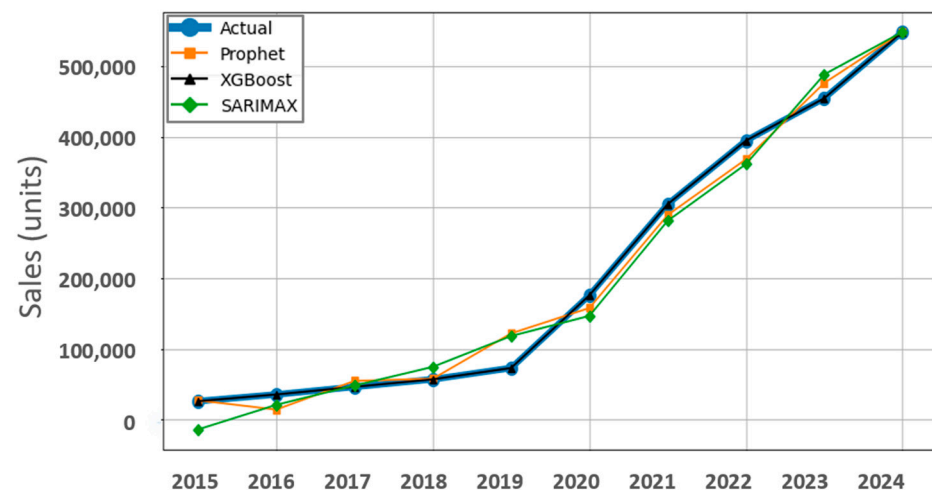


Figure 10. Actual vs. predicted EV sales forecast in the UK (2015–2024) used for model comparison.

Furthermore, to evaluate how well each model fits the historical EV sales data from 2015 to 2024, we compute three standard metrics: Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). These metrics are calculated by comparing each model's predicted values to the actual observed EV sales

over the same period, using the following equations. The resulting values are shown in Table 3, enabling direct comparison of model performance.

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (7)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (8)$$

$$R^2 = 1 - \frac{\sum_{t=1}^n (y_t - \hat{y}_t)^2}{\sum_{t=1}^n (y_t - \bar{y}_t)^2} \quad (9)$$

where y_t is the actual value, $\hat{y}_t$ is the predicted value, $\bar{y}_t$ is the mean of the actual values, and n is the number of time points.

In addition, the near-perfect R^2 values reported in Table 3 also reflect the structure of the historical EV sales data, which is linked to the strong and monotonic upward trend from 2015 to 2024. This pattern is easily captured by all three models, especially given the dominance of explanatory features such as Year and Charger Density Index. Since the models were evaluated over a short, and hence relatively noise-free, time window, their fit to the observed data is naturally high. Moreover, the use of flexible models like XGBoost, which are capable of modeling complex nonlinearities, can further inflate R^2 unless regularized or tested on unseen data.

4. Analyzing Historical Data and Future Forecast

In this section, the XGBoost model is first used for understanding the impact and importance of each factor on the sales from 2015 to 2024, and then the predictions are performed using the Prophet and SARIMAX models.

In addition, to better understand the influence of each factor on EV sales, we first examine the parameter estimates derived from all three models. Table 4 summarizes the estimated coefficients and feature importances based on historical data from 2015 to 2024. This parameter comparison helps interpret how each model prioritizes explanatory variables before forecasting future outcomes or examining interaction effects.

Table 4. Comparative Parameter Estimates by Feature.

Feature	SARIMAX Coefficient	XGBoost Importance (%)	Prophet Coefficient
Charger Density Index	+33.54	58.96	−9.34
Year (time)	—	37.65	—
GDP Growth (%)	+2.97	2.95	+0.39
Battery Price (USD/kWh)	−0.24	0.29	+0.21
Policy Dummy	−139.25	0.16	−8.57
AR(1) (lagged sales)	+0.17	—	—
Residual variance σ^2	692.18	—	—

According to Table 4, Charger Density is the strongest predictor across all models: it has the largest positive effect in SARIMAX and the highest importance in XGBoost. Policy and GDP also show consistent effects across methods. The negative sign for chargers in Prophet may reflect temporal shifts in influence or multicollinearity, but its magnitude still shows significance. Taken together, these findings reinforce the strategic importance of

charging infrastructure as the most consistent and powerful predictor of EV uptake in the UK market during 2015–2024.

