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# Technical performance evolution of BEVs: range, consumption and weight projections to 2050

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ABSTRACT

Battery Electric Vehicles (BEVs) are assuming a pivotal role in the road electrification, with continuous advancements in technology. This UK-focused study analyses the evolution of the technical parameters of BEVs between 2011 and 2024 and forecasts their development to 2050 for a range of scenarios (pessimistic, realistic and optimistic) focusing on range, energy consumption and vehicle weight. The research is underpinned by a data set of the technical specifications of 575 BEV models. The relationships between the parameters were revealed by machine learning (Random Forest and SHAP), with the forecast performed using the Prophet. The driving range of a typical C segment Sports Utility Vehicle (SUV) is forecast to increase by between 60 % and 180 %, vehicle weight and energy consumption varied between 1051–2000 kg and 267–286 Wh/mile, respectively, depending on the scenarios and underlying assumptions. The findings provide evidence-based insights for automotive technology planning and weight-based fiscal policy responses.

## 1. Introduction

The increase in air pollution on a global scale is causing severe and irreversible damage to human health and the environment. Transportation-related air pollution and the effects of greenhouse gas (GHG) emissions on human and environmental health have been extensively researched for many years (Anenberg et al., 2019; Colvile et al., 2001; Kampa and Castanas, 2008; Mehlig et al., 2023; Ramanathan and Feng, 2009). Road transportation is a key contributing source to global GHG emissions, estimated at 11.9 % (Ritchie, 2020). Battery electric vehicles (BEVs) have emerged as a potential technological solution to the Grand Societal Challenge (GSC) of global warming (Voegtlin et al., 2022).

This study aims to analyse the historical development of BEV technical characteristics to aid predicting their future evolution. The analysis focuses on the UK market to ensure data homogeneity. The study has three main objectives: (1) to examine the evolution of the technical parameters of BEVs between 2011 and 2024 in the UK market, (2) to identify the key variables and their relationships, and (3) to forecast the evolution of battery development to 2050 under a range of scenarios (pessimistic, realistic optimistic scenarios). In the scenarios, different vehicle weight, target range, vehicle battery weight ratio assumptions are analysed. An underlying aim of the forecasting and analysis is to start to shape evidence to inform discussions of industry and politicians, as to the likely environmental impacts of scaling up BEV manufacture and use.

The paper is structured as follows: Section 2 is a literature review of the historical development of BEVs and the battery

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technologies. Section 3 details the methodological approach and dataset characteristics; section 4 presents the research findings and the development of the technical characteristics of BEVs over the period 2011–2024 and the projections for 2050 under different scenarios. The fifth section discusses the analysis and findings, and policy and further study recommendations are made. In the conclusions, the implications of the study's results and findings for future research and policy are set out.

## 2. Literature review

In the late 19th century, BEVs actually started to develop earlier than Internal Combustion Engine Vehicles (ICEVs) (Corrigan, 2022). However, in the early 20th century, Henry Ford's mass production of the Model T caused a revolutionary change in the automotive market. Following this development, oil deposit discoveries facilitated greater access to liquid fuels and contributed to lower prices (Bin Ahmad et al., 2022). The fact that petrol has a higher energy density compared to batteries in this era, in part resulted in BEVs being overshadowed for a long time (DOE, 2014; Harding, 1999). It was not introduced again until 1990 when car manufacturers responded to the California Air Resources Board's (CARB) initiative for more efficient, lower emission vehicles (Sperling and Gordon, 2009). The launch of Tesla's Roadster in 2008 was a pivotal turning point for BEVs and ensured that BEVs entered the roads permanently (Schreiber et al., 2024).

Although the 2008 Tesla Roadster model was an important milestone for BEVs, it did not become widespread among consumers immediately due to its relatively high cost to ICEVs. Its status as a high-performance luxury vehicle limited its market reach, enabling the way for other manufacturers to develop more affordable and practical BEVs for mass adoption (Milosheska, 2013). The Mitsubishi i-MiEV is the first mass-produced BEV (Jha, 2009). It was launched in the UK market in January 2011. Following the i-MiEV, the Peugeot iOn and Citroen C-Zero were also launched in the UK in the same period. However, all three vehicles were in the mini-BEV (A segment) (EV Database, n.d.). Unlike these small urban vehicles, the Nissan Leaf was launched in the UK in March 2011 as a Full-size BEV. It marked a significant milestone as the first mass-market full-size BEV (Carranza et al., 2014; Nakada and Nakazawa, 2013). The Nissan Leaf offered comparable price and performance features to C segment ICEVs, while drawing a much cleaner environmental image. However, when compared to similarly sized ICEVs such as the Vauxhall (Opel) Corsa, it exhibited longer re-energising time, shorter range on a full tank/charge and had approximately twice the kerb weight (Parkers.co.uk, n.d.a).

Since 2011, many more new models have been introduced in the UK. By 2024, 575 BEVs were available for sale. By the end of 2023, BEVs accounted for 16.5 % of newly registered vehicles in the UK (DfT, 2024) (See Fig. 1). During this period, mini BEVs sales have been over-taken by the C (Small Family Car) and D (Large Family Car) segments. The market share of SUV vehicles, which benefit from optimal battery placement and increased carrying capacity capabilities, continues to be preferred by consumers.

The shift in trends of BEV segments has led to a significant increase in vehicle weights. It is a source of concern for vulnerable road users, is considered to increase road degradation and associated non-exhaust particulate matter. Countries such as France, Norway, Switzerland and Estonia have introduced weight-based taxation to try and address these concerns, whether BEVs or ICEVs (See Fig. 2) (Nix, 2024). While France, Norway and Estonia tax vehicle weight on first registration, Switzerland these taxes are applied annually. As vehicle weights increase, the amount of tax to be paid gradually increases in each country. As part of BEV incentive frameworks, governments implement lower weight-based taxation for BEVs compared to ICEVs, despite BEVs' higher weight resulting from their battery systems (Wohlschlager et al., 2024). However, the gross vehicle weight for BEVs remains at 3500 kg (UK Government, n.d.).

Despite the increase in the number of BEVs (IEA, 2024a), electric vehicles have not yet been fully accepted and become the primary mode of road transportation. Potential users indicate high initial costs, inadequate charging infrastructure, long charging times and limited range as the main adoption barriers (Fei et al., 2025; Guo et al., 2024; Li et al., 2023; Lv et al., 2024; Naseri et al., 2023; Thorhauge et al., 2024). Battery technology development plays a critical role in potentially overcoming these obstacles.

Lithium-ion battery technology is systematically improving with time, as research and development has increased the gravimetric energy density from 150 Wh/kg in 2010–2011 to 250–260 Wh/kg in 2024. However, this technology is expected to reach its

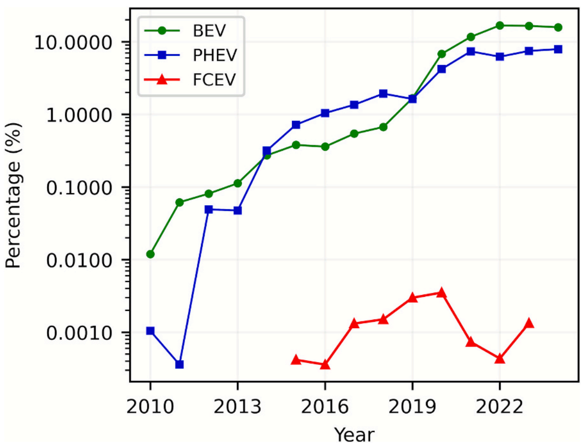


**Fig. 1.** Percentages of sales of electric vehicle types in the UK between 2010 and 2024 (Authors' analysis based on data from IEA, 2024a .

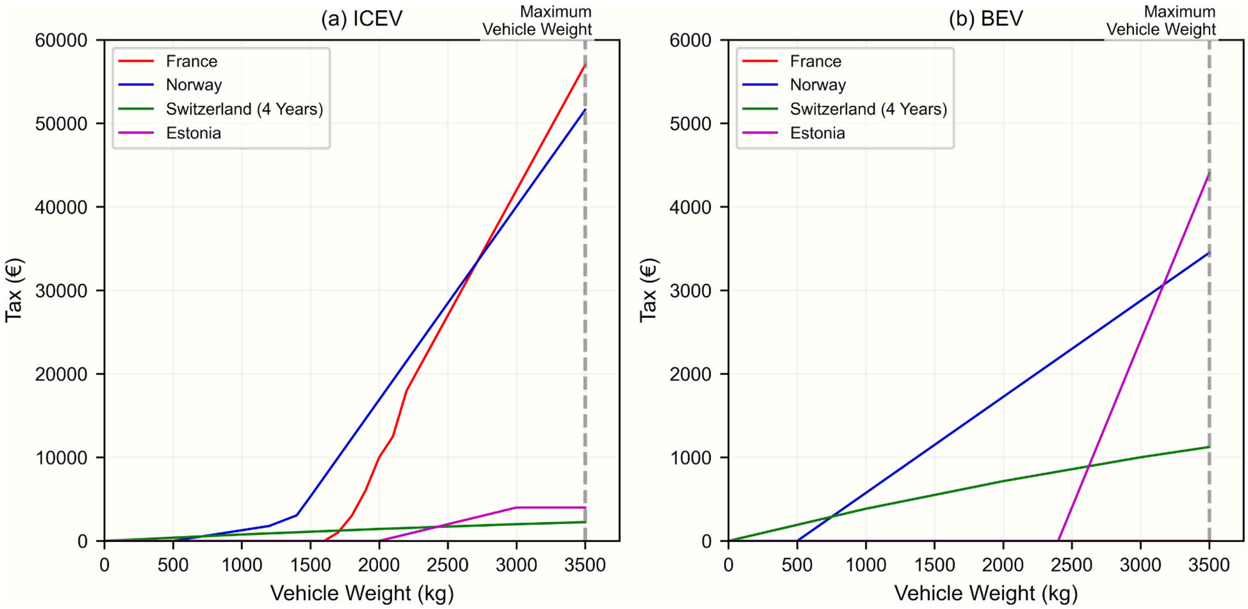


**Fig. 2.** Vehicle weight taxation in France, Norway, Switzerland and Estonia (Authors' analysis based on data from (Nix, 2024)).

physicochemical limit of approximately 350 Wh/kg by 2030–2035 (Janek and Zeier, 2023; König et al., 2021). Alternative technologies with higher energy density, such as solid-state batteries (SSB) are also being developed and are close to mass production (Joshi et al., 2025). Theoretically, SSBs have a gravimetric energy density of 393 Wh/kg (Deng et al., 2020; Janek and Zeier, 2016). However, as this technology is in an early stage of development, they are expected to achieve energy densities of 500 Wh/kg in the future (He et al., 2021). The use of organic electrode materials may more than double this to 1,200 Wh/kg (Zhao et al., 2021).

Whilst there are numerous approaches and innovations to the physical structure and chemistry of batteries, it is suggested there is an underlying, systematic improvement in specifications with time, gaining higher energy densities per unit of weight and volume, using less critical materials. The expected evolution of battery technology, from current lithium-ion to future solid-state batteries, is just one-step in the development trajectory of BEVs.

## 3. Methodology

### *3.1. Data Collection*

A dataset of the technical specification of 575 BEVs available in the UK market between 2011 and 2024 was compiled (European Commission, 2024; EV Database, n.d.). The temporal distribution of the dataset is predominantly weighted towards recent vehicles: of the total 575 models, 502 (87 %) are from the 2020–2024 period, 57 (10 %) from 2016 to 2019, and only 16 (3 %) from 2015 and earlier (Table 1). The variables in the dataset are year of availability, manufacturer, model, segment, car body, energy consumption, range, charging time, battery capacity (Useable and Nominal), charging power, fast charging power, weight, dimensions (length,

**Table 1**
Dataset distribution.

| Year | Vehicle numbers | Percentage |
|---|---|---|
| 2011 | 4 | 0.7 % |
| 2012 | 0 | 0.0 % |
| 2013 | 3 | 0.5 % |
| 2014 | 4 | 0.7 % |
| 2015 | 5 | 0.9 % |
| 2016 | 9 | 1.6 % |
| 2017 | 14 | 2.4 % |
| 2018 | 12 | 2.1 % |
| 2019 | 22 | 3.8 % |
| 2020 | 51 | 8.9 % |
| 2021 | 87 | 15.1 % |
| 2022 | 99 | 17.2 % |
| 2023 | 111 | 19.3 % |
| 2024 | 154 | 26.8 % |

width, height), top speed, total torque, total power, and acceleration.

