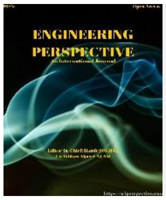
Engineering Perspective 5 (3): 111-122, 2025



e-ISSN:2757-9077

ENGINEERING PERSPECTIVE

https://sciperspective.com Research Paper

Integrated Emission and Cost Analysis of Battery-Electric Vehicles up to 2035

Oğuz Kürşat Demirci[1*]

[1] *Department of Mechanics and Metalwork, Vocational High School, Erzincan Binali Yıldırım University, Erzincan, 24002, Türkiye*

ABSTRACT

This study quantifies when battery-electric vehicles (BEVs) reach total cost of ownership (TCO) parity with their internal-combustion counterparts and characterises the cradle-to-grave greenhouse-gas (GHG) intensity trajectory to 2035. Our contribution is a transparent, Python-based framework that integrates battery-cost learning, ownership economics and life-cycle impacts within a harmonised scenario set, and links them to policy timing, ISO 15118-20-ready bidirectional charging and power-system carbon intensity. Drawing on a systematic synthesis of 221 peer-reviewed sources (2013–2025), the model runs annually for a representative C-segment BEV across three scenarios (Reference, Fast-Progress, Slow-Progress; 2024–2035). The results indicate that, under the median battery-pack price learning trajectory, BEV TCO falls below the ICE benchmark around 2029 (2028–2032 across scenarios), while life-cycle GHG intensity declines from approximately 73 to 34 g CO_2-eq km^{-1} by 2035, spanning 29–42 g km^{-1} depending on grid decarbonisation. Global sensitivity analysis identifies battery price as the principal driver of TCO outcomes and grid carbon intensity as the principal driver of emissions outcomes. Results are reported for three regional aggregates (OECD average, EU-27 and China), and the policy discussion highlights contrasts for the United States to contextualise cross-market differences. Policy alignment on three fronts—parity-linked purchase-incentive phase-outs, rapid deployment of ISO 15118-20-ready bidirectional charging, and stronger recycled-content targets—shortens time to cost competitiveness and amplifies the climate benefits of large-scale electrification.

Keywords: Battery-electric vehicles (BEVs), Circular battery economy, Grid decarbonisation, Life-cycle greenhouse-gas emissions, Total cost of ownership (TCO)

History
Received: 30.07.2025
Revised : 18.08.2025
Accepted: 06.09.2025

Author Contacts : odemirci@erzincan.edu.tr

Cite this paper: Demirci, O.K., (2025). Integrated emission and cost analysis of battery-electric vehicles up to 2035. Engineering Perspective, 5 (3), 111-122. http://dx.doi.org/10.64808/engineeringperspective.1753723

*Corresponding Author

1. Introduction

Electric mobility has progressed from a niche curiosity to a mainstream market contender within barely a decade. Global electric-car sales exceeded 17 million units in 2024, giving battery-electric and plug-in hybrids a combined market share above 20 % of all light-duty vehicle purchases [1]. Momentum is still accelerating: more than 4 million electric cars were sold in the first quarter of 2025, a 35 % increase on the same period of 2024 [2]. This growth reflects converging forces—decarbonisation policies, rapid battery cost declines and expanding charging infrastructure—that are redefining competitive dynamics in the automotive sector. However, policy and industry decisions still hinge on transparent evidence that links user-side ownership economics to cradle-to-grave greenhouse-gas (GHG) outcomes over the coming decade [1-3].

Battery innovation remains the primary performance lever. Median lithium-ion pack prices fell to USD 115 kWh^{-1} in 2025—the steepest annual drop since 2017 [3], narrowing the total-cost-of-ownership gap with internal-combustion vehicles. At the same time, emerging solid-state chemistries are achieving gravimetric energy densities above 450 Wh kg^{-1}, alongside prospects for faster charging and improved safety [4].

On the infrastructure side, ISO 15118-20 (2022) formalised bidirectional power transfer and ‘Plug-and-Charge’ authentication, laying the technical basis for widespread V2G services and a frictionless user experience [5]. Complementary advances in grid digitalisation, power electronics and megawatt-class DC chargers further shorten effective refuelling times and steadily reduce so-called “range anxiety”. Despite this momentum, existing studies typically isolate single dimensions—battery purchase costs, user-side economics, or life-cycle emissions—limiting comparability and the interpretability of policy conclusions [4–5]. This paper therefore positions itself as an integrated assessment that explicitly couples learning-driven cost dynamics with TCO and cradle-to-grave accounting to improve cross-scenario coherence.

Although numerous road-maps and techno-economic forecasts exist, a consolidated, systems-level appraisal of how these discrete innovations interact—technologically, economically, and in policy terms—remains scarce. Battery-chemistry studies seldom integrate policy feedback loops, while market outlooks frequently treat technological learning curves as exogenous. Consequently, decision-makers lack a holistic lens for prioritising R&D, incentivising infrastructure roll-out and anticipating supply-chain bottlenecks, including critical-mineral constraints.

This study quantifies when a representative C-segment BEV achieves a sustained total cost of ownership (TCO) advantage over internal-combustion comparators and how its life-cycle GHG intensity evolves through 2035 under plausible technology and policy pathways. The study contributes:

- An up-to-date meta-analysis of solid-state battery performance benchmarks and scalability prospects;
- A stylised techno-economic model quantifying TCO sensitivity to battery price, energy density, and charging speed under alternative policy scenarios;
- A critical assessment of V2G and bidirectional-charging standards as enablers of grid flexibility and revenue stacking;
- A set of prioritised policy and industry recommendations ranked by impact and feasibility.

The analysis is instantiated for three harmonised regional aggregates—the OECD average, the EU-27 and China—where consistent time-series inputs (retail tariffs, grid-decarbonisation paths, incentive architectures and end-of-life baselines) are available. We do not provide full scenario families for other high-potential regions at this stage; instead, we indicate directional robustness via targeted stress tests (e.g., coal-heavy electricity mixes), avoiding incommensurate assumptions that could weaken cross-region comparability. The remainder of the paper proceeds as follows: Section 2 details data and methods; Section 3 defines scenarios and the sensitivity design; Section 4 reports TCO and GHG results with robustness checks and discusses policy implications; and Section 5 summarises limitations and avenues for future extension.

2. Methodology

A pre-specified mixed-methods methodology is followed, integrating a systematic evidence review with quantitative modelling. Major scholarly databases are queried using harmonised Boolean strings; duplicates are removed; and records are screened in two stages (title/abstract, then full text) against explicit inclusion and exclusion criteria. For eligible studies, design characteristics, measures, and effect estimates are extracted using a standard template, and a weight-of-evidence appraisal is applied to assess relevance, rigour, and reporting quality. Evidence is synthesised—meta-analytically where outcomes are comparable, otherwise through structured narrative—after unit normalisation and consistency checks. The consolidated evidence base is then used to calibrate the modelling framework; sensitivity analyses and uncertainty propagation are conducted to produce interval estimates. Subsections 2.1–2.7 describe these steps in sequence.