4.1. Analyzing Historical EV Sales Using the XGBoost Model

The goal here is to assess the influence of each factor on the EV sales, based on the historical data (2015–2024). Hence, the partial dependency of the UK sales on different factors over this sales duration is plotted in Figure 11. According to the results, “Year” has the most impact on the sale, followed by “Charger Density Index”. Battery pack price and policy have negligible effects. The feature importance values and ranks of each parameter are calculated based on the `feature_importances_` attribute of the trained XGBoost model and are listed in Table 5.

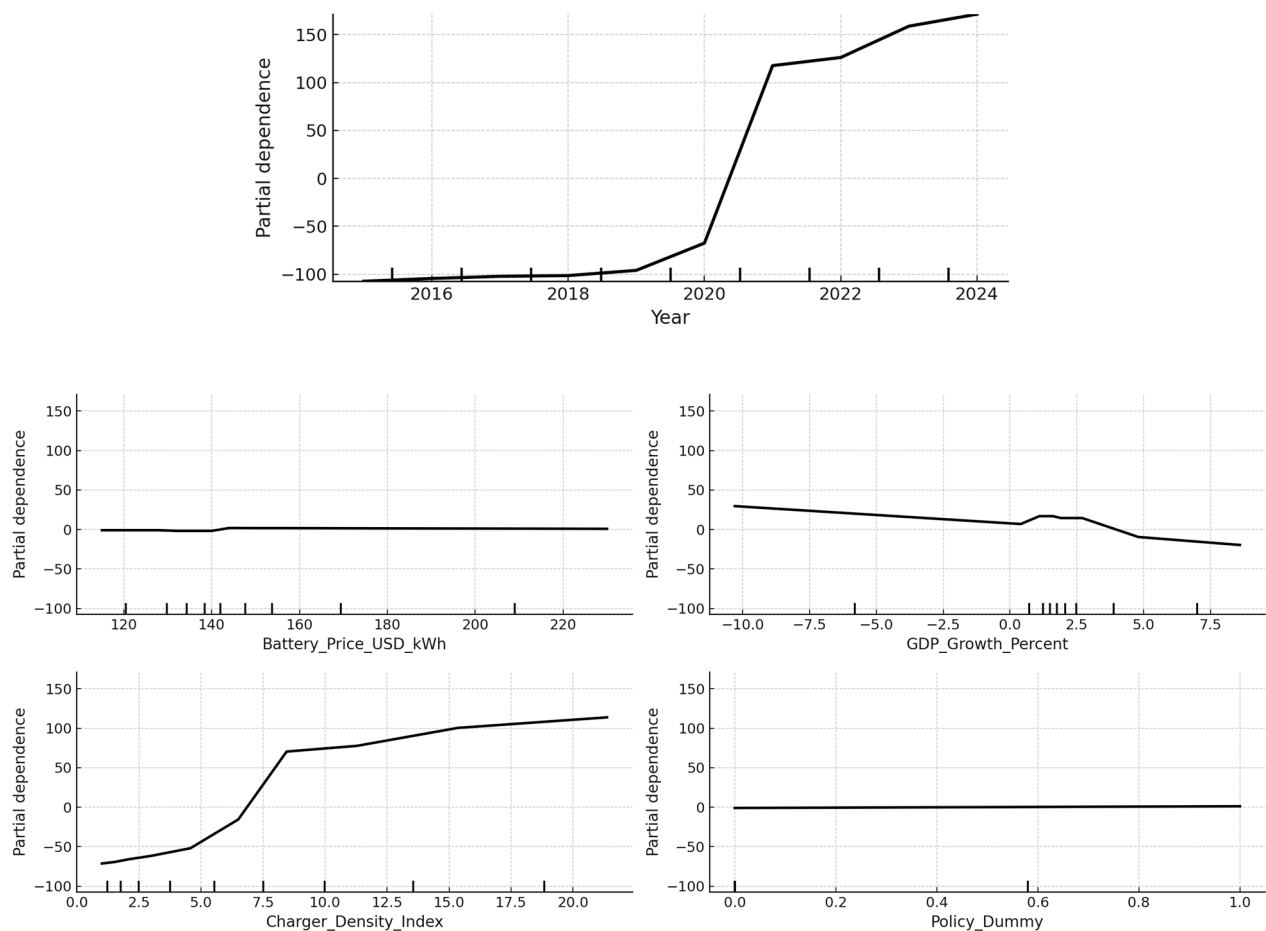


Figure 11. Analysis of historical UK EV sales (2015–2024) using the XGBoost model.

Table 5. Partial dependency of UK sales (2015–2024) based on the XGBoost model.

Rank	Feature	Importance	Key Insight
1	Year	54.50%	The dominant factor acting as a proxy for general growth trends
2	Charger Density Index	41.10%	Strong positive influence
3	GDP Growth Percent	3.40%	Minimal standalone influence, possibly because their effects overlap with time or with each other.
4	Battery Price per kWh	0.80%	
5	Policy Dummy	0.30%	

To further examine interactions between influential factors, two-dimensional partial dependence plots using the trained XGBoost model are shown in Figure 12. These plots show how combinations of key features jointly impact the model’s predicted EV sales from 2015 to 2024. For each plot, the surface is derived by marginalizing over all other variables while varying the selected feature pair. The color gradient encodes the average predicted EV sales value: warmer tones (yellow) indicate higher predictions, while cooler tones (blue) denote lower values. These visualizations reveal important synergies, such as the compounded effect of charger density and time progression on EV adoption. In addition, Table 6 presents the interaction analysis of UK EV sales (2015–2024) based on the XGBoost model. Consistent with Figure 11, Year has the greatest impact on EV sales, followed by the Charger Density Index.