The dataset comprises range data from New European Driving Cycle (NEDC) and Worldwide Harmonised Light Vehicles Test Procedure (WLTP) tests. Manufacturers declared ranges using NEDC tests until 2017, which were fully replaced by WLTP from early 2019. Where both were reported, NEDC yielded 10–25 % higher values than WLTP. Moreover, real-world BEV range varies significantly across conditions and differs from test data (Al-Wreikat et al., 2022, 2021). To reflect real-world conditions and account for temperature and driving variations, EV Database (n.d.) Real Range values were used instead of manufacturer-reported test results. Real Range methodology averages multiple driving conditions (cold, mild, motorway, urban) and provides adjusted estimates, thereby eliminating inter-test variability whilst adapting values to real-world usage.

This data was supplemented with details of the battery specification i.e., battery weight was derived by dividing the battery capacity by the battery gravimetric density, then the battery-to-unladen weight ratio was calculated using this derived battery weight and the vehicle's unladen weight (König et al., 2021).

### 3.2. Trend and relationship analysis

Driving range, energy consumption and charging time are identified as key variables. These three variables are identified as primary consumer barriers in BEV adoption literature. Range anxiety is the most frequently cited variable in BEV adoption (Guo et al., 2024; Naseri et al., 2023; Thorhauge et al., 2024). Alongside range, charging time influences perceptions of convenience and raises consumer concerns, whilst consumption costs play a determining role in consumer decisions (Fei et al., 2025; Li et al., 2023; Lv et al., 2024). The selection of these three parameters as core variables was driven by their capacity to define a technical adoption triangle, encompassing range anxiety, ease of use, and economic viability. Other variables associated with these core variables were designated as sub-variables.

- Charging time sub-variables: charge power and battery capacity
- Range sub-variables: battery capacity, consumption, weight, and height
- Consumption sub-variables: vehicle performance parameters, weight, and dimensions

The non-linear nature of the relationships between variables necessitated the use of more comprehensive analysis methods including machine learning. In a first step, random forest regression models were used to assess the relative importance of each technical parameter on range and consumption (Zhao et al., 2023). The study trained Random Forest models comprising 100 decision trees to predict range and consumption across the entire dataset (575 vehicles). To test model reliability, 5-fold cross-validation was applied, dividing data into five subsets with four used for training and one for testing in each iteration. These analyses determine the extent to which the specified sub-variables explain range and consumption. However, the number of sub-variables available is too large to perform the relationship analysis and future forecasting. Therefore, the most important sub-variables were selected. Random Forest feature importance analysis has been applied to identify the most influential variables. To reduce the complexity of numerous sub-variables, Random Forest feature importance analysis was applied to identify the most influential variables. As a result of the analysis, variables with an importance score above 5 % have been selected for use in the further analysis.

SHAP (SHapley Additive exPlanations) analysis was used to interpret the results obtained from the Random Forest model (Ullah et al., 2022). A SHAP value was calculated for the most important sub-variables and key variables. This method quantifies the marginal contribution of each feature to the prediction for each individual observation in the dataset, providing a more detailed understanding of how each variable affects the model's output at every data point. This approach facilitates for example, how the impact of how a 1 kWh increase in battery capacity impacts driving range (Maklin, 2022; Neubauer et al., 2024).

To assess the model's ability to predict beyond the observed data range, backcasting was performed. This involved training a Random Forest regression model on 2011–2019 data (73 vehicles) and using it to predict 2024 vehicle characteristics (154 vehicles). This approach captures technological advances within the dataset period.

### 3.3. Future forecasting

For the future scenarios, sub-variables with more than 5 % influence on key variables in the Random Forest analysis were utilised. In addition, to eliminate the effect of a potentially changing frontal area on the future scenarios, the analysis was applied by dividing vehicles into segments and car bodies with fixed frontal areas. The analysed vehicles were selected as C-Hatchback, C-SUV, D-SUV, D-Saloon, E-SUV, F-SUV and N-Small Passenger Van vehicle groups. This approach allows dimensional effects on energy consumption to be isolated, before predicting expected battery capacity, vehicle weight and range.

Additionally, the future scenarios reflect three emerging, front-running technologies based on literature: lithium-ion batteries with improved gravimetric density of 350 Wh/kg, and potential SSB with 500 Wh/kg and 1200 Wh/kg densities. For the future scenario, a dataset was created consisting of battery gravimetric density, vehicle weight, battery-to-unladen weight ratio, battery weight, nominal battery capacity, useable battery capacity, vehicle consumption, and range.

The Prophet model developed by Meta (Facebook, 2023) was utilised for the future scenario to predict vehicle weight and vehicle consumption. This time series model can capture trend changes by analysing historical trends and can work with outliers and missing data (Facebook, 2023; Taylor and Letham, 2018). While Prophet is configured to generate forecasts of vehicle weight and consumption, the battery weight, battery capacity, and range values are derived through the scenario analysis.

### 3.4. Scenario analysis

The Prophet forecasts were examined for 4 scenarios: pessimistic, realistic, optimistic-1 and optimistic-2. These scenarios are based on literature-grounded battery technology limits. Currently, LIB energy densities have reached the range of 250–260 Wh/kg. The pessimistic scenario assumes that despite incremental improvements, lithium-ion technology fails to reach its theoretical physicochemical limit of 350 Wh/kg (König et al., 2021) and completes its development at 300 Wh/kg density. This reflects potential manufacturing constraints, cost-performance trade-offs, or unforeseen technical limitations that prevent achieving theoretical maxima.

The realistic scenario assumes LIBs reach their physicochemical limit (350 Wh/kg) by 2035. However, SSBs remain uncommercialized due to issues preventing mass adoption, including chemo mechanical challenges, ionic conductivity, dendrite formation, interface instability, and manufacturing and cost problems (Janek and Zeier, 2023).

The Optimistic-1 scenario is based on SSBs overcoming their challenges after 2035 and achieving successful integration into vehicles. In this scenario, gravimetric density rises from 350 Wh/kg to the literature-projected 500 Wh/kg by 2050 (He et al., 2021; Zhao et al., 2021). The Optimistic-2 scenario assumes theoretical limits beyond practical limits are reached. This is achieved with lithium sulphur and sulphur-based $Li_7P_3S_{11}$ electrolyte or Li-free cathodes and solid electrolytes (Surendran and Thangadurai, 2025; Wang et al., 2019), with gravimetric density reaching 1,200 Wh/kg by 2050.

This study targets 600 miles of range for vehicles across scenarios. The 600-mile figure draws on mainstream ICEV vehicles (Parkers.co.uk, n.d.b) (See Appendix Table A.1) and serves as a representative parity benchmark, selected to directly address range anxiety stemming from decades of ICEV driving habits. In terms of technical feasibility, current high-end BEVs already offer substantial range. For instance, the Lucid Air claims 516 miles (EPA estimate) (Lucid Motors, 2023),whilst Mercedes-Benz (2025) announced that its Vision EQXX prototype targets 1,000 km range.

Industry forecasts reinforce this trajectory. The BloombergNEF (2024) report projects BEVs will achieve 1,000 km range through advances in battery chemistry and efficiency. Similarly, Fraunhofer ISI et al. (2025) report identifies 1,000 km ranges as explicit strategic targets for future models.

Taken together, sectoral expectations and the current state of ICEV vehicles mean the 600-mile reference point represents a convergence of consumer expectations and technical trajectory, chosen as both a behavioural/conventional and technology-driven benchmark.

Research identified each vehicle segment has a typical average battery-to-unladen weight ratio. Whilst some manufacturers and models increase this ratio to extend range, this is unusual and only for a few specific outlying models. Therefore, a current average battery weight ratio and the maximum incremental weight ratio for each vehicle group were adopted. Except for the Optimistic 2 scenario, the current average battery weight ratio is increased to the incremental maximum weight ratio over the forecasting period noting each segment has a maximum vehicle weight. The maximum weight limit for each vehicle segment is constrained by the minimum weight observed in the next higher segment (e.g., the maximum weight allowed for C-SUV models is capped at the minimum weight found in D-SUV models) (Sivaprasad, 2024). Another important issue is the useable battery capacity-nominal capacity ratio. For safety and charging lifespan reasons, manufacturers do not allow the nominal battery capacity to be used (See Appendix Table A.2). The nominal battery capacities of the vehicles are obtained with battery weight ratios and gravimetric density values.

While creating these scenarios, 2 main elements have been determined as the ultimate goals; to maximise range and to minimise consumption, the hill climbing optimisation algorithm has been used. This algorithm is based on the Kaizen philosophy, which operates on the principle that when improvement cannot be achieved in one part of a system, development in another part can still create overall improvement for the whole system (Ceylan and Ceylan, 2012). The flow diagram has been created to illustrate this process (See Appendix Fig. A.1).

In accordance with this diagram, to reach the target range (600 miles), vehicle weight is incrementally increased according to the Prophet model results. During this development period, battery weight, gravimetric density, and battery capacity also increase. These factors collectively contribute to bringing the vehicle's range closer to the target range. If this target range is reached, the range will be fixed, and the vehicle weight will be reduced by increasing gravimetric density. As vehicle weight decreases, consumption and battery capacity do not increase. However, if the target range is not reached in the scenarios, a new target range is determined. The target range will be the maximum range of the previous low scenario. When the maximum range of the low scenario is reached, the battery weight will be fixed, and the vehicle weight and consumption will be reduced. The pessimistic scenario also maintains current trends without increasing vehicle weight. Therefore, scenarios will be realised with a dual approach. This dual approach allows examination of both range maximisation and consumption minimisation.

## 4. Results

### 4.1. Historical developments

Since 2011, BEVs have undergone significant changes in their technical features, especially in range and battery capacity. These changes reflect both market demands, the strategic orientation of manufacturers and underlying technological developments. It has led to BEV fleet transformation. This transformation has led to an increase in vehicle weights and dimensions over time. The quest for extended range has led manufacturers to install larger battery packs that increase vehicle weight despite improvements in battery energy density. This trend parallels the overall weight increase observed in ICEVs in recent years and contributes to the increase in autobesity (Fuller, 2023). This results in an increase in energy consumption and rare earth raw materials.

Through the analysis period (2011–2024) the battery electric vehicle fleet has observed a significant increase in range, battery capacity and vehicle weight, in excess of estimates (Asef et al., 2021). BEVs were introduced to the market in 2011 with an average battery capacity of 20 kWh, vehicle weight of 1700 kg and range of 50 miles. By 2024 these specifications had jumped to an average battery capacity of 80 kWh, vehicle weight of 2750 kg and range of 250 miles. This upward trend stems from changing market dynamics and range anxiety: Initially dominated by smaller vehicles (A, B, C segments), the market later shifted toward premium models (C, D, E) and various body styles (SUV, Saloon, Hatchback) with larger batteries.

Energy consumption is influenced by many different parameters: aerodynamic design, powertrain efficiency, vehicle weight and battery management systems (Semeraro and Schito, 2022; Sweeting et al., 2011). Due to these multiple factors, the change in energy consumption over the 2011–2024 analysis period is slower and non-linear compared to other factors. Improvements in electric motor efficiency, power electronics and battery management systems have prevented a dramatic increase in energy consumption in heavier vehicles (Burnham et al., 2021). Energy consumption in early BEVs was generally limited to the 250–300 Wh/mile range. However, over time, with the introduction of more vehicles in the C, D and E segments, this consumption band has widened and reached the range of 250–400 Wh/mile.