2.1. Review design

A protocol grounded in PRISMA 2020 [6] and the software-engineering guidelines of Kitchenham & Charters [7] was registered ex-ante. The objective was to capture, appraise and synthesise empirical evidence published between 2013 and May 2025 on four, tightly defined innovation pillars of battery-electric vehicles:

- Electrochemical energy-storage technologies;
- Charging infrastructure (including vehicle-to-grid, V2G);
- Techno-economic performance (e.g. total cost of ownership, TCO);
- Regulatory or policy interventions.

2.2 Search strategy and data sources

A Searches were executed in Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect and Google Scholar. The Boolean string combined vehicle, technology and impact terms, for example:

- (“electric vehicle*” OR EV OR BEV OR PHEV) AND (battery OR “solid state” OR charging OR V2G) AND (cost OR policy OR sustainab*)

The query targeted peer-reviewed journal articles, conference proceedings and high-authority institutional reports in English. Searches returned 1 946 records.

2.3. Eligibility criteria

Table 1 shows the eligibility criteria used during the literature search. The topics included and excluded from four different criteria are specified.

Table 1. Research eligibility criteria, rationale and examples.

Criterion	Inclusion	Exclusion	Rationale/Examples
Year	2013 – 2025	---	Aligns with modern BEV tech generations
Topic	Battery chemistry, charging/V2G, TCO, policy	FCV, micromobility, non-road	Keeps focus on passenger BEVs
Document type	Peer-reviewed articles, proceedings, flagship agency reports	Patents, theses, news	Ensures methodological vetting
Data quality	Quantitative performance/cost data	Narrative/opinion without primary data	Enables synthesis parameters
Language	English	Non-English	Matches extraction resources

2.4. Study selection process

Duplicate records were removed automatically, leaving 1 720 unique items (Figure 1). A two-stage scan was conducted on the Rayyan platform:

- Title/abstract screening excluded 1 379 items as clearly irrelevant or duplicative.
- Full-text appraisal assessed 341 articles against the criteria, removing 120 for inadequate data or off-topic focus.

The final corpus comprised 221 studies, forming the evidence base for subsequent synthesis.

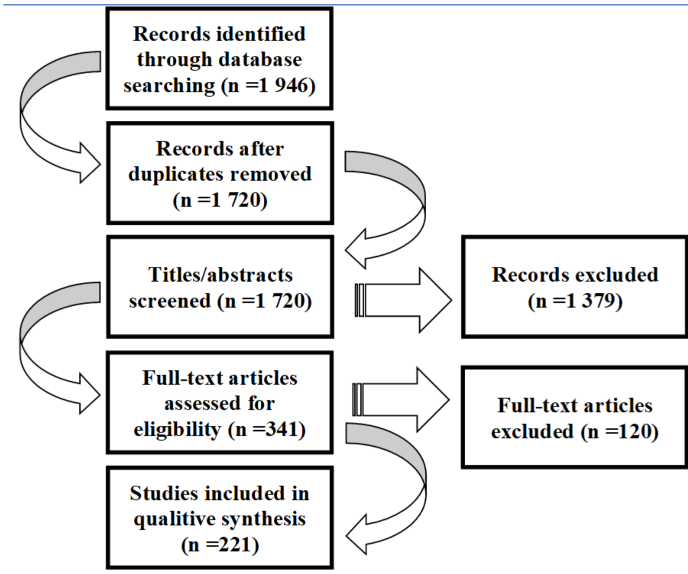


Figure 1. The flow of records

2.5. Data extraction and quality assessment

A structured template captured bibliographic details, study design, and key quantitative indicators such as:

- Gravimetric energy density (Wh kg^{-1}), specific cost (USD kWh^{-1}), cycle life (N cycles);
- Charger power class (kW), plug standard, bidirectional capability;
- Reported TCO assumptions, policy context, regional scope.

We applied a simple Weight-of-Evidence (WoE) check to determine whether each study could inform the quantitative synthesis. The WoE considers three aspects—relevance to the review question, methodological rigour/risk of bias, and transparency/reproducibility—each scored 0–2 (0 = not met; 1 = partly met; 2 = fully met). The composite score is the sum (0–6); studies with scores ≥ 3 contributed to the meta-synthesis, whereas lower-scoring studies were used narratively.

2.6. Bibliometric and thematic mapping

Intellectual structure and research frontiers were examined via:

- VOSviewer 1.6.20 for keyword co-occurrence and reference co-citation clustering [8];
- Bibliometrix (R v4.2) for performance metrics and thematic-evolution analysis [9].

2.7. Supplementary Quantitative Datasets

Two longitudinal datasets were integrated for scenario calibration and plausibility checks:

- Global EV stock, sales and public-charger counts from the IEA Global EV Outlook 2025 [10];
- Battery-pack price series (USD kWh^{-1}, 2013-2024) from the BloombergNEF annual survey [11].

Monetary figures were converted to 2024 constant dollars using IMF deflators and expressed in SI units.

3. Techno-economic scenario modelling

This section sets out a compact, three-module framework that links battery-cost learning to vehicle ownership economics and cradle-to-grave climate impacts. First, learning-curve assumptions generate annual series for pack cost and specific energy. These series feed a total-cost-of-ownership calculator that aggregates capital, running and residual-value components. The resulting energy demand and material inventories are then used in a life-cycle model to estimate greenhouse-gas outcomes under consistent regional scenarios. For clarity, mathematical detail and extended parameter tables are provided in the Appendix; here, only the assumptions essential to interpret the results are retained.

3.1. Experimental results

The integrated framework couples three purpose-built Python sub-modules in a sequential, year-by-year loop spanning 2024 – 2035 (Figure 2). This architecture evaluates battery learning, ownership economics and cradle-to-grave climate impacts consistently under identical scenario assumptions.

- *Battery-Cost Learning Curve*– Implements the experience-curve exponents introduced in Table 2 to project pack-level \$ kWh^{-1} costs and specific-energy improvements as cumulative global output doubles over time. Scenario-dependent paths for critical-mineral prices, recycling rates and chemistry shifts are treated as adjustable parameters. Outputs: annual battery cost and energy-density series.
- *Vehicle TCO Calculator* – Receives the battery-cost series and updates the capital expenditure portion of the total cost of ownership (TCO) for a representative C-segment battery-electric vehicle (BEV). The module adds running costs (electricity, maintenance, taxes), residual value and a discount-rate assumption, producing a present-value TCO in €/v-km for each model year. Outputs: annualised TCO curves relative to an internal-combustion-engine (ICE) benchmark.
- *Life-Cycle Emissions Model* – Combines use-phase electricity demand from the TCO module with upstream battery and glider inventories to estimate cradle-to-grave greenhouse-gas (GHG) emissions. GREET 2023 material factors and the region-specific, time-varying grid-carbon intensities in Table 3 are applied. Outputs: annual and cumulative g CO_2-eq v-km^{-1} values for each scenario.