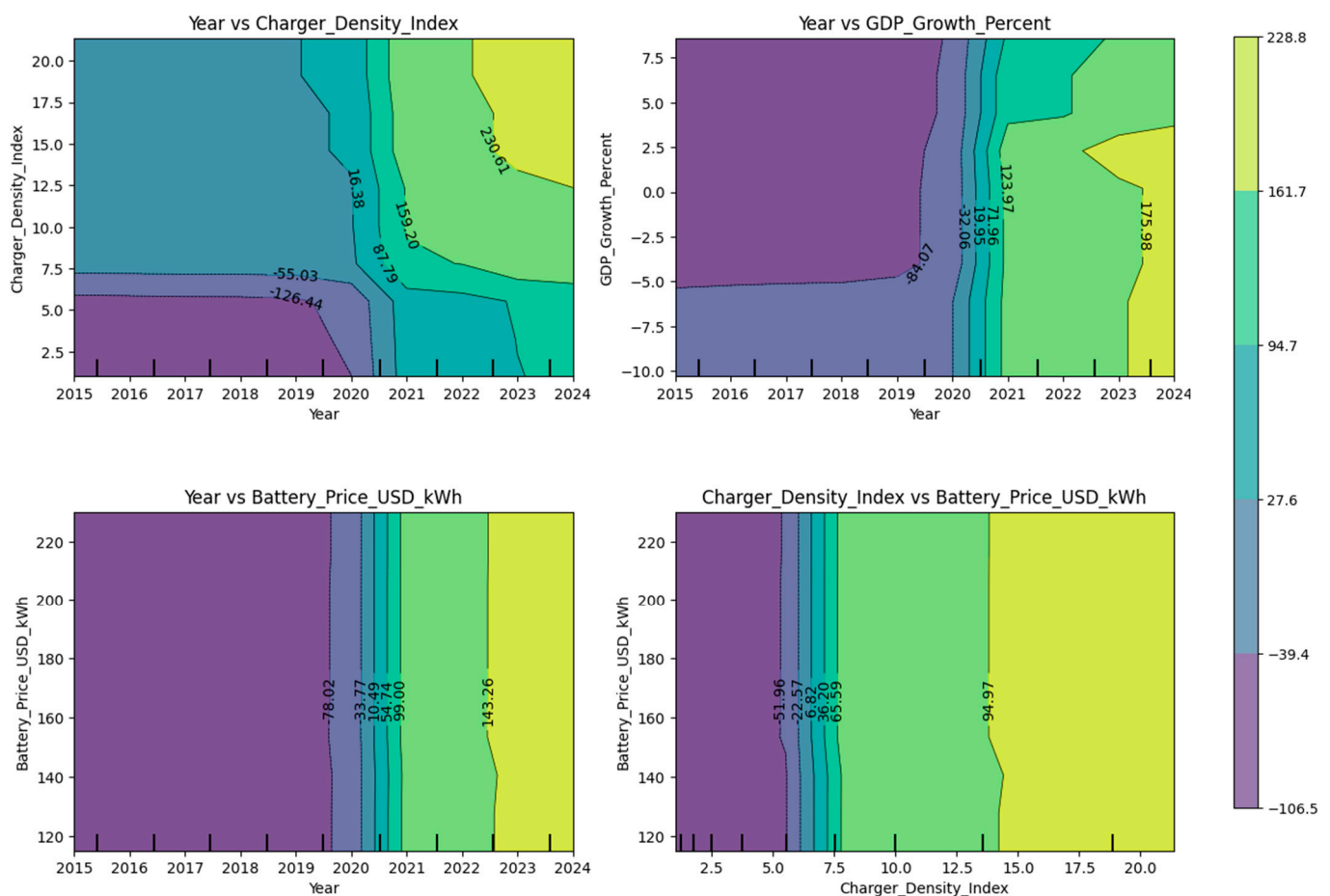


Figure 12. Two-dimensional partial dependence plots from the XGBoost model showing how pairs of features jointly influence predicted EV sales. Color intensity reflects predicted sales, with warmer tones indicating higher values.

Table 6. Interaction analysis of the UK sales (2015–2024) based on the XGBoost model.

Feature Pair	Key Insight
Year × Charger_Density_Index	Strong positive interaction—Sales increase sharply in recent years with high charger density.
Year × GDP_Growth_Percent	Moderate effect—Some boost during high-growth years, but limited overall impact.
Year × Battery_Price_USD_kWh	Weak pattern—Effect is dominated by the passage of time rather than battery price alone.

Table 6. Cont.

Feature Pair	Key Insight