### 4.2. Trend analysis

Literature identifies range, consumption and charging time as the main variables affecting BEV choice and adaptation (Fei et al., 2025; Guo et al., 2024; Li et al., 2023; Lv et al., 2024; Naseri et al., 2023; Thorhauge et al., 2024). Factors highly correlated with these main variables serve as sub-variables. Fig. 3 shows the system dynamics of these main and sub-variables. According to this structure, the increase in range directly increases BEV adaptation, while the decrease in consumption and charging time positively affects adaptation. The cases where the relationship between the variables is weak are shown with dashed lines. A more detailed analysis of this complex relationship network between the variables is carried out using machine learning methods.

The charging time parameter is directly related to the grid capacity and connections, then on-board charging rates and consumer behaviour (for example opting for slower rates to maintain battery health). Therefore, this study focuses only on range and consumption parameters. These two parameters are directly related to the vehicle technology and design, making them more reliable for projections.

Two basic feedback loops are defined in the system dynamics model. The balancing (B1) feedback loop includes range, consumption, weight, height and battery capacity. The reinforcing (R2) feedback loop consists of consumption, weight, length and height, along with external variables such as acceleration, total power, total torque and maximum speed. Random Forest regression model has been applied to determine how strongly each variable in these loops affects range and consumption.

The Random Forest analysis yielded Mean Squared Error (MSE) and R-squared ($R^2$) values for both variables. Model reliability was tested using 5-fold cross-validation (CV), dividing the data into five subsets with four used for training and one for testing in each

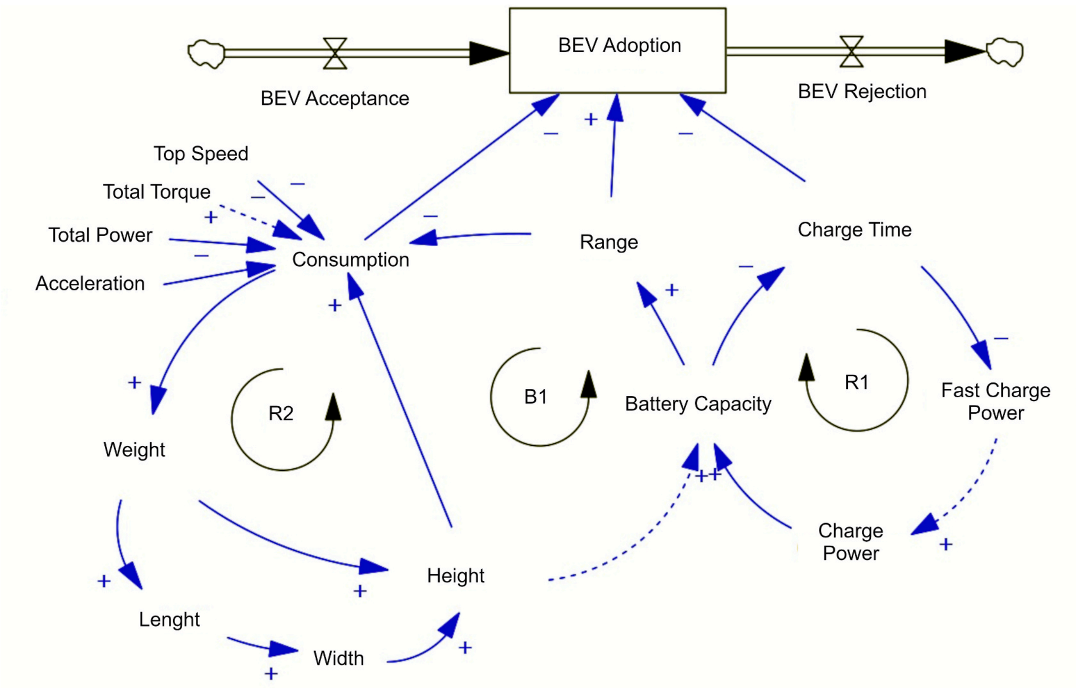


**Fig. 3.** Relationship system dynamics of the BEV technical specification.

iteration (See Table 2).

The results showed that the range variable was highly explanatory with the dataset ($R^2 = 0.98$). Cross-validation confirmed model robustness with similar results (average CV score = 0.96), indicating no overfitting. The vehicle consumption also had a high explanatory power ($R^2 = 0.87$, average CV score = 0.82), though less accurate than range predictions. This is largely due to the absence of the engine efficiency parameter in the dataset (Ma et al., 2020; Sawulski and Ławryńczuk, 2019).

The regression results confirm sub-variables strongly predict the main variables; however, the large number of variables creates a complex structure for relationship analysis and projections. Random Forest feature importance analysis has been applied to identify the most influential variables (higher score than 5 %).

Random Forest feature importance analysis results revealed the variables with the greatest influence in explaining key variables (See Fig. 4). Battery capacity is the most successful variable in explaining range at 88 %, whilst vehicle consumption represents the second most important variable at 9 %. Range can be explained at 97 % by these two variables. Other sub-variables score below 5 %, having minimal influence on range. For vehicle consumption, frontal area (71.5 %) and vehicle weight (16.5 %) explain 87 % of variation. Other sub-variables of consumption have less than 5 % influence. These findings reflect known core engineering and energy conservation principles. The modelling structure for relationship analysis and future forecasting has therefore been simplified to battery capacity and vehicle energy consumption for range and frontal area and vehicle weight for vehicle energy consumption.

The backcasting test yielded an average absolute error of 13 miles with R2 = 0.60. The model exhibits systematic conservative bias and underestimates average range by 5 %. Although this performance is lower than cross-validation (R2 = 0.98) reflecting interpolation accuracy, it confirms the model's moderate ability to capture directional technology evolution trends.

### *4.3. Relationship analysis*

The power, effect and validity of the important variables has been determined with the random forest results. However, SHAP is used to determine specific relationship patterns and directions between key and sub variables. SHAP values are calculated for the sub-variables that have more than 5 % influence on key variables (range and consumption). Specifically, SHAP analysis is applied to quantify the relationships between the key variable of range and its significant sub-variables (battery capacity and consumption). Furthermore, for the key variable of energy consumption, the SHAP analysis assesses its relationships with frontal area and vehicle weight as the most influential sub-variables.

The SHAP analysis results reveal the relationships between range and battery capacity or consumption in detail (See Fig. 5). In this analysis, each point represents a vehicle, and the colour scale of the points shows the value of the other sub-variable. In the graphs, the x-axis represents the battery capacity or vehicle consumption, while the y-axis shows the marginal effect of these variables on the range. The SHAP baseline value (y-axis 0 point) is 223.78 miles.

When the relationship between range and battery capacity is analysed, a strong approaching linear correlation is observed. The homoscedasticity of the points in the SHAP graph and the continuity of the distribution indicate that the range estimates are consistent at different battery capacity values. SHAP values range from −150 to +150 miles, indicating the amount of deviation of each battery capacity level from the baseline. A battery capacity of approximately 65 kWh corresponds to the baseline value, with lower capacities producing negative and higher producing positive SHAP values. If the battery capacity is reduced to 40 kWh, the range decreases to approximately 124 miles (baseline − 100 miles), while if the battery capacity is increased to 100 kWh, the range can reach 324 miles (baseline + 100 miles).

The range-consumption relationship is also nearly linear, but the distribution patterns of the relationship differ from the battery capacity. The homogeneity of the distribution (homoscedastic structure) is weaker than in the battery capacity analysis with notable gaps in the high consumption region (above 400 Wh/mile). The marginal effect of consumption on range is reflected in the variation of SHAP values between −60 and +60 miles. The baseline value is in the 300–320 Wh/mile band. Reducing consumption to 250 Wh/mile increase range by approximately 40 miles in the model predictions.

The colour scale analysis in the SHAP graphs reveals the complex relationship between battery capacity and consumption. Although there are examples of a high battery capacity-low consumption combination, it is commonly observed that vehicles with high battery capacity exhibit high consumption. This pattern stems from the gravimetric and volumetric energy density level of lithium-ion batteries: higher battery capacity adds weight and volume to vehicle, which rises consumption.

Optimal capacity-consumption balance observes generally in low-height saloon models such as the Tesla Model 3 and BMW i4, or C-segment hatchbacks such as the Volkswagen ID3.

The results of the SHAP performed to analyse the relationships between vehicle consumption and frontal area and weight are presented in Fig. 6. In this graph, the y-axis shows the marginal change of vehicle consumption. The expected SHAP baseline value (i.e. the 0 point on the y-axis) is 305.74 Wh/mile. The SHAP value reveals the deviations from this value.

The relationship between vehicle consumption and frontal area exhibits a continuous structure with relatively low

**Table 2**
Random forest regression results for range and vehicle consumption.

| | Range (Mile) | Vehicle consumption (Wh/mile) |
|---|---|---|
| Mean squared error | 131.73 | 289.04 |
| R-squared score | 0.98 | 0.87 |
| Mean cross-validation score | 0.96 | 0.82 |

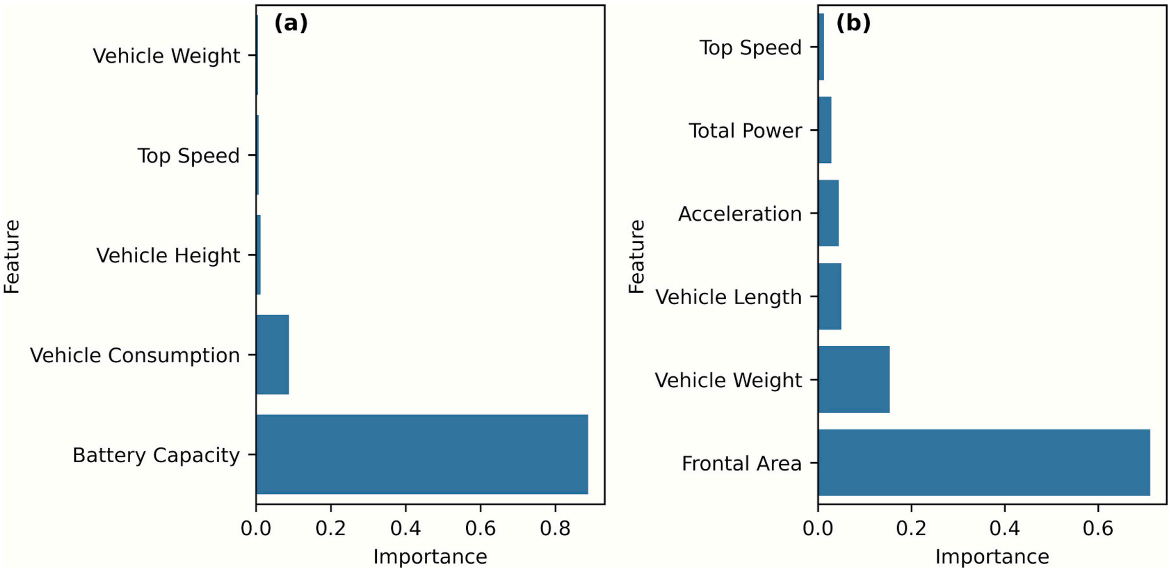


**Fig. 4.** Random forest feature importance of (a) range and (b) vehicle consumption indicators.

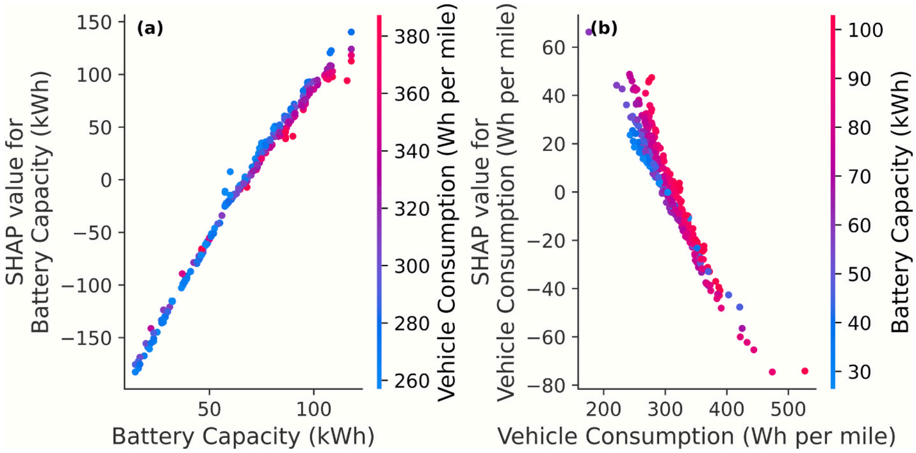


**Fig. 5.** SHAP values showing the impact of (a) battery capacity and (b) vehicle consumption on BEV range predictions.

heteroskedasticity. However, predictions cluster mostly between 2.5–3.5 $m^2$ frontal areas, with a clear discontinuity above 3.5 $m^2$. This discontinuity is mainly due to the N segment vans and some premium F segment SUV models. The fluctuation of the SHAP value between −50 and +125 Wh/mile is the result of the great influence of the frontal area on the consumption. The increase in frontal area between 2.5–3.0 $m^2$ causes an increase of approximately 50 Wh/mile (−25 to +25) in consumption, while a rapid and significant increase beyond 3.0 $m^2$ cause much steeper consumption growth.