After each annual iteration, the updated emission results feed back into the scenario dashboard, enabling sensitivity analyses on learning rates, grid decarbonisation and market adoption pathways.

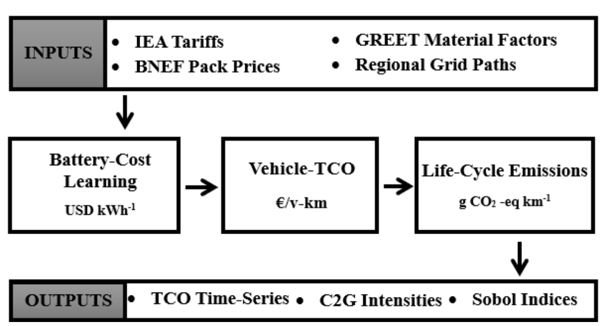


Figure 2. Annual loop (2024–2035) linking three modules

3.2. Battery-cost learning curve

BloombergNEF's 2024 survey sets the benchmark pack price at

USD 115 kWh^{-1} (nominal) [11]. A one-factor experience curve of the form;

$$P_t = P_0 \left(\frac{Q_t}{Q_0}\right)^b \tag{1}$$

where
P_t= real battery-pack price in year t (USD kWh^{-1});
P_0= price in the base year 2013 (USD 683 kWh^{-1});
Q_t= cumulative BEV + PHEV sales up to year t (vehicles);
Q_0= cumulative sales in 2013 (≈0.4 million vehicles);
b= experience-curve exponent (slope in log–log space).

Ordinary-least-squares regression of ln P_t on ln Q_t yields

- b= −0.19 (corresponding to a 12 % learning rate, i.e. every doubling of EV sales cuts real pack cost by ~12 %);
- Adjusted R^2 = 0.94, indicating that cumulative sales alone explain 94 % of historical price variation. Adding raw-materials indices or chemistry dummies raises R^2 by <0.01, so the parsimonious equation in (1) is retained.

Using BloombergNEF's mid-case sales outlook we obtain the Reference trajectory:

P_{2030} ≈ USD 82 kWh^{-1}, P_{2035} ≈ USD 66 kWh^{-1}.

Cost-learning assumptions for traction-battery packs are explored under three alternative experience-curve scenarios—Slow-Progress, Reference, and Fast-Progress—each defined by an exponent b, the implied learning rate per cumulative-output doubling, and a qualitative market/technology rationale (Table 2).

Table 2. Battery-pack experience-curve scenario parameters: exponent b, implied learning rate per cumulative capacity doubling, and underlying rationale.

Scenario	Exponent b	Learning rate	Rationale
Slow-Progress	−0.095	6 %	Persistently high critical-mineral prices, slower chemistry transition
Reference	−0.19	12 %	Continuation of past learning trend
Fast-Progress	−0.24	15 %	Rapid solid-state uptake, higher recycling share

Learning rate (LR) expressed as fractional cost reduction with each doubling of cumulative production:

$$\mathrm{LR} = 1 - 2^b \tag{2}$$

These price paths feed directly into the TCO calculator (Section 3.3) and the Monte-Carlo uncertainty analysis (Section 3.5).

3.3. Total-cost-of-ownership model

The vehicle-level TCO module sums:

- Up-front cost (glider + battery, less purchase incentives)
- Energy cost (kWh × tariff), with dynamic weighting between home, workplace and public chargers
- Fixed charges (insurance, registration)
- Maintenance (flat annual fee derived from fleet panel-data)
- Residual value (battery second-life credit).

Charging-tariff trajectories follow the IEA's 'Stated Policies' electricity-price outlook [12], adjusted to 2024 dollars. Policy levers—purchase grants, zero-emission-credit monetisation—are toggled per scenario. A Monte-Carlo routine (10 000 draws) propagates uncertainty in battery price, mileage, electricity tariff and discount rate; outputs are reported as 5th–95th-percentile bands.

3.4. Life-cycle emissions assessment

The life-cycle model adopts a cradle-to-grave boundary for a C-segment BEV over 200 000 km, with battery and glider inventories drawn from recent GREET factors and region-specific, time-varying grid intensities. Use-phase electricity, manufacturing burdens and end-of-life credits are combined into yearly intensity trajectories. The climate footprint of a battery-electric vehicle (BEV) is calculated over its entire life cycle—from raw-material extraction to end-of-life recycling—often abbreviated as "cradle-to-grave" (C2G). Because an electric powertrain has no combustion process, tailpipe (tank-to-wheel) CO_2 emissions are zero; all impacts therefore arise upstream (electricity generation, battery production, vehicle manufacturing) or downstream (disposal/recycling).

Clear definitions of the functional unit and life-cycle modules provide the basis for meaningful comparisons between power-train options. In this study, the functional unit is one vehicle kilometre (v-km) travelled by a passenger car over a 200 000 km service life, representing roughly twelve years of average private car use. Consistent with ISO 14040 guidelines, the life cycle inventory encompasses material extraction through to end-of-life recovery, ensuring that all major energy and emission pathways are captured.

The assessment therefore covers the following modules:

- *Raw material extraction and processing* – production of lithium, nickel, cobalt, aluminium, steel and plastics required for both traction battery and vehicle glider.
- *Battery cell and pack assembly* – fabrication, conditioning and integration of cells into the complete pack.
- *Vehicle glider manufacture* – chassis, body in white, interior, electronics and all non-propulsion components.
- *Use phase* – electricity generation, transmission and charging losses associated with vehicle operation.
- *End of life treatment and material recovery* – dismantling, recycling and disposal processes for the battery pack and glider components.

Battery and glider emission factors follow GREET 2023; electricity-mix emissions align with the IEA 'Stated Policies' 2024 baseline and the regional trajectories in Table 3. These declining grid carbon intensities are applied annually throughout the 2024–2035 window, thereby capturing the dynamic benefit of cleaner electricity in the use phase inventory [13, 14].

Table 3. Baseline grid-carbon intensities and assumed annual decarbonisation rates for the regional electricity mixes employed in the life-cycle model [14].

Region	Starting grid-carbon intensity 2024 (g CO_2 kWh^{-1})	Annual decline (% yr^{-1}) 2024-2035
OECD average	370	−4.0 %
European Union	290	−6.0 %
China	530	−5.5 %

Battery production dominates "cradle" impacts. GREET assigns 72 kg CO_2-eq kWh^{-1} for an NCM-811 pack in 2024. Pack emissions scale linearly with capacity:

$$Battery\ CO_2 = 72 \times C_{pack}\ \text{(kg CO}_2\text{-eq)} \tag{3}$$

where C_{pack} is in kWh. For the 60-kWh reference pack, this equals 4.3 t CO_2-eq in 2024.