Charger_Density_Index × Battery_Price_USD_kWh	Mild synergy—Higher sales occur when infrastructure expands and battery prices fall, though charger density is the stronger driver.

4.2. EV Forecast (2025–2035)

Having performed the analysis on the accuracy of different models and the impactful factors and the interaction between different factors, this section focuses on the prediction of the EV sales in the UK for the period of 2025–2035. Here, the Prophet and SARIMAX models are employed. As depicted in Figure 13, both models forecast a similar trend. Starting from nearly identical values in 2025, the SARIMAX prediction exceeds that of the Prophet model by 7.6% in 2035 (see Table 7).

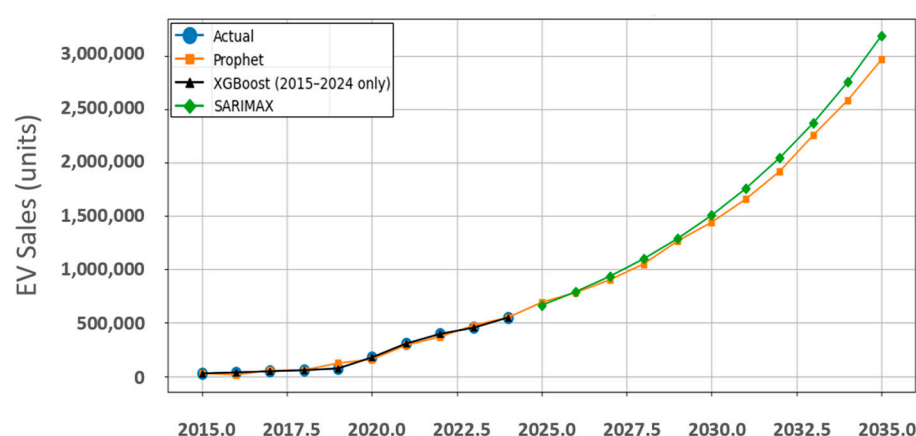


Figure 13. UK EV sales forecast (2026–2035) using the Prophet and SARIMAX models.