When the relationship between consumption and vehicle weight is examined, it shows a consistent and continuous distribution with low heteroskedasticity. A similar relationship is observed for frontal area. Although aerodynamic design has some influence, aerodynamic drag is primarily impacted by the frontal area of a vehicle. The relationship structure is not linear but exhibits polynomial characteristics. The impact of the vehicle's weight change on consumption (SHAP values) varies between −20 and +40 Wh/mile, after which the graph stops showing continuity. A particularly striking point in the graph is the increasing slope at positive values. This finding shows that BEVs are more tolerant in terms of energy consumption up to approximately 2300 kg vehicle weight (Weight Unladen). Consumption increases minimally until this critical weight, after which SHAP values rapidly rise from 0 to +20 Wh/mile. The colour scale in the graph represents frontal area, showing that heavier vehicles often have a larger frontal area.

The SHAP analysis reveals different relationships patterns between range and consumption parameters. While range shows a strong, predictable and near-linear relationship with battery capacity and consumption, the relationship between consumption and vehicle dimensions exhibits a more complex structure. In particular, the relationship between vehicle frontal area and consumption less interpretable, while the relationship with weight is more consistent and explainable. Based on these insights, the scenario and

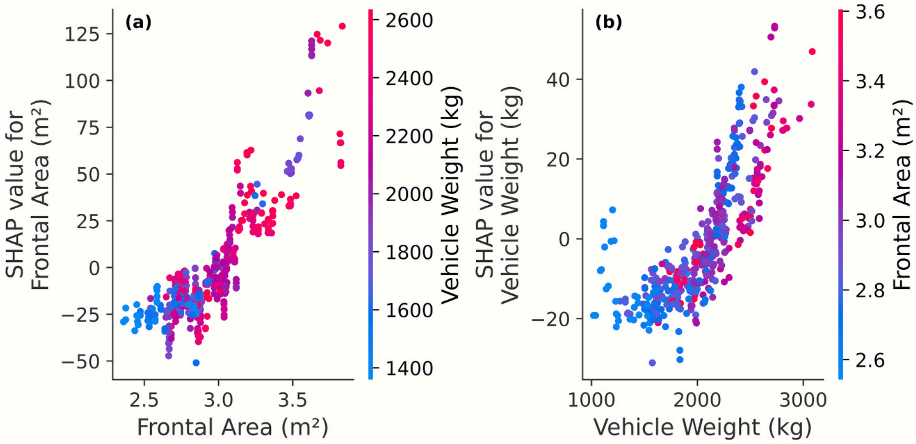


**Fig. 6.** SHAP values showing the impact of (a) frontal area and (b) vehicle weight on BEV consumption predictions.

forecasting analysis are classified by segment and car body. This approach controls for the known geometric impacts on vehicle performance.

### 4.4. Future forecasts

Future projections are performed for seven different vehicle groups (C-Hatchback, C-SUV, D-SUV, D-Saloon, E-SUV, F-SUV and N-Small Passenger Van) using the Prophet time series model. The analysis uses observed (real-world) data from 2011 to 2024, informing the forecasts for the four scenarios from 2025 to 2050. This section presents the C-SUV results as they have the one of the largest market shares, while other vehicle groups are detailed in Appendix A Figs. A.2–A.13.

The forecasting results are analysed in terms of four main technical parameters: range, battery capacity, energy consumption and vehicle weight. C-SUV projections target a maximum range of 600 miles and vehicle weight of 2000 kg. In 2024, the average battery weight ratio in the C-SUV models is 11 %. However, new generation models such as Kia EV3 and Hyundai Kona have aimed to reach higher battery capacity and thus higher range by increasing the battery weight ratio to 13 %. Based on this trend, C-SUV battery weight ratio is projected to reach 13 % during forecasting period. In addition, due to battery management and safety requirements, manufacturers do not use the nominal battery capacity (Reiter et al., 2018). Useable capacity averages at 95 % of nominal capacity for C-SUV models. Using these parameters, specific projection models for the C-SUV segment have been developed for each scenario. The results

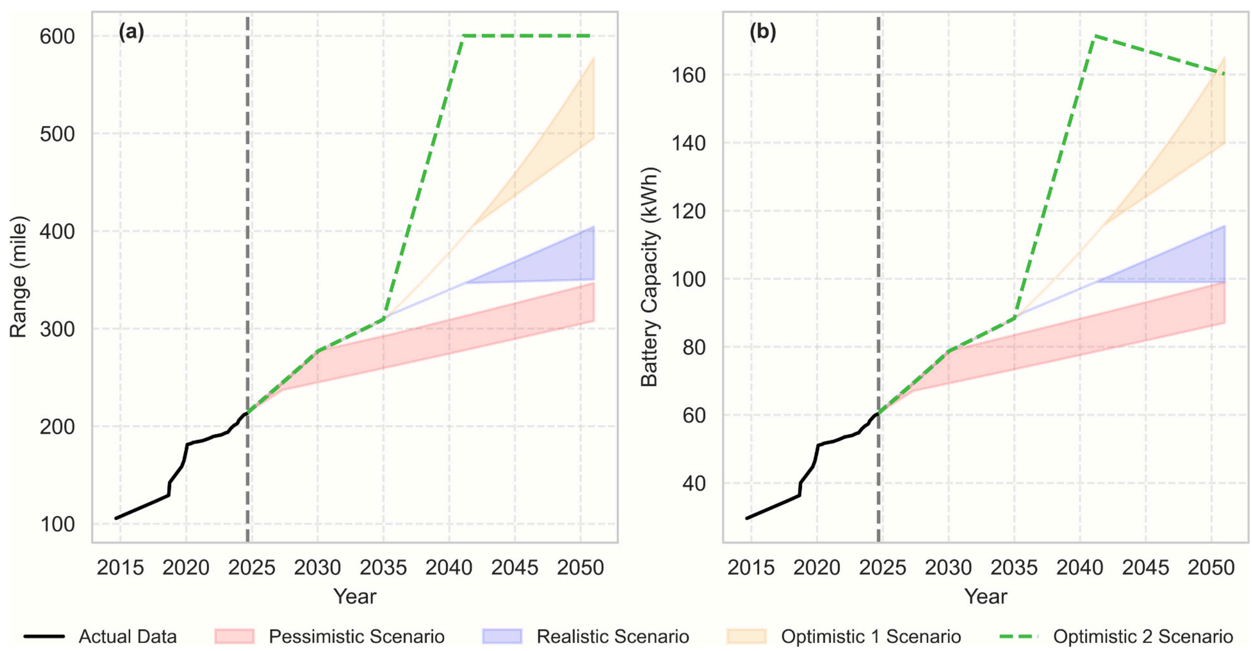


**Fig. 7.** Forecast of C-SUV (a) range and (b) battery capacity development under battery technology scenarios (2025–2050).

of the analyses are presented in detail in Figs. 7–8. Fig. 7 shows all approaches, while Fig. 8 display only the range maximisation of the pessimistic scenario for clarity. In the consumption minimisation approach, it is assumed that consumption and vehicle weight remain constant at the values in 2024.

In the pessimistic scenario, battery gravimetric density does not show a development after reaching 300 Wh/kg, which falls short of the industry-projected 350 Wh/kg target, modelling a future where technological advancement stalls. This scenario therefore requires vehicle weight to increase to gain additional battery capacity. Since a similar increasing range trend is assumed for all scenarios, the pessimistic case shows faster increases in vehicle weight, battery weight and consumption than the other scenarios. Therefore, the pessimistic scenario reaches the 2000 kg maximum weight first, by 2030.

After 2030, an alternative strategy to continue the range improvements has been followed: This strategy gradually increases the battery-to-vehicle weight ratio, allowing battery capacity and range to improve. This approach becomes necessary because by 2030, as both the gravimetric density improvements and vehicle weight optimisation reach their practical limits. Therefore, battery-to-vehicle weight ratio increase becomes the primary remaining lever for continued range enhancement after other optimisation methods have been maximised. Stable vehicle weight and dimensions ensure a near constant vehicle energy consumption. This method has been preferred to maximise the range. With this approach, despite constant vehicle dimensions and weights, the battery capacity has reached 99 kWh, and the range has extended to 346 miles by 2050 through improved gravimetric density and higher battery ratio. In the energy consumption minimisation approach, although the vehicle weight is kept constant at 2024′s values, the battery capacity increases to 87 kWh and the range reaches 308 miles.

In the realistic scenario analysis, it is predicted that the battery gravimetric density will reach 350 Wh/kg in 2035. According to the Prophet model results, the vehicle weight also reaches its maximum level in the same year. With both weight and density reaching their limits in 2035, this scenario gradually increases battery weight ratio to 13 % by 2050. This emerges with vehicles that have a battery capacity of 166 kWh and a range of 404 miles, but still below the target range.

This result led to a strategy of underlying energy consumption minimisation, with a revised 346-mile range target (the maximum of pessimistic scenario). This target range would be reached in 2042. Beyond 2042, the strategy is to reduce vehicle weight and consumption by keeping the battery weight constant. By 2050, C-SUVs are expected to be weighing 1720 kg, 99 kWh battery capacity and 350-mile range. It is estimated that consumption values will return to 2024 levels, especially thanks to the reduction in vehicle weight.

The Optimistic-1 scenario is based on the assumption that SSBs will be used after 2035. This scenario projects a gradual increase in gravimetric density to 500 Wh/kg from 2035 to 2050. Battery weight ratio also increases to 13 % after 2035.

In the analysis, the range maximisation approach is first adopted. By 2050, this approach reaches 578-mile range and 165 kWh battery capacity, but still slightly below the 600-mile target. Therefore, a new target range of 404 miles, which is the maximum range of the Realistic scenario, was adopted. Once this target range was achieved, the focus shifted from further extending range to minimising energy consumption by reducing vehicle weight. In the Optimistic-1 scenario, the battery weight has been kept constant after the target range (404 mile) reaches in 2041. However, unlike the realistic scenario, the battery capacity continues to increase due to the improve in gravimetric density. By 2050, BEVs reach a range of 495 miles with a battery capacity of 140 kWh. This approach also reduces vehicle weight below 1700 kg, and the consumption will decrease to approximately 280 Wh/mile.