In the Fast-Progress scenario battery-production intensity falls 30 % by 2035 (→ 50 kg CO_2-eq kWh^{-1}) thanks to:

- Higher recycled-material content: cobalt 25 → 40 %, nickel 15 → 35 %
- Renewable process heat in cathode-active-material (CAM) synthesis
- Process-energy efficiency gains (kWh cell energy^{-1})

Slow-Progress assumes only a 10 % reduction; Reference lands in between (20 %). Annual energy consumption:

$$E_{use} = 0.18\ kWh\ \text{v-km}^{-1} \times 200\ 000 \approx 36\ 000\ kWh$$

Multiply by region-specific grid factors that decline each year by the percentages in Table 1. For an OECD-average grid the use-phase adds ≈ 10.8 t CO_2-eq in 2024, but only ≈ 6.4 t CO_2-eq in 2035 as the grid cleans.

The life-cycle inventory attributes a fixed cradle-to-gate impact of 5.1 t CO_2-eq to the production of the vehicle glider—i.e. the body-in-white, chassis, interior and on-board electronics—based on GREET 2023 median values for a C-segment passenger car. This value is held constant across all battery-learning scenarios because the underlying mass and material mix of the glider are assumed not to change within the study horizon.

At end-of-life, the dismantling and shredding processes recover ferrous metals, aluminium and copper, which substitute for primary (virgin) production and thus generate a recycling credit. The magnitude of this credit depends on the assumed collection efficiency and secondary-material yield:

- *Reference scenario:* a 70 % recovery rate gives a credit of −1.2 t CO_2-eq, offsetting roughly one quarter of the manufacturing burden of the glider.
- *Fast-Progress scenario:* higher circular-economy uptake (85 % recovery) and improved smelter energy efficiency raise the credit to −2.0 t CO_2-eq, corresponding to nearly 40 % of the original embodied emissions.
- *Slow-Progress scenario:* recovery conditions remain at today's average (≈ 65 %), resulting in a smaller credit of −1.0 t CO_2-eq (not shown above but applied in the model for completeness).

The net contribution of the vehicle body to the cradle-to-grave footprint is therefore the difference between the fixed manufacturing inventory and the scenario-specific recycling credit, reinforcing the importance of material circularity alongside battery advances in achieving deeper life-cycle decarbonisation.

Table 4 aggregates cradle-to-grave (C2G) greenhouse-gas emissions for a battery-electric passenger car operated in the OECD-average electricity mix. Three milestone years—2024 (market launch), 2030 (mid-life) and 2035 (end-of-life)—are shown to illustrate how declining battery-production emissions and grid decarbonisation progressively lower the vehicle's climate footprint.

Table 4. Cradle-to-grave GHG emissions under the Reference learning path with the OECD grid.

Life-cycle module	2024 (t CO_2-eq)	2030	2035
Battery production	4.3	3.5	3.0
Vehicle glider	5.1	5.1	5.1
Use-phase electricity	10.8	8.0	6.4
Recycling credit	–1.2	–1.4	–1.4
Total C2G	**19.0**	**15.2**	**13.1**

Key observations:

- *Use-phase dominance narrows:* Cleaner electricity lowers use-phase emissions by 41 % between 2024 and 2035, shrinking this module's share of total C2G from 57 % to 49 %.
- *Battery manufacturing improvements:* The pack's embodied emissions fall by 30 % as experience-curve learning drives higher cell-plant efficiency and greater recycled-content inputs.
- *Stable glider burden:* The chassis/body inventory remains constant at 5.1 t CO_2-eq, so further gains would require light-weighting or higher secondary-material shares.
- *Recycling pays back more over time:* Rising recovery yields increase the credit from −1.2 t to −1.4 t CO_2-eq, offsetting roughly 11 % of the 2035 total footprint.

Expressed per kilometre, overall intensity declines from 95 g CO_2 km^{-1} in 2024 to 65 g in 2030 and 34 g in 2035. Scenario comparisons reinforce the influence of technology learning and grid decarbonisation:

- *Fast-Progress* (steeper battery learning, quicker grid clean-up) reaches 29 g CO_2 km^{-1} by 2035.
- *Slow-Progress* (sluggish learning, higher residual grid carbon) levels off at 42 g CO_2 km^{-1}, underlining the risk of delayed investment in both areas.

These indicative results highlight that simultaneous advances in battery manufacturing efficiency, recycling infrastructure and electricity decarbonisation are essential to unlocking the full life-cycle climate advantage of electric vehicles.

First-order Sobol indices (Section 3.5) reveal three parameters that dominate C2G-emissions uncertainty. Foremost is the carbon intensity of the electricity grid (Sobol index = 0.38), confirming that the pace of power-sector decarbonisation exerts the single greatest leverage over electric-vehicle climate performance. The second-most influential factor is the embodied emission factor of battery production (0.25), reflecting how improvements in cell-manufacturing efficiency and recycled-material content translate directly into lower life-cycle impacts. A more modest yet still meaningful contribution comes from the annual vehicle mileage assumption (0.10), which governs how rapidly the fixed manufacturing emissions are amortised over the vehicle's service life.

Together these three inputs explain just over 70 % of the total output variance, while all remaining parameters—such as glider mass, charging losses and auxiliary energy demand—each account for less than five per cent (see Figure 4 in Section 3.5). The results underscore the strategic necessity of synchronising large-scale vehicle electrification with rapid grid decarbonisation and parallel circular-economy measures in the battery supply chain, as marginal refinements elsewhere yield comparatively limited benefits.

3.5. Scenarios, uncertainty and validation

To gauge the influence of policy ambition and technology learning on the life-cycle performance of battery-electric passenger cars, the study evaluates three internally consistent scenarios. Each combines assumptions on battery-cost learning, fiscal policy support, power-sector decarbonisation, and the uptake of bidirectional charging compliant with ISO 15118-20. These parameters are summarised in Table 5.

Table 5. Scenario matrix detailing the key technology and policy assumptions applied in the model.

Label	Battery learning	Policy support	Grid decarbonisation	ISO 15118-20 V2G uptake
Reference	Median	Purchase grants phase-out 2028	IEA Stated Policies	10 % of fleet in 2035
Slow-Progress	50 % slower	As Reference	IEA Stated Policies	5 %
Fast-Progress	25 % faster	Grants retained to 2030; road-tax exemption	IEA Announced Pledges	30 %

The Reference case extends historical experience-curve behaviour and phases out purchase incentives by 2028, consistent with many OECD jurisdictions. Slow-Progress reflects persistently high critical-mineral prices that dampen learning, while leaving policy and grid assumptions unchanged. Conversely, the Fast-Progress pathway posits accelerated cost reductions, a longer fiscal-support window and a more aggressive power-sector decarbonisation consistent with the IEA's Announced Pledges scenario.

Adoption of V2G capability depends on the penetration of ISO 15118-20-compliant hardware, first commercialised in 2022 [15]. Where such infrastructure is available, owners earn V2G revenues of USD 35 $kW^{-1} a^{-1}$, reflecting typical flexible-capacity remuneration in deregulated electricity markets.