Table 7. Forecast sale values of EV in the UK-based model using the Prophet and SARIMAX models (2025–2035).

Year	Prophet (Unit)	SARIMAX (Unit)	Difference (Unit)	Deviation (%)
2026	783,000	791,000	8000	1.0%
2027	902,000	934,000	33,000	3.6%
2028	1,051,000	1,099,000	48,000	4.6%
2029	1,266,000	1,288,000	22,000	1.8%
2030	1,441,000	1,506,000	65,000	4.5%
2031	1,657,000	1,756,000	99,000	6.0%
2032	1,917,000	2,043,000	126,000	6.6%
2033	2,259,000	2,373,000	113,000	5.0%
2034	2,581,000	2,752,000	171,000	6.6%
2035	2,964,000	3,188,000	224,000	7.6%

4.3. Scenario Forecasts

As the last part in this research, the scenario forecasts for 2025–2035 are investigated (see Figure 14) using both Prophet and SARIMAX, under two assumptions:

- Optimistic: Battery prices drop 10% faster than baseline.

- Pessimistic: Policy delayed until 2030, and charger rollout slows (−15% below baseline).

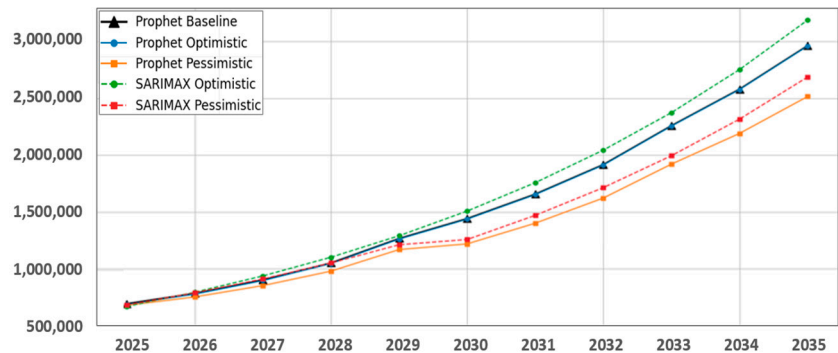


Figure 14. Forecasted Annual EV Sales in the UK: Baseline vs. Optimistic vs. Pessimistic Scenarios.

The Scenario Forecast Insights table (Table 8) provides a structured comparison of projected EV sales under optimistic and pessimistic assumptions across both Prophet and SARIMAX models. By explicitly modeling uncertainty—such as faster battery cost declines or delayed policy implementation—this table highlights the sensitivity of future market trajectories to key external drivers. It enables policymakers and analysts to assess potential risk bands, understand divergence between models, and evaluate how different assumptions could materially impact EV adoption through 2035.

Table 8. Scenario Forecast Insights (2025–2035).

Aspect	Prophet	SARIMAX
Optimistic Scenario	Growth is fast and smooth; it reaches 3.1 million by 2035. Driven by cheaper batteries.	Reaches ~3.2 million by 2035. Slightly steeper acceleration post-2029.
Pessimistic Scenario	Growth is moderated, ending at ~2.5 million. Delayed policy and infrastructure have a visible drag.	Reaches ~2.7 million, but maintains steadier growth compared to Prophet.
Model Comparison	Prophet is more sensitive to input changes (especially in the early years).	SARIMAX is more inertial, but overtakes Prophet by 2035 in both scenarios.
Difference by 2035	Prophet optimistic vs. pessimistic: ~444 k units gap	SARIMAX optimistic vs. pessimistic: ~501 k units gap