The Optimistic-2 scenario assumes SSBs has become the dominant battery technology with gravimetric densities reaching 1200 Wh/kg. Since the Prophet model is also valid in this scenario, the vehicle weight reaches 2000 kg in 2035. However, the exceptionally

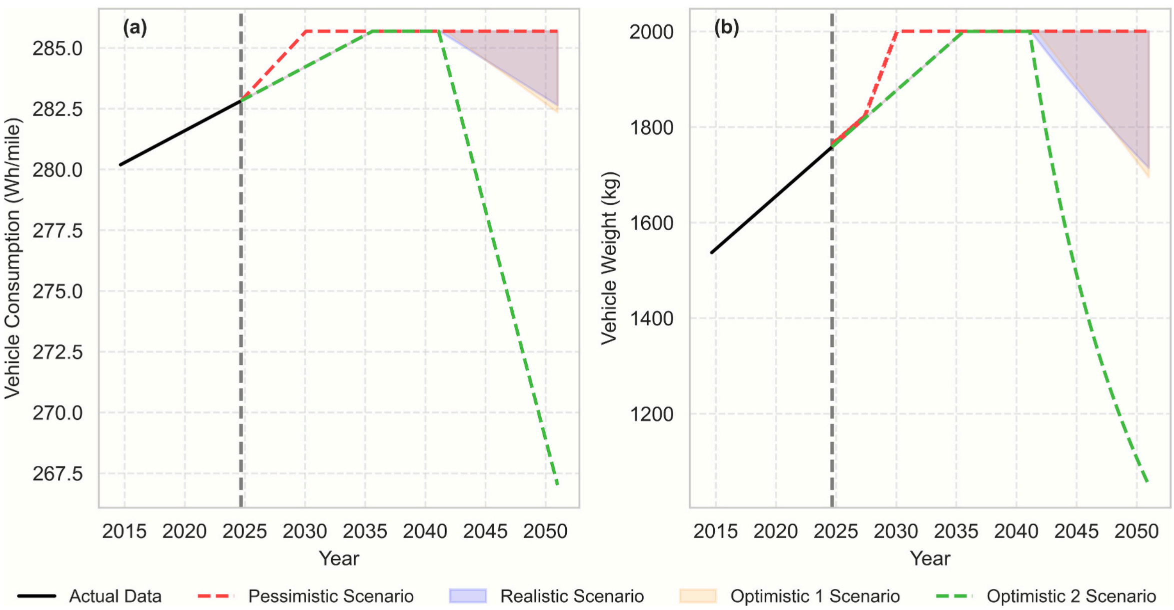


**Fig. 8.** Forecast of C-SUV (a) vehicle consumption and (b) vehicle weight development under battery technology scenarios (2025–2050).

high gravimetric energy density allows battery weight ratio to remain at 11 %.

The target range of 600 miles is reached in 2041 in this scenario. After 2041, a different strategy is followed from the other scenarios, by keeping the range constant and aiming to reduce the vehicle weight more rapidly. This approach improves vehicle performance and reduces the charging time. By 2050, the consumption and battery capacity drop to 267 Wh/mile and 160 kWh, respectively. The vehicle weight decreases to 1100 kg, similar to the weight of ICEV C-Segments (Alzaghrini et al., 2024).

The analysis results for four different scenarios in the Figs. 7 and 8 have been evaluated using the confidence intervals of the Prophet model and Random Forest models. The models indicate uncertainty margins of ± 11 miles for range, ±17 Wh/mile for consumption, and ± 50 kg for vehicle weight.

## 5. Discussion

The look back and review of the technical evolution of BEVs between 2011 and 2024 clearly illustrates that the range and weight of BEVs have continued to increase through this period. This research suggests manufacturers BEV development strategies have been to aggressively prioritise extending driving range. Range anxiety is still a significant concern for prospective BEV consumers (Guo et al., 2024; Thorhauge et al., 2024). The increasing sales growth rate of PHEVs worldwide in recent years (IEA, 2024a) is one of the types of evidence of this situation. Therefore, it suggests manufacturers will maintain this strategy. The study has also revealed that the gains in driving range are directly related to battery capacity, which has led to an inevitable growth of vehicle dimensions and weight. Future advances in battery technology, design and chemistry are proposed to change the direction of this development trajectory (Pei et al., 2025).

Random forest and SHAP analyses have proven that the battery capacity increase has a greater effect on range than all other parameters. This suggests heavy vehicles are in the short- and medium-term unavoidable in BEVs and reveals that the ‘light vehicle = efficient vehicle’ paradigm in ICEVs is not fully valid for BEVs. This finding aligns with the fundamental energy balance principle: Range = Battery Capacity / Consumption. However, the consumption model itself depends on an independent random forest model where frontal area dominates (R2 = 0.87). This two-tier structure demonstrates that the apparently simple battery-range relationship actually stems from the interaction of multiple physical processes. Whilst battery capacity directly determines energy storage, factors affecting consumption (aerodynamic drag, friction losses, motor efficiency, regenerative braking efficiency) control how efficiently this energy is used. Indeed, the consumption model’s lower performance compared to the range model arises from the absence of efficiency elements not present in the dataset. Future developments in consumption could alter the range-battery capacity-consumption balance, reducing battery capacity’s influence on range whilst increasing consumption’s importance. The backcasting test results offer insight into these developments, with range in 2024 increasing beyond the 2011–2019 trend. Consequently, range improvement can be achieved not only through larger batteries but also through design optimisations that reduce consumption. This could lead to vehicles achieving higher range values at the same weight beyond future predictions, or lighter vehicles at the same range.

On the other hand, the increase in battery capacity has a significant impact on consumption, vehicle dimensions and vehicle weight due to the increase in battery weight and volume. The range increase trend has also given rise to the ’autobesity’ phenomenon of BEVs, which has become more prevalent in recent years, will continue (Fuller, 2023). Rohith et al. (2023) predict that similar trends will be observed for light commercial vehicles, buses, and trucks.

Future projections comprehensively reveal the opportunities and challenges facing BEV technology. Analyses conducted under four different scenarios highlight that BEV technology has significant future potential. Even pessimistic scenarios show promising results: Range values in the C segment easily exceed 300 miles, while they reach 400 miles in higher segments. The realistic scenario suggests range anxiety will diminish substantially by 2035 and largely disappear by 2050. The Optimistic-1 scenario, in which the battery gravimetric energy density increases to 500 Wh/kg, indicates more striking results; range approximately reach to 600 miles. These findings show that the Optimistic-2 scenario, in which the battery gravimetric energy density increases to 1,200 Wh/kg, may not even be necessary to eliminate range anxiety. Parallel investments such as fast charging infrastructure are expected to eliminate range anxiety in many countries. These results suggest that BEV technology will be increasingly successful in the medium and long term.

The most critical success factor is the developments in battery technology. By 2035, lithium-ion batteries are expected to near their physicochemical limits, which will prompt a need to find alternative technologies. At this point or earlier, the commercialisation of SSBs will play a critical role in sustaining the development of BEV technology. Overcoming the main challenges faced by SSB technology, such as thermal management and manufacturing (Rahardian et al., 2019; Zaman and Hatzell, 2022) should hopefully realise these forecast developments.

Vehicle weight and size optimisation constitute another critical dimension of future projections. In all scenarios, vehicle weight is expected to reach its maximum level by 2035. After this milestone, development is expected to split into two paths depending on technological developments, consumer preferences and country regulations. The first one is based on decreasing weight and consumption. Consumption can be collectively reduced through improvements in inverter and motor efficiency (Gobbi et al., 2024), advanced regenerative braking systems (Yang et al., 2024), efficient thermal management systems (Hwang et al., 2024), reduced conversion losses via wide bandgap semiconductors (Suthar et al., 2025), and aerodynamic optimisation (Connolly et al., 2024). In addition, driving dynamics introduced by autonomous vehicles enhance efficiency whilst reducing consumption and weight (Tu et al., 2024). The other, however, is focused on maximising range regardless of weight, as developments in consumption and weight reduction regulations do not occur in this direction.

Segment-based analyses show that each vehicle groups will respond differently to this optimisation process. It has been observed that vehicle weight and size optimisation provide more efficient results, especially in the C-Hatchback, C-SUV, D-SUV and D-Saloon segments. These segments can combine low consumption with high range. This finding suggests that manufacturers will likely tend to produce these segments and prioritise weight reduction while focusing on range maximisation.

The range-battery capacity-weight relationship, which is important in vehicle transformation, will bring about not only a technological change but also a socio-political and techno-political transformation. The weight increase that will occur especially in premium luxury segments with the aim of higher range is expected to prompt governments and regulatory authorities to develop new policies that take into account the social and environmental impacts of heavier, larger vehicles. The increase in average BEV weight extends emergency braking distances and increases collision energy. Road infrastructure degradation is accelerated by the exponential increase in stress on road surfaces with vehicle weight (Le Vern et al., 2022; Mofolasayo, 2020). These concerns and trends suggest national transportation should consider a shift to weight-based taxation. This is likely to drive manufacturers towards methods such as Cell-to-Pack/Chassis (CTP/CTC) systems for more effective battery integration and weight reduction (Chen et al., 2022), or towards SSBs which enable more efficient placement than LIBs through direct bipolar stacking at cell level, offering advantages for higher energy density (Janek and Zeier, 2016).

Currently, BEVs' weight-based taxation remain passive or not implemented at all because of incentives to encourage early BEV adoption. However, as BEV market penetration increases and reaches mainstream adoption levels, governments are likely to phase out these incentives and align with more standard vehicle taxation policies, including weight-based taxes. As premium vehicles tend to be significantly heavier due to larger battery packs and premium features, they are likely to face the highest taxation. This may lead to a shift in the balance of tax burden to higher into higher end vehicles and associated market prices. The higher overall vehicle pricing intended to shift consumer preferences towards lighter and more efficient alternatives that are suitable for daily use such as C segment vehicles, saloon models or lightweight D-SUV models.

The technical parameter-focused forecasting model identifies technical concerns facing BEVs. However, beyond these technical considerations, consumer preferences, economic factors, and national policies significantly shape BEV technical specifications. For instance, the prioritisation of long driving ranges in Europe and the UK (IEA, 2024b) has led to the widespread adoption of NMC batteries, which offer higher energy storage capabilities (Manthiram, 2020). Conversely, the high cost of NMC chemistries (McKinsey & Company, 2024) and the substantial safety packaging required to mitigate thermal runaway (Kim et al., 2017) have directed adoption towards Premium and SUV segments, where the price gap with ICEVs is narrower compared to economy models (IEA, 2024b). In contrast, the Chinese market has prioritised cost efficiency over range maximisation (IEA, 2024b). This approach favoured the adoption of LFP batteries to leverage their lower costs and reduced thermal runaway risks, thereby enabling the mass production of smaller, affordable vehicles (Lu and Zhu, 2024). These market-specific trajectories underscore the interplay between technical capabilities, consumer priorities, and policy environments in shaping BEV technology development.

Within the study's scope, consumer driving habits are assumed to continue as with ICEVs. However, this behavioural model may change over time with the newcomers. Such change, through the formation of BEV-specific usage patterns, will affect the balance between range requirements and charging infrastructure availability. Consumer acceptance of shorter ranges compared to ICEVs and tolerance of longer charging times may reduce manufacturers' motivation to produce high-range and consequently heavy vehicles. This will also influence government measures such as weight taxation. This preference shift may alter the trajectory of policy makers' interventions regarding weight taxation or safety.

## 6. Conclusion

This study analysed the technical specifications and development of 575 BEV models from 2011 to 2024. The analysis and established trends underpinned forecasts of the continual technology development through to 2050. Through the period 2011–2024, vehicle and battery weights were observed to increase significantly despite improvements in battery gravimetric density. This weight increase was accompanied with significantly extended driving range capabilities in all segment types.

The SHAP analysis results have helped clarified the evolution of BEV technical features between 2011 and 2024. Results show highly correlated, near-linear relationships between range and both battery capacity and consumption. Battery capacity's positive impact on range outweighs the negative effect of weight on consumption up to a certain point.

Future projections show that there will be significant reductions in range anxiety towards 2035. Even in pessimistic scenarios, range will increase thanks to advances in battery technology. However, this increase will drive larger, heavier vehicles on the roads. Therefore, consumption minimisation strategies will become increasingly important. After 2035, developments in battery technology and the spread of SSBs will constitute an important milestone for BEVs. All four scenarios predict that BEVs will be more permanent on the roads.