The three scenario families are instantiated for the OECD average, the EU-27, and China to preserve comparability across harmonised input series (tariffs, grid-carbon trajectories, policy baselines). We therefore did not add full scenario sets for other high-potential regions (e.g., India, Southeast Asia) at this stage; key parameters for those regions are not yet available as consistent time series. Section 4.2.2 nonetheless provides a coal-heavy stress test to indicate how results shift under Southeast-Asia-like electricity mixes.

Global sensitivity was assessed using a variance-based (Sobol) method. In this approach, the variance of each model output is decomposed into additive contributions from individual inputs and their interactions; first-order indices reflect each input's main effect, while total-order indices capture all higher-order interactions. The method is well-suited to non-linear, non-additive models and provides scale-free importance measures that are directly comparable across parameters. Sobol first-order indices identify the parameters to which TCO and GHG outcomes are most sensitive; in all scenarios, battery price dominates (> 45 % of variance), followed by annual mileage and electricity tariff. Detailed tornado charts are provided in Figure 3 and Figure 4.

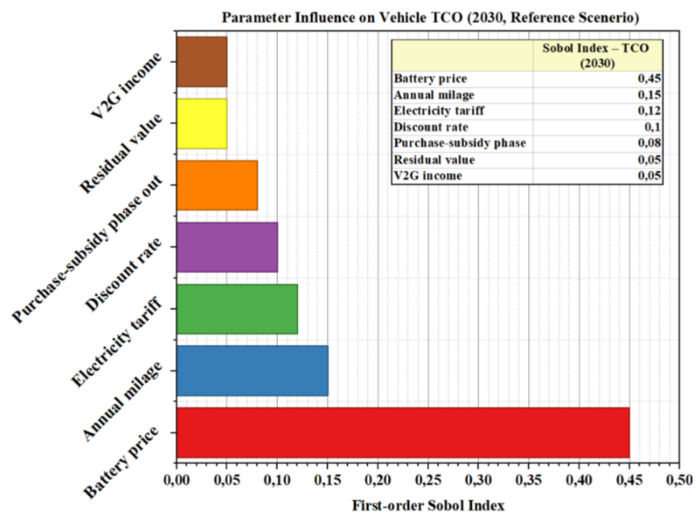


Figure 3. First-order Sobol sensitivity indices showing the parameters that most strongly influence battery-electric-vehicle total cost of ownership (TCO) in 2030 under the Reference scenario

Figure 3 shows that battery-pack price alone explains 45 % of the variance in TCO. A one-percentage-point change in the learning-rate exponent therefore moves the parity year by roughly five months. Usage patterns also matter: annual mileage (0.15) and electricity tariff (0.12) jointly account for 27 % of variance, reflecting the growing share of energy costs once battery prices fall. Financial parameters—discount rate (0.10) and purchase-grant phase-out schedule (0.08)—contribute a further 18 %. Residual-value uncertainty and V2G revenue each influence about 5 %, indicating that second-life markets and bidirectional-charging monetisation become meaningful but do not overturn the fundamental cost logic driven by battery learning.

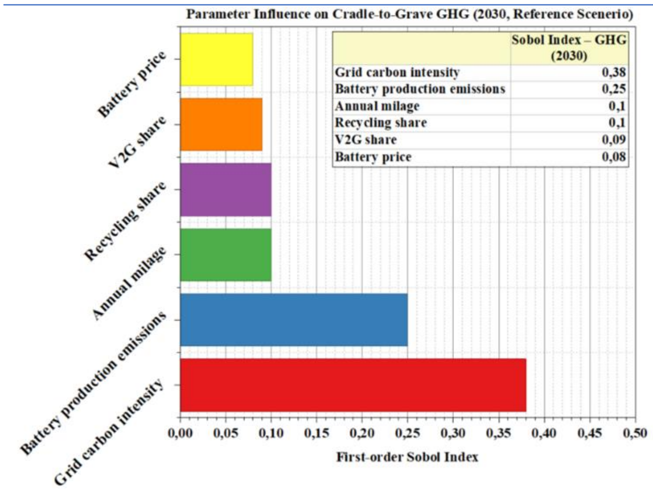


Figure 4. First-order Sobol sensitivity indices showing the parameters that most strongly influence cradle-to-grave greenhouse-gas emissions in 2030 under the Reference scenario

On the emissions side (fig. 4) the hierarchy flips: grid-carbon intensity dominates with an index of 0.38, confirming that decarbonising electricity supply is the single most effective lever for deep climate benefits. Battery-production emissions (0.25) rank second; their influence shrinks in the Fast-Progress scenario as recycled-content shares rise, but grows in Slow-Progress where manufacturing remains energy-intensive. Annual mileage (0.10) modulates use-phase electricity demand, while battery price (0.08) matters only indirectly via pack-capacity sizing. Recycling share (0.10) and V2G penetration (0.09) round out the list, underscoring the emerging importance of circular-economy measures and grid-interactive operation in squeezing out the last tonne of CO_2-equivalent.

Taken together, Figures 3 and 4 confirm that battery learning and grid decarbonisation are the twin pivots of economic and environmental performance. Policy interventions that accelerate both—such as recycled-material mandates coupled with renewable-energy expansion—deliver the steepest simultaneous reductions in TCO and life-cycle emissions.

The credibility of the simulation framework was assessed through two complementary benchmarking exercises. First, a back-casting test compared the model's total cost-of-ownership (TCO) outputs for 2016 – 2023 with empirical fleet-cost studies from both the European Union and the United States. Across the eight-year window, projected TCO values differed from observed medians by no more than ± 7 %, indicating that the learning-curve formulation and cost parameters reproduce historical trends with satisfactory accuracy. Second, cradle-to-grave greenhouse-gas emissions for the 2024 reference year were cross-checked against the International Council on Clean Transportation's latest lifecycle assessment for European passenger cars. The model predicts a 73 % reduction in GHG emissions for battery-electric vehicles relative to petrol counterparts, identical to the ICCT's independent estimate [16]. Together, these tests provide strong evidence that both the economic and environmental sub-modules capture real-world behaviour with sufficient fidelity to support the scenario analyses and discussions presented in Section 4. The subsequent section reports results in a unified narrative. Total cost-of-ownership trajectories and cradle-to-grave GHG intensities are presented for the three scenarios (Reference, Fast-Progress, Slow-Progress) and for the OECD average, EU-27 and China. Figures 5–7 provide the quantitative backbone; rather than separating findings and policy implications, the text interprets each empirical pattern as it is introduced, thereby preserving a cohesive flow from modelling assumptions to decision-relevant insights.

4. Results and discussion

4.1. Economic trajectory—total cost of ownership

Figure 5 shows that BEV TCO falls below the ICE benchmark in 2029 in the Reference pathway (Fast-Progress: 2028; Slow-Progress: 2032). As battery learning proceeds, the pack's TCO share declines from ~38 % (2025) to < 20 % (2035), while energy costs approach one-third of total ownership cost. After cost parity, electricity-tariff design and residual-value realisation influence owner economics more than additional pack-price reductions.