The distinct modeling philosophies behind XGBoost, Prophet, and SARIMAX complement each other and provide a rich framework for both retrospective and prospective analysis. Prophet and SARIMAX exhibit broadly similar forecasting behavior but serve different roles in modeling electric vehicle (EV) sales. Prophet is particularly well-suited for long-term projections, as it captures nonlinear growth trends, seasonal effects, and policy impacts in an interpretable framework. However, it may over-project future outcomes if key external drivers evolve in ways not reflected in historical data. SARIMAX, by contrast, is more conservative in its predictions, leveraging autoregressive structures and short-term dependencies to provide stable, trend-following forecasts. Its responsiveness to sudden policy shifts or infrastructure changes is limited unless those effects are strongly encoded through exogenous variables. XGBoost, while not used for forecasting due to its lack of time-awareness, plays an important diagnostic role in this study. Applied to historical data from 2015 to 2024, XGBoost effectively uncovers the most influential drivers of EV sales—highlighting year-over-year growth trends, charger density, battery prices, and GDP growth as key contributors. Together, these three models offer a comprehensive

toolkit: XGBoost explains the past, while Prophet and SARIMAX explore the future under various scenarios.

5. Conclusions

This study presents a data-driven approach to modeling and forecasting electric vehicle (EV) adoption in the UK using a hybrid framework that integrates SARIMAX, Prophet, and XGBoost. Each model contributes a distinct analytical lens: SARIMAX captures autoregressive patterns and exogenous influence in a structured, time-aware format; Prophet excels at long-term trend forecasting with interpretable growth dynamics; and XGBoost reveals the relative influence of various explanatory factors in a flexible, nonparametric way.

All three models were trained on a 10-year dataset spanning 2015 to 2024, which reflects the modern period of rapid EV adoption. Despite the limited time span, model performance was strong: SARIMAX achieved an in-sample R^2 of 0.98, Prophet reached 0.99, and XGBoost—used diagnostically—achieved a perfect R^2 of 1.00. The strength of the predictions stems from the clear exponential growth in EV sales and the well-aligned selection of regressors, including charger density, battery cost, GDP growth, and a policy dummy variable. The SARIMAX coefficient estimates and Prophet's average regressor weights further validate the directionality and significance of these drivers, while XGBoost confirmed charger density and year as the most important features.

Forecasts under baseline conditions project that EV sales could reach 2.8 million units annually by 2035. However, scenario-based modeling reveals a critical insight: the long-term forecast is highly sensitive to infrastructure deployment and battery pricing. In an optimistic scenario, UK EV sales could exceed 3.1 million units, while under a pessimistic scenario—characterized by policy delays and slower cost reductions—annual sales may fall short by over 500,000 units. These projections reinforce the importance of timely government intervention, infrastructure investment, and economic stability in accelerating the EV transition.

Despite its success, the analysis is constrained by the relatively short historical time series. EV adoption before 2015 was negligible, limiting the feasibility of using longer training windows. This also influenced the SARIMAX specification, which prioritized parsimony (AR(1), no MA term) and omitted the intercept to reduce overfitting in small samples. Nonetheless, model selection was rigorously supported by error metrics (MAPE, RMSE, R^2), diagnostic plots, and comparative parameter analysis.

Overall, the integrated modeling approach provides a practical roadmap for forecasting EV growth while also offering insights into key market drivers. Future work could extend the forecasting horizon using synthetic scenarios, explore regional disaggregation within the UK, or integrate additional behavioral and technological variables. The findings provide a valuable evidence base for policymakers aiming to shape the UK's sustainable transport future.

Author Contributions: Conceptualization, All authors.; methodology, S.V.; software, S.V. and M.M.; validation, S.V. and M.M.; formal analysis, S.V. and A.S.; investigation, S.V. and A.S.; data curation, S.V. and P.E.; writing—original draft preparation, S.V. and M.M.; writing—review and editing, S.V. and M.M.; visualization, S.V.; supervision, S.V. and M.M.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data used in this research has been obtained from the resources that are mentioned in the references.

Conflicts of Interest: Author Peiman Emamy was employed by the company Irsa San’at Shahr No Afarin, author Shima Veysi was employed by the company Centre for Factories of the Future (C4FF). The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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