Several important unexamined risks could emerge in these scenarios and future penetration of BEVs. The most important of these is the raw material supply risk. The proliferation of BEVs may be strained by the supply of precious metals used in battery cathodes (Hao et al., 2019). Research to be conducted in this area should continue to the evaluation of resource needs from an economic and environmental perspectives. Additionally, this study's UK market focus could be expanded through comparative regional research. Similar analyses in regions with high penetration rates such as China—which exhibit different market dynamics, battery chemistry preferences, and policy frameworks—and their comparison with Europe would prove valuable for understanding regional variations in BEV technology evolution (Mai et al., 2025). Furthermore, the growing BEV penetration will need to go hand in hand with the evolution of electrical energy infrastructure. Although the increase in range values reduces infrastructure dependency, the need for fast charging stations, especially in intercity trips, is expected to continue. In addition, the load on the power grid from the growing fleet of electric vehicles is expected to put further strains on electricity grid capacity and reliability. Future research should continue to explore how the energy needs of BEVs can be supplied from renewable energy sources and support net zero target (Chen and Ma, 2024).

### Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Claude to improve the language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

### CRediT authorship contribution statement

**Abdullah Isilti:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Conceptualization. **James E. Tate:** Writing – review & editing.

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### Appendix A

The Appendix has been structured in order to present the data used in the study and the results obtained in a more detailed and explanatory manner.

The appendix section has been structured to present the data used within the research scope and the obtained results in a more detailed and explanatory manner.

Table A.1 shows selected mainstream ICEV examples that match the BEV categories projected in this study, including their fuel capacity and consumption data. Each vehicle category possesses different range values with its various variations. The aforementioned range values have been documented by WLTP (Parkers.co.uk, n.d.b). Based on these ICEVs, the target range for BEVs has been determined as 600 miles.

**Table A1**
ICEV fuel tank capacities, consumption and segments (Parkers.co.uk, n.d.b).

| Segment-Car Body | Vehicle | Fuel Tank Capacity(l) | Consumption (mpg) |
|---|---|---|---|
| C-Hatchback | Vauxhall (Opel) Corsa | 40–44 | 45–70 |
| C-SUV | Volkswagen Tiguan | 58–60 | 30–55 |
| D-SUV | Audi Q5 | 54–70 | 30–45 |
| D-Saloon | Skoda Superb | 45–66 | 30–45 |
| E-SUV | BMW X5 | 70–80 | 24–42 |
| F-SUV | Mercedes G Class | 96–100 | 25–30 |
| N-Small Passenger Van | Citroen Berlingo | 53–60 | 37–57 |

Table A.2 demonstrates the evolution of technical specifications in recent years for 575 BEV models examined in the UK. This table presents the maximum vehicle weight of each segment and vehicle body type, determined according to the minimum weight of the next higher segment (Sivaprasad, 2024). The F-SUV and N-Small Passenger Van categories, as the highest segment groups, have their maximum weights set at the legal limit of 3500 kg Gross Vehicle Weight (GVW) (UK Government, n.d.). Additionally, the table also includes average and maximum battery-to-vehicle weight ratios and useable-to-nominal battery capacity ratios.

**Table A.2**
Vehicle weight and battery weight ratio limits.

| Segment-Car Body | Maximum Weight Unladen (EU) (kg) | Average Battery Weight Ratio | Maximum Battery Weight Ratio | Useable Capacity/Nominal Battery Capacity |
|---|---|---|---|---|
| C-Hatchback | 2050 | 12 % | 14 % | 95 % |
| C-SUV | 2000 | 11 % | 13 % | 95 % |
| D-SUV | 2520 | 12.50 % | 15.80 % | 95 % |
| D-Saloon | 2400 | 12.70 % | 15 % | 96 % |
| E-SUV | 2720 | 13.30 % | 15 % | 93 % |
| F-SUV | 3500 (GVW) | 13.50 % | 15.50 % | 95 % |
| N-Small Passenger Van | 3500 (GVW) | 9 % | 12 % | 93 % |

presents the flow diagram underlying the research methodology. According to this methodology, the target range in each scenario is determined as 600 miles. To achieve this target, the vehicle weights are increased to the maximum vehicle weights specified in . The Average Battery Weight Ratio values are increased to the Maximum Battery Weight Ratio values. However, it is not possible to achieve this target in all scenarios. Therefore, an alternative approach is adopted for each scenario. In this approach, the new target range is determined as the maximum range of the previous scenario. Thanks to this approach, the vehicle weight and energy consumption are reduced after each range is reached. In the pessimistic scenario, the calculations are carried out using the current average. Therefore, each scenario (except Optimistic-2) employs two approaches: range maximisation with heavier vehicles, and consumption minimisation with lighter vehicles. heavier vehicles, and consumption minimisation with lighter vehicles.

The results of future scenario analyses for the C-SUV are presented in Section 3.4. In this section, the projection results for C-Hatchback, D-SUV, D-Saloon, E-SUV, F-SUV and N-Small Passenger Van are presented in Figs. A.2–A.13, respectively.

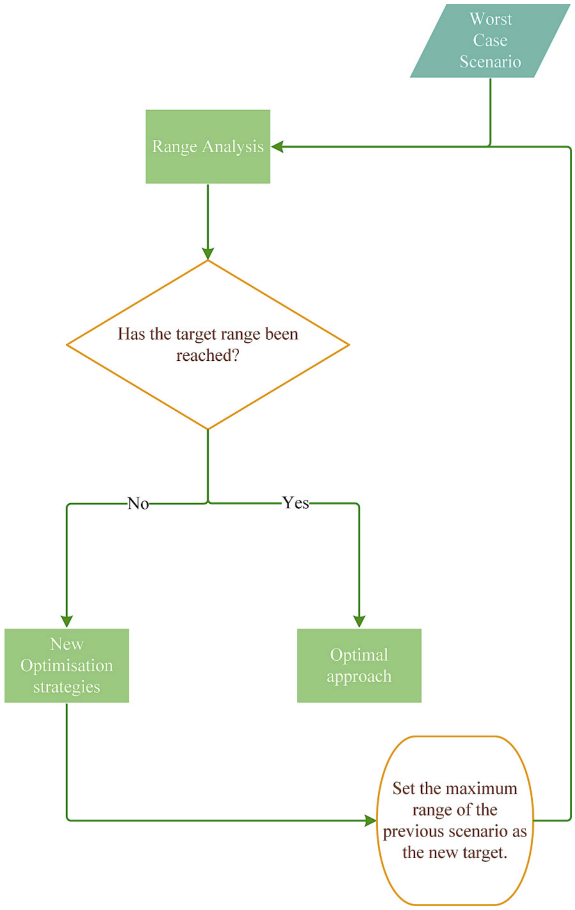


**Fig. A1.** Methodology flow diagram for Range Limit Decision

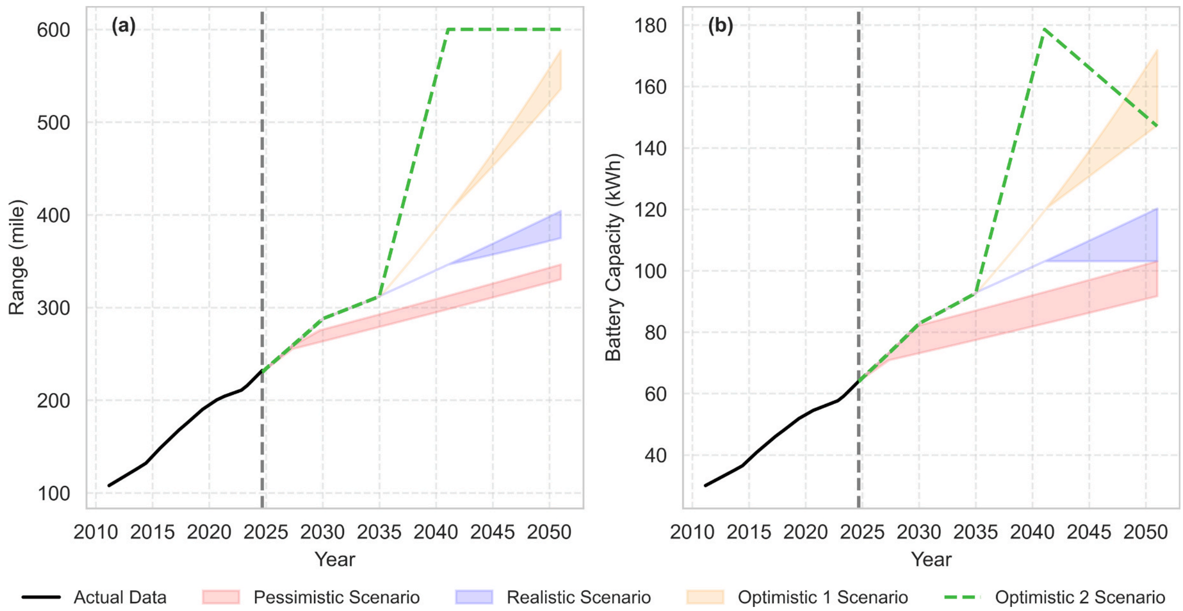

**Fig. A2.** Forecast of C-Hatchback (a) Range and (b) Battery Capacity Development under Battery Technology Scenarios (20252050)

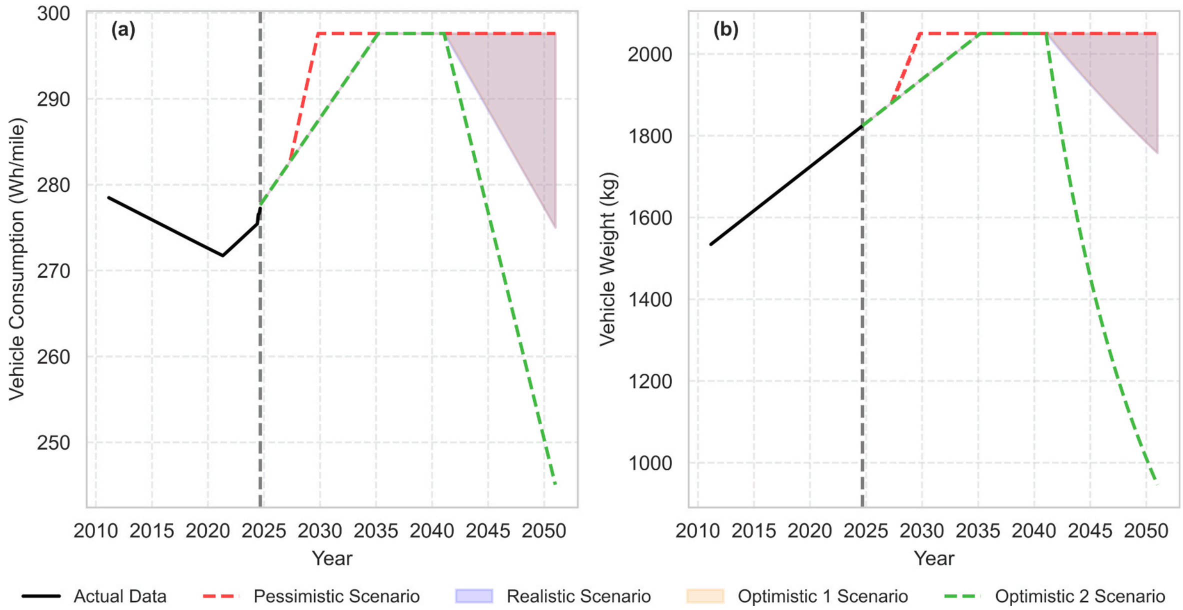


**Fig. A3.** Forecast of C-Hatchback (a) Vehicle Consumption and (b) Vehicle Weight Development under Battery Technology Scenarios (20252050)