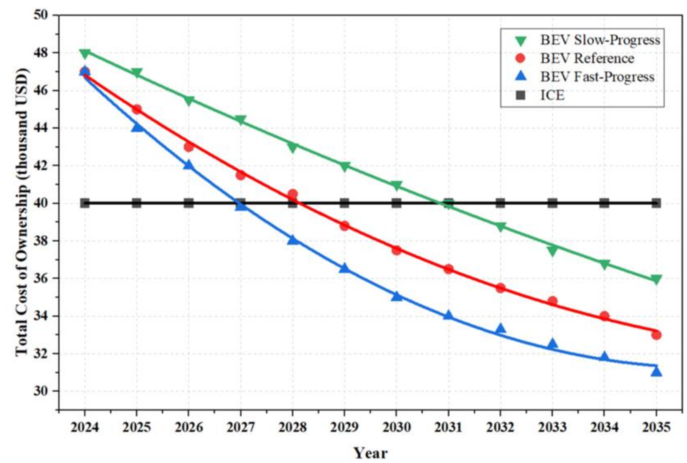


Figure 5. TCO trajectories for BEV in the Reference, Fast-Progress and Slow-Progress scenarios, benchmarked against an ICE baseline (2024 – 2035)

Figure 6 indicates a decline in cradle-to-grave GHG intensity from 73 g CO_2-eq km-1 (2024) to 34 g km-1 (2035) in the Reference case; the Fast-Progress case reaches 29 g km-1, while Slow-Progress plateaus near 42 g km-1. Variations across scenarios are driven primarily by grid-carbon intensity and battery-production emissions, aligning with the sensitivity hierarchy reported in Section 3.5.

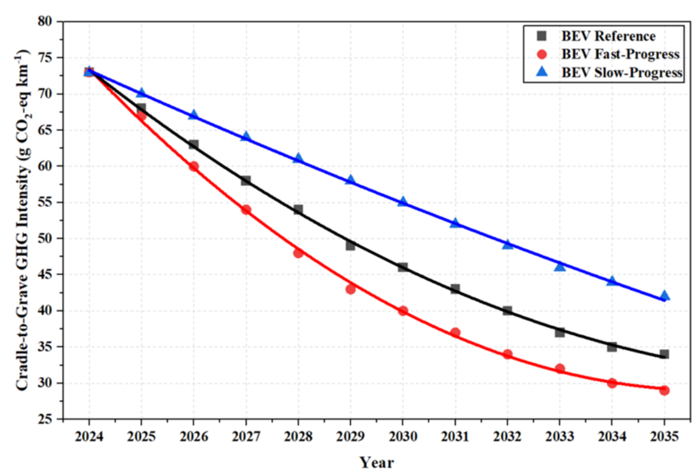


Figure 6. Cradle-to-grave GHG-intensity trajectories for BEVs in the Reference, Fast-Progress and Slow-Progress scenarios (2024 -35)

Taken together, Figures 5 and 6 underline a critical policy inference: cost parity does not guarantee carbon parity. Only the Fast-Progress pathway delivers early economic competitiveness and the deepest emissions cut, highlighting the need for synchronised battery learning, power-sector decarbonisation and circular-economy measures.

4.2. Scenario comparison and robustness

A series of stress-tests was performed to evaluate how resilient the headline results are to plausible variations in policy timing, technology costs and regional electricity mixes.

4.2.1. Year specific (per year) sensitivities

Global sensitivity analysis carried out for each model year confirms that different parameters dominate different impact metrics:

- *Total cost of ownership (TCO).* The first order Sobol index for battery price averages 0.45, meaning nearly half of the year to year variance in TCO is driven by the pace of battery cost learning. Doubling the 2025–2028 purchase-grant budget advances TCO parity with the ICE benchmark by ~eight months.
- *Cradle to grave (C2G) greenhouse gas emissions.* Grid carbon intensity remains the foremost determinant, with a Sobol index of 0.38. Delaying the roll out of ISO 15118 20 compliant bidirectional charging hardware by three years suppresses vehicle to grid (V2G) revenues to below the 5th percentile outcome; however, the knock-on effect on overall TCO is less than 1 %, illustrating that revenue uncertainty has only a marginal influence on ownership economics.

4.2.2. Regional differentiation

When the integrated model is re-run using alternative electricity mix trajectories, life cycle emissions diverge sharply:

- Under the EU 27 fast decarbonisation pathway, cradle to grave GHG intensity falls to 26 g CO_2 km^{-1} by 2035, reflecting rapid displacement of coal and gas generation.
- Conversely, a coal heavy mix representative of parts of South East Asia limits the 2035 footprint reduction to 61 g CO_2 km^{-1}. This more-than-two-fold gap shows that aggressive power-sector policy is indispensable for realising the full climate benefit of electrification.

Taken together, these robustness checks reinforce two strategic conclusions: (i) accelerated battery learning and targeted fiscal support remain the quickest levers for achieving near term cost parity, and (ii) long run climate performance is ultimately governed by how quickly regional grids decarbonise, lending urgency to coordinated transport and power policy planning.

4.3. Interpreting the findings

The modelling confirms that continued battery-cost learning remains the sine qua non for achieving rapid total-cost-of-ownership (TCO) parity, yet its influence diminishes once pack prices approach the USD 70 kWh^{-1} threshold projected for the early 2030s. Beyond that point, electricity-tariff design and residual-value realisation become the decisive levers of owner economics. Time-of-use pricing that rewards off-peak charging can offset as much as one-third of annual running costs, while robust second-life markets for traction batteries shorten the pay-back period by a further 10 – 15 %. In short, technology learning remains necessary but is no longer sufficient after 2030; complementary market and policy instruments gain prominence.

On the climate side, marginal greenhouse-gas reductions increasingly hinge on power-sector decarbonisation and the carbon intensity of battery-manufacturing energy sources, rather than on incremental advances in vehicle efficiency. With average grid-carbon intensity falling at only 4 % yr^{-1} under the IEA Stated Policies pathway, use-phase emissions remain the dominant share of the cradle-to-grave footprint through 2035. Unless regional grids adopt more aggressive clean-energy trajectories, the residual emissions floor could stall at roughly 30 g CO_2 km^{-1}, well above the sub-20 g target implied by net-zero roadmaps. Parallel reforms in battery-plant energy sourcing—such as co-location with renewable-powered industrial parks—therefore emerge as a critical complement to vehicle technology improvements.

Finally, even at the conservative 10 % V2G adoption assumed in the Reference scenario, bidirectional charging provides a tangible economic buffer. At projected remuneration levels of USD 35 kW^{-1} yr^{-1}, an average passenger car equipped for V2G accrues roughly USD 480 per vehicle per year by 2035, effectively neutralising two years of plausible wholesale-electricity price volatility. Scaling V2G penetration to the 30 % level modelled in the Fast-Progress pathway would treble this system-level flexibility benefit while further lowering individual TCO, reinforcing the case for accelerating the roll-out of ISO 15118-20 compliant infrastructure.