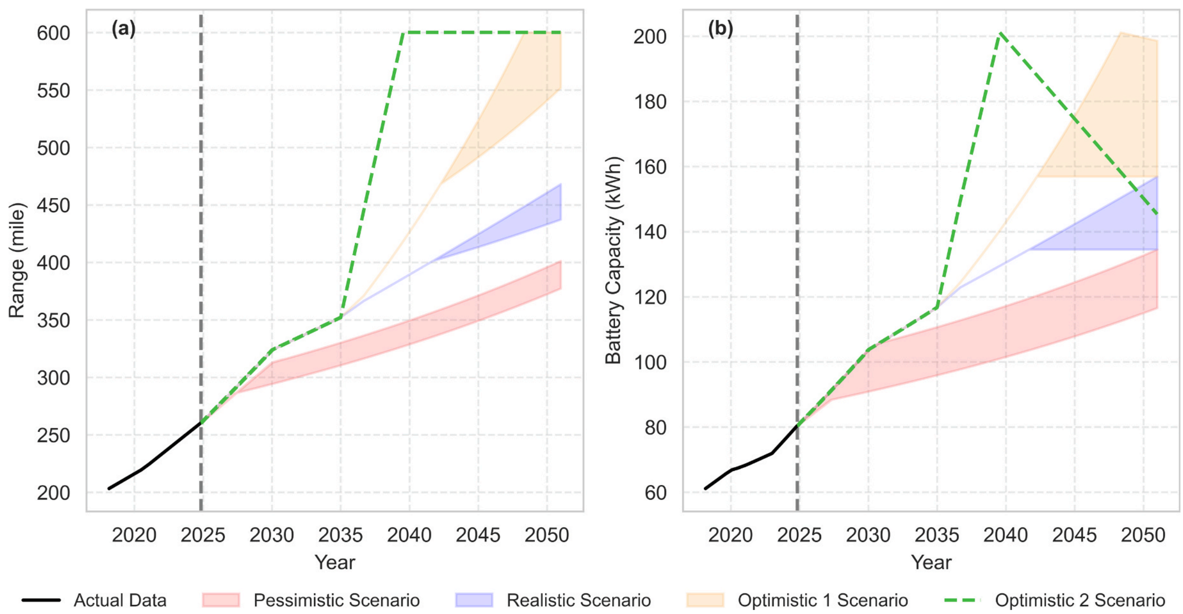


**Fig. A4.** Forecast of D-SUV (a) Range and (b) Battery Capacity Development under Battery Technology Scenarios (20252050)

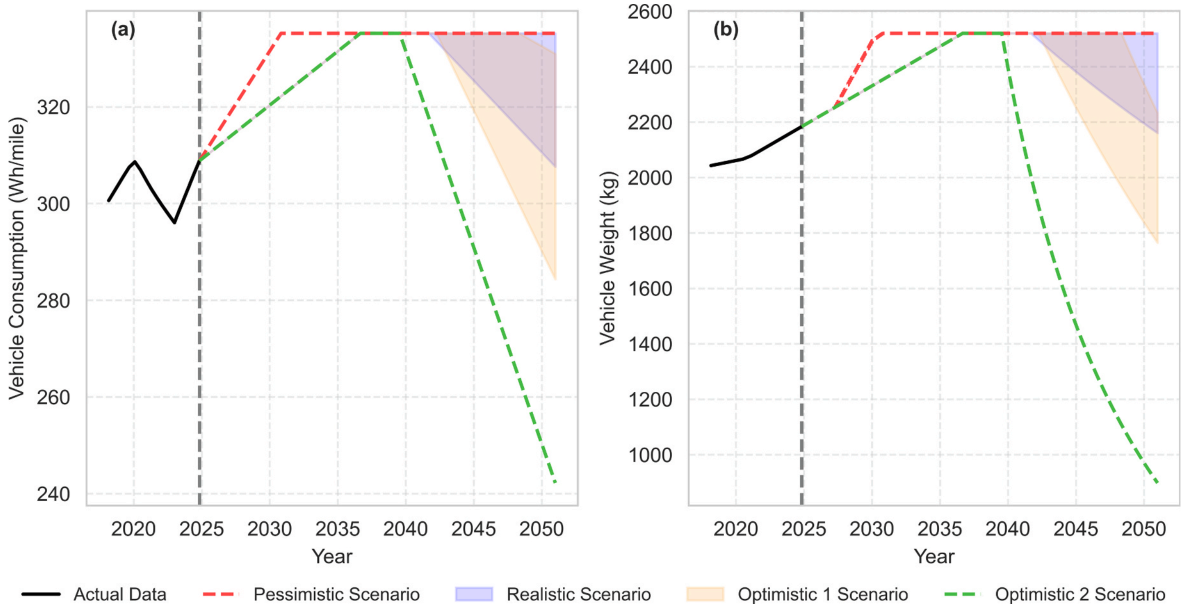


**Fig. A5.** Forecast of D-SUV (a) Vehicle Consumption and (b) Vehicle Weight Development under Battery Technology Scenarios (20252050)

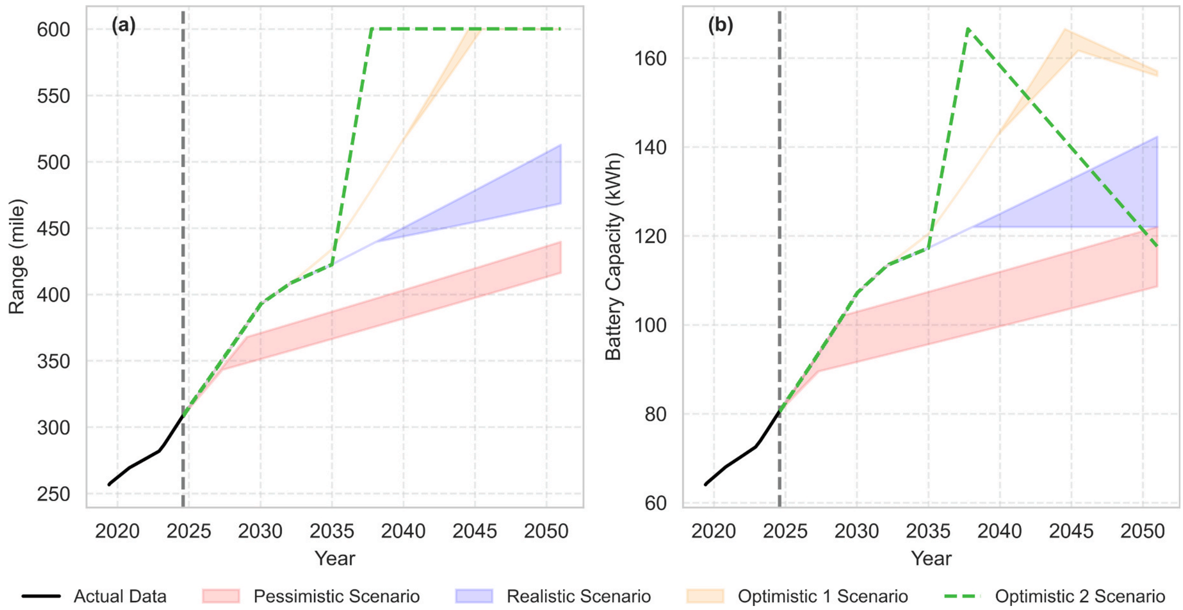


**Fig. A6.** Forecast of D-Saloon (a) Range and (b) Battery Capacity Development under Battery Technology Scenarios (20252050)

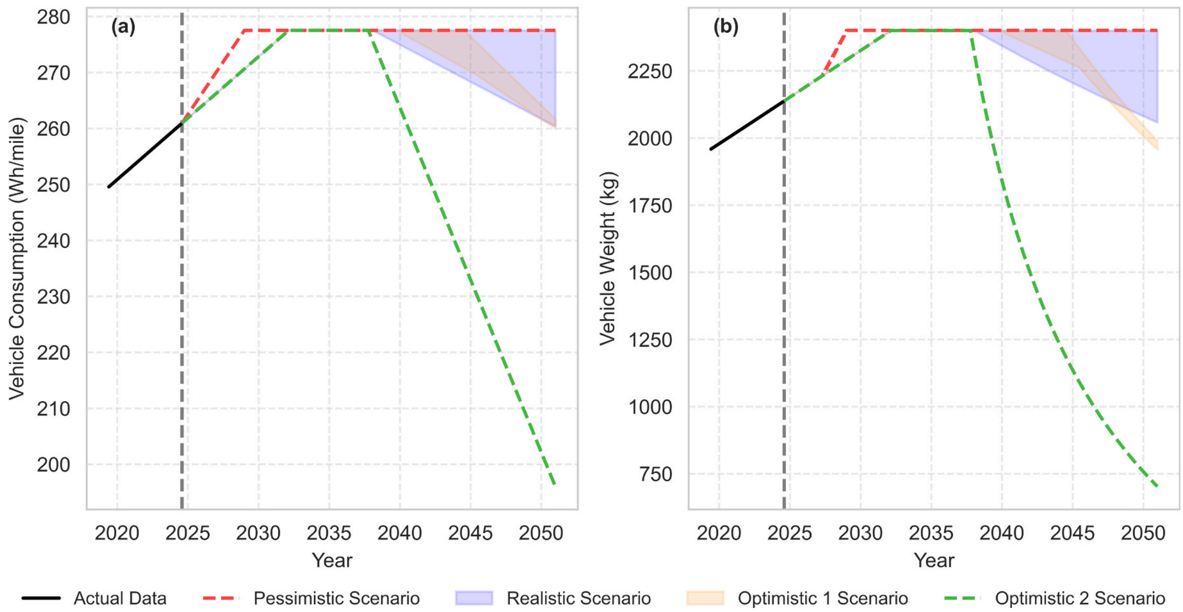


**Fig. A7.** Forecast of D-Saloon (a) Vehicle Consumption and (b) Vehicle Weight Development under Battery Technology Scenarios (20252050)

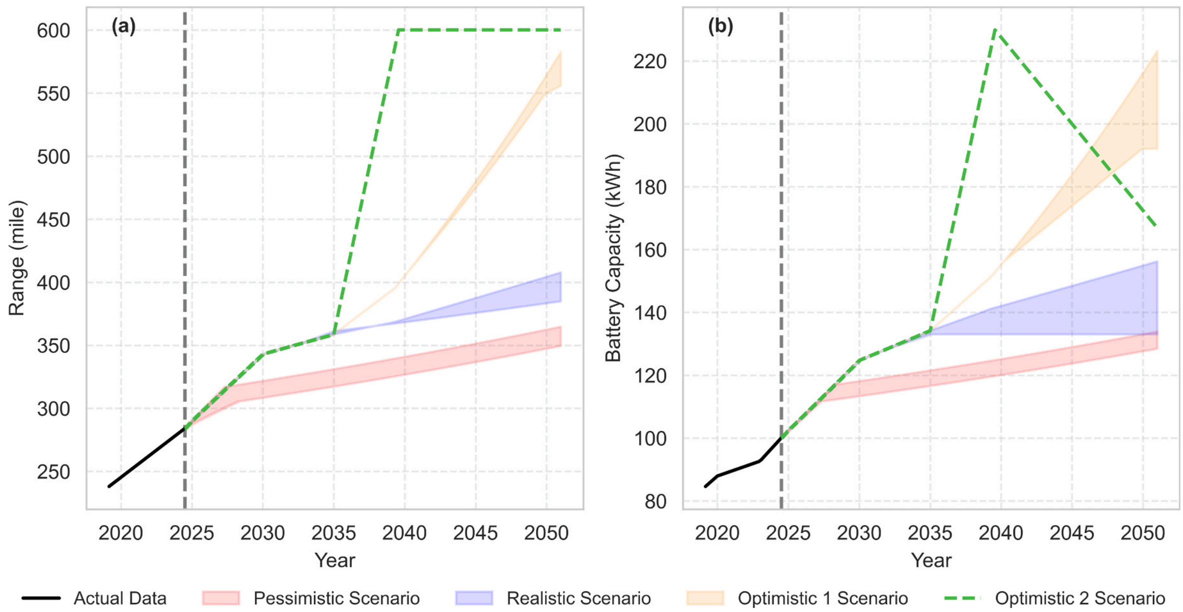


**Fig. A8.** Forecast of E-SUV (a) Range and (b) Battery Capacity Development under Battery Technology Scenarios (20252050)

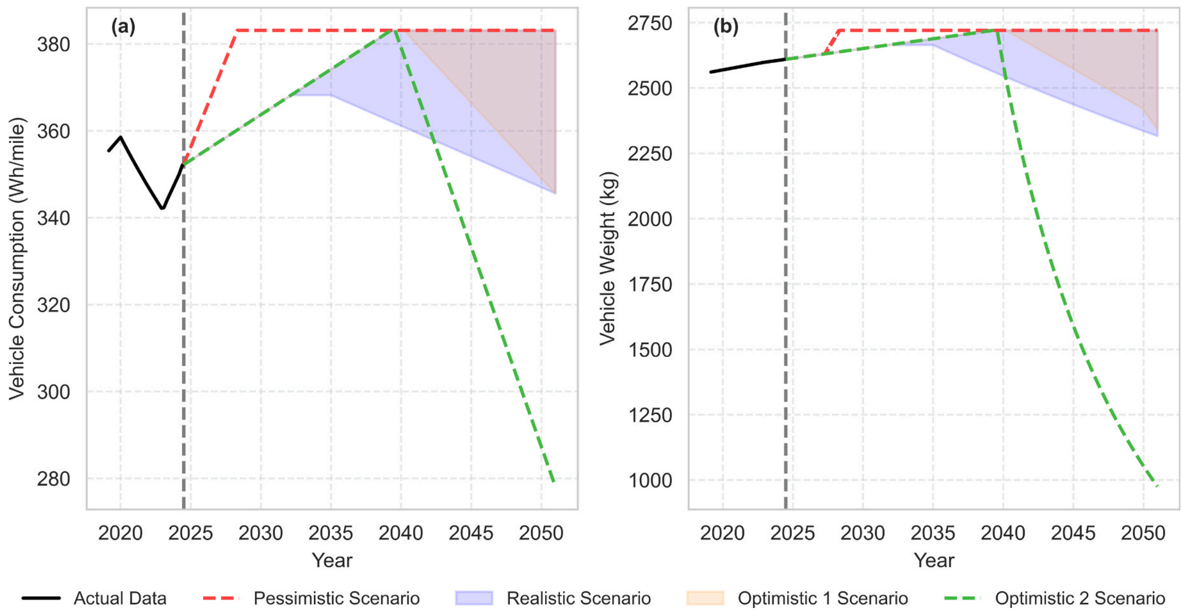

**Fig. A9.** Forecast of E-SUV (a) Vehicle Consumption and (b) Vehicle Weight Development under Battery Technology Scenarios (20252050)

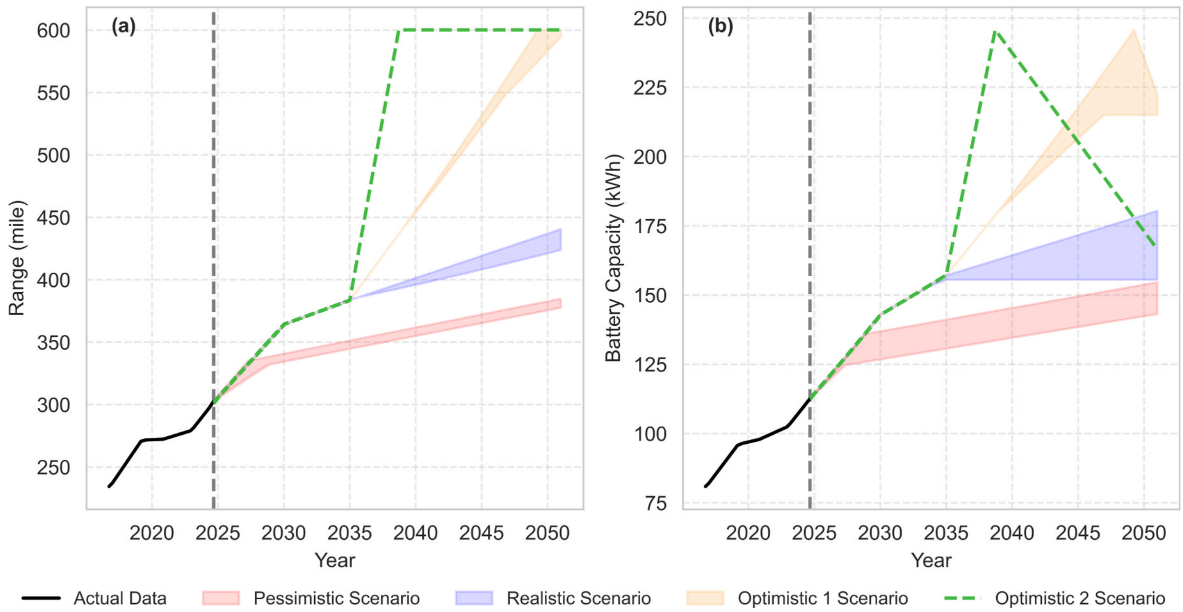

**Fig. A10.** Forecast of F-SUV (a) Range and (b) Battery Capacity Development under Battery Technology Scenarios (20252050)

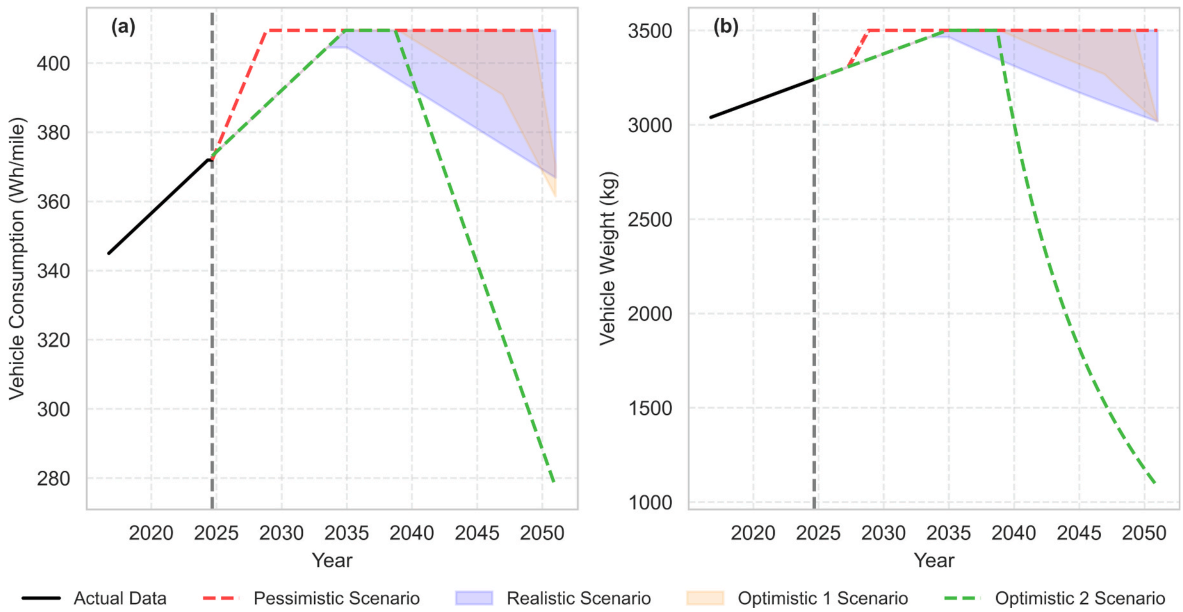


**Fig. A11.** Forecast of F-SUV (a) Vehicle Consumption and (b) Vehicle Weight Development under Battery Technology Scenarios (20252050)

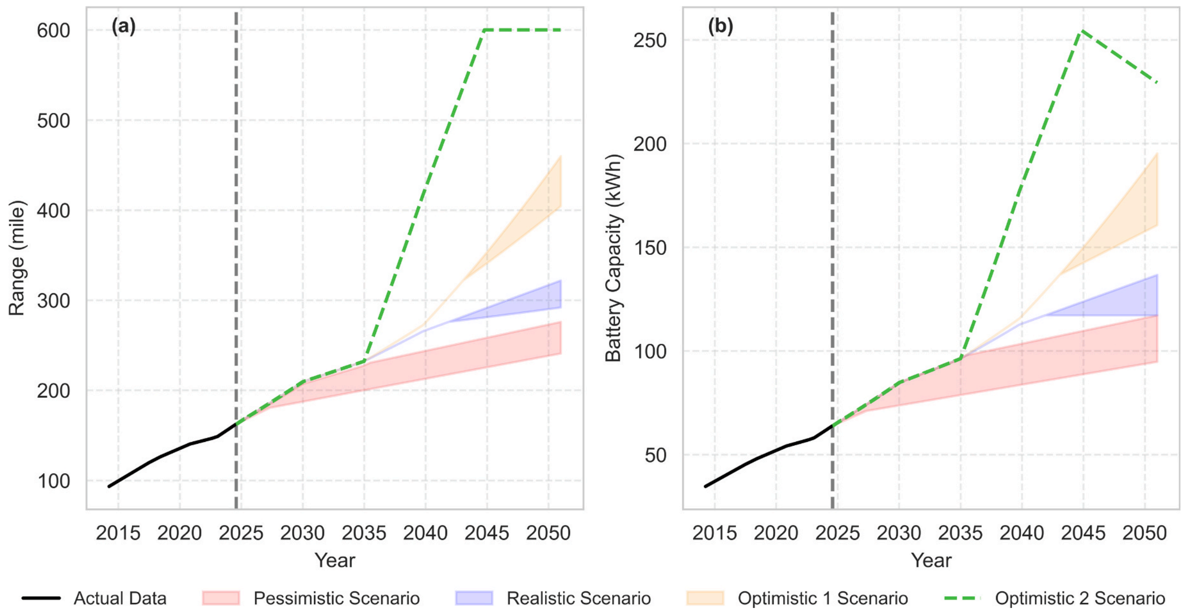


**Fig. A12.** Forecast of N-Small Passenger Van (a) Range and (b) Battery Capacity Development under Battery Technology Scenarios (20252050)

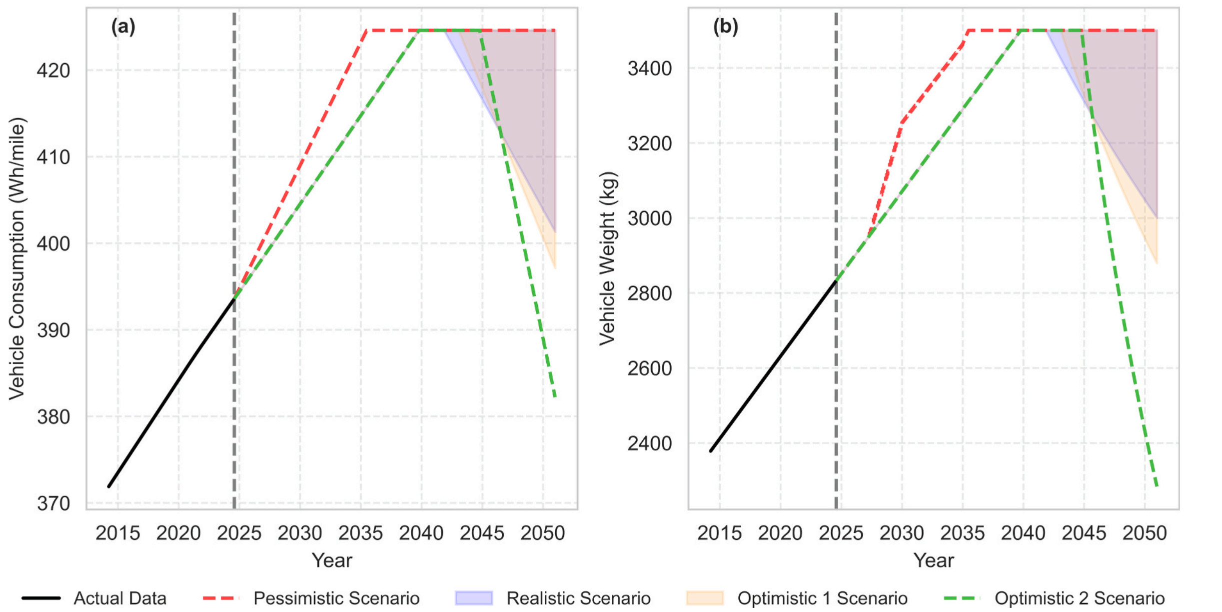


**Fig. A13.** Forecast of N-Small Passenger Van (a) Vehicle Consumption and (b) Vehicle Weight Development under Battery Technology Scenarios (20252050)

## Data availability

Data will be made available on request.

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