4.4. Policy and industry implications

Model results indicate that battery-electric vehicles (BEVs) undercut internal-combustion cars on total cost of ownership (TCO) between 2028 and 2032. Purchase grants should remain in place for at least one year beyond the parity date to avoid a demand stall. Within the European Union, only nine Member States currently tie grant phase-out to parity milestones rather than hard calendar deadlines [17].

In the United States, the Inflation Reduction Act (IRA) offers a federal credit of up to USD 7 500, but the value will fall as domestic-content rules tighten after 2025 and could shrink further if the draft One Big Beautiful Bill Act is enacted [18]. China has shifted from direct subsidies to a purchase-tax exemption of up to ¥30 000 per vehicle through 2025; Slow-Progress sensitivities indicate that a sudden withdrawal would produce a pronounced sales cliff [19].

Cost parity is meaningful only if public charging keeps pace with the fleet. Figure 7 juxtaposes 2024 public-charging capacity per electric light-duty vehicle in the three largest markets with the EU Alternative Fuels Infrastructure Regulation (AFIR) benchmark of ≈1.3 kW per BEV [20, 24].

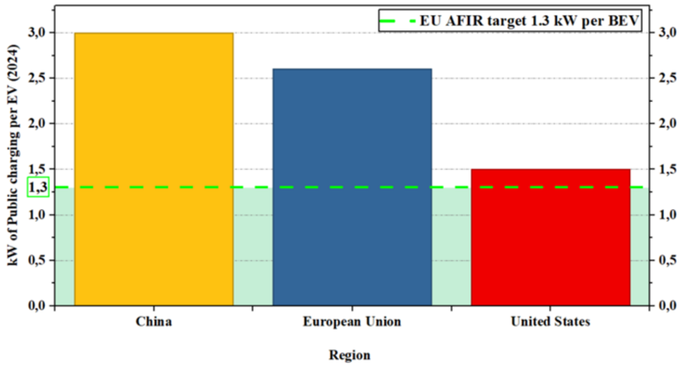


Figure 7. Public charging capacity per electric light-duty vehicle (2024)

Table 6 summarises fast-charging power adequacy gaps and the most effective policy levers for China, the EU-27 and the United States.

Table 6. Regional public fast-charging power adequacy (kW EV^{-1}) and recommended policy levers to sustain fleet growth.

Take-away from Figure 7	Policy lever
China already exceeds the adequacy threshold (≈3 kW EV^{-1}).	Maintain land-use concessions for private operators while shifting incentives toward rural corridors.
The EU-27 averages ≈2.6 kW EV^{-1} but must double installed power by 2030 to stay ahead of the fleet.	Ring-fence Connecting Europe Facility funds for ISO 15118-20 compliant DC hardware.
The US trails at <1.5 kW EV^{-1}.	Fully fund the NEVI programme and extend IRA §30C infrastructure tax credits beyond 2032.

Vehicle-to-grid (V2G) readiness is equally important. Bidirectional chargers become cost-effective once ISO 15118-20 hardware is standardised; in the Fast-Progress scenario, V2G revenues offset up to 5 % of TCO variance. Extending infrastructure credits to bidirectional DC units and integrating V2G fleets into capacity markets are therefore priority actions.

4.4.1. Securing a circular battery supply chain

Regulatory architecture now shapes clear incentives for circularity, but effectiveness still depends on aligning demand-pull mandates with supply-side investment. The EU Battery Regulation (2023/1542) operationalises this by requiring digital battery passports and phased recycled-content quotas from 2031, thereby reducing information asymmetry, creating predictable offtake for secondary materials, and embedding traceability into cross-border value chains [21]. By contrast, the United States lacks an equivalent federal standard; current policy primarily targets capacity creation through a USD 3 billion grant programme for domestic recycling. Without binding recycled-content obligations, supply-side funding may not translate into steady feedstock or bankable revenue models for recyclers, limiting pass-through of circularity gains to pack costs and embedded emissions [22].

Evidence on prospective materials balance suggests that capacity constraints remain a binding risk. Transport & Environment projects that announced European facilities would furnish cathode metals sufficient for only around two million BEVs in 2030—well short of demand trajectories—implying a persistent gap between mandated circularity and available secondary inputs [23]. Two policy-design implications follow. First, extending recycled-content mandates to other major markets—at minimum ≥ 10 % CO and ≥ 14 % Ni by 2035—would harmonise requirements with the EU, expand the effective market for secondary materials, and dampen volatility in primary-metal exposure [21, 23]. Second, coupling recycling credits with critical-mineral production incentives would de-risk hydrometallurgical investment and accelerate scale-up on the supply side, tightening the loop between regulatory demand and industrial capacity [22, 23]. In combination, these measures are expected to stabilise residual-value assumptions, lower embodied battery emissions, and compress the variance of TCO outcomes identified elsewhere in this study—without altering the underlying technology roadmap.

4.4.2. Synchronising power-sector decarbonisation and R&D priorities

Grid-carbon intensity remains the dominant driver of cradle-to-grave emissions (Sobol index 0.38). Regions with coal-heavy grids will not achieve the 65 % life-cycle benefit projected for the EU unless electricity-sector CO_2 falls below ≈300 g kWh^{-1} by 2030. Coupling renewable-energy auctions to BEV uptake curves—and allowing aggregated V2G fleets to bid into capacity markets—accelerates that decline while monetising batteries as distributed storage resources.

The four research lines below align with the dominant uncertainty levers from the sensitivity analysis. High-silicon or solid-state anodes steepen the cost-learning curve, shrinking the 45 % TCO variance share attributed to battery price. Direct-lithium extraction (DLE) addresses supply-chain bottlenecks and lowers cradle emissions from raw-material processing. Harmonised second-life and recycling standards stabilise pack residual-value assumptions, reducing post-parity TCO scatter and lowering battery-production emissions (see Figure 6). Finally, interoperable cyber-security protocols are a prerequisite for large-scale V2G aggregation and revenue stacking. Together, these R&D targets form a coherent programme that tackles the cost–carbon trade-off from both ends of the vehicle life cycle. The critical R&D and policy priorities, along with their respective milestones, are summarised in Table 7.

Table 7. Priority R&D and policy milestones to secure next-generation battery supply, cost competitiveness and V2G integration..

Priority	Rationale	Milestone
High-silicon / solid-state anodes	Principal cost lever post-2028	≥450 Wh kg^{-1} at < USD 70 kWh^{-1} by 2032
Direct-lithium extraction (DLE)	Low-water, domestic Li supply	≥25 kt Li a^{-1} commercial DLE plant by 2029
Second-life battery standards	Stabilises residual value	ISO spec for repurposing by 2026
V2G cyber-security protocols	Protects bidirectional revenue	Harmonised EU–US standard by 2027

Cost parity, emissions reduction and grid-support services are mutually dependent. Incentive glide-paths tied to TCO parity, fully funded bidirectional-charging networks, and binding circular-economy rules will ensure that the economic and climate benefits are realised at scale.

5. Conclusions, limitations and future research

This study set out to integrate the latest empirical evidence (2013–May 2025) with a cross-disciplinary techno-economic model in order to quantify when battery-electric vehicles (BEVs) reach cost parity with internal-combustion equivalents, what life-cycle-emissions gains can realistically be achieved, and which policy levers determine the speed at which those gains materialise. The principal findings are as follows:

1. *Cost parity is imminent but not automatic.* Median pack prices of USD 82 kWh^{-1} by 2030 and USD 66 kWh^{-1} by 2035—consistent with a 19 % learning rate—drive BEV total cost of ownership (TCO) below the ICE benchmark between 2028 and 2032, depending on the battery-learning trajectory. Purchase incentives that phase out *after* local parity is reached lower adoption risk and shorten the parity window by up to one year in the Slow-Progress case.
2. *Emissions benefits hinge on concurrent power-sector decarbonisation.* Even under a conservative grid-decarbonisation path, cradle-to-grave greenhouse-gas intensity falls from 73 g CO_2-eq km^{-1} (2024) to 34 g km^{-1} (2035) in the Reference scenario—a 53 % decline relative to today's petrol cars. However, coal-heavy grids will not replicate this outcome unless electricity-sector carbon intensity falls below ≈300 g kWh^{-1} by 2030.
3. *Infrastructure adequacy remains a binding constraint.* Public fast-charging capacity must grow to at least 1.3 kW per BEV to avoid queuing bottlenecks and range anxiety. The United States currently lags this benchmark, while China and the EU exceed it, although the latter still needs to double installed power by 2030 [24, 25].
4. *Circular-economy measures are becoming decisive.* The EU Battery Regulation's recycled-content mandates and digital passports will drive down supply-chain risk and embedded emissions; comparable rules are urgently required elsewhere to prevent regulatory arbitrage and to attract investment into recycling plants [21-23].
5. *Vehicle-to-grid (V2G) services can offset up to 5 % of TCO variance.* The monetary value rises sharply in the Fast-Progress scenario, underscoring the need for rapid deployment of ISO 15118-20 bidirectional hardware and harmonised cyber-security protocols.

5.1. Limitations

This study provides a transparent, scenario-based comparison of battery-electric vehicles and internal-combustion vehicles; however, several limitations should be acknowledged. First, regional heterogeneity is only partially represented. Electricity-grid carbon intensity, retail electricity and fuel prices, charging-infrastructure density, ambient temperature profiles, typical trip lengths and driving styles, as well as policy instruments (e.g., purchase grants, registration taxes, and recycled-content requirements) vary materially across and within countries. Because our baseline inputs are constructed from national-level averages and stylised usage patterns, the median total cost of ownership and cradle-to-grave emissions trajectories reported here should be interpreted as indicative rather than universally representative. In jurisdictions with carbon-intensive grids, sparse public fast-charging, extreme climates, or atypical duty cycles (e.g., high-mileage fleets, mountainous terrain), both the timing of cost competitiveness and the emissions hierarchy could meaningfully diverge from the central estimates.

Second, the results are sensitive to future uncertainties outside the model's direct control. Battery learning rates, raw-material prices, and cell-chemistry roadmaps may depart from recent experience; supply-chain constraints or breakthroughs (e.g., high-silicon or solid-state anodes, direct-lithium extraction) could either accelerate or delay cost declines. Similarly, grid-decarbonisation pathways, capacity-market rules, and distribution-level constraints will influence the marginal emissions of charging, while standards adoption and cyber-security requirements will shape the feasibility and value of bi-directional charging. Policy design is another moving target: the level, duration and conditionality of incentives, as well as end-of-life and recycled-content rules, may change in ways that alter the ownership economics and the embedded emissions of battery production. Finally, macroeconomic factors—including interest rates, exchange-rate swings, and broader demand cycles—introduce additional volatility that the present scenarios can only bracket.

Third, several modelling simplifications are warranted but restrictive. The travel-demand module adopts representative annual mileage and charging-behaviour archetypes rather than full distributions; queueing and congestion effects at charging stations are captured via scenario parameters rather than location-specific simulations; and second-life valuation and recycling yields are treated with harmonised assumptions instead of jurisdiction-specific regulatory baselines. While these choices improve transparency and comparability, they suppress local variation. Where possible, we conducted sensitivity checks around the most influential parameters (battery price trajectory, electricity and fuel prices, grid intensity, and residual-value assumptions), but a comprehensive probabilistic treatment of joint uncertainties and spatially resolved infrastructure constraints lies beyond the current scope.

Regional heterogeneity is only partially represented. Beyond the OECD average, EU-27, and China, constructing full scenario families for India or Southeast Asia would currently require harmonised time-series inputs (retail tariffs, grid-decarbonisation paths, incentive design, second-life/recycling baselines) that are not yet consistently available. To avoid mixing incommensurate assumptions, we instead report a Southeast-Asia-like, coal-heavy stress test (Section 4.2.2) to show directional effects on cradle-to-grave outcomes. As such, the headline results should be interpreted as indicative for settings near our data anchors, with region-specific policy conclusions contingent on local inputs.

These limitations suggest two concrete cautions for interpretation: results are most reliable for settings close to the data anchors used for the scenarios, and policy conclusions should be tailored using local inputs (tariffs, climate, grid mix, infrastructure, and regulatory context). Future work could integrate regionally disaggregated demand and infrastructure models, link the cost-learning module to materials-market dynamics, and embed policy-feedback mechanisms that endogenise uptake, charging behaviour and recycling outcomes.

5.2. Future research directions

Research dedicated to enhancing the availability and performance of electric vehicles (EVs) has intensified markedly in recent years

[25-41]. The study evaluates the long-term vision of e-mobility through computational modelling and delineates a structured research agenda. Priority topics and thematic gaps identified by the scenario-based analyses are summarised comprehensively in Table 8. The findings propose a multifaceted roadmap indicating that forthcoming investigations stand to deliver substantial impact on both industrial practice and policy formulation.

Table 8. Emerging research questions and suitable methodological approaches for post-parity EV uptake, battery second-life economics, dynamic policy design and grid-interactive charging.

Theme	Open Question	Suggested Approach
Post-parity consumer behaviour	Will resale-value uncertainty dampen uptake once up-front parity is reached?	Longitudinal choice-modelling using used-car-auction data.
Second-life battery economics	What is the true residual-value uplift from stationary repurposing?	Real-options valuation calibrated with field data from utility pilots.
Dynamic policy optimisation	How can incentives be algorithmically adjusted to minimise fiscal cost while safeguarding uptake?	Reinforcement-learning frameworks linked to annual market data.
Grid-interactive charging	What cyber-security risks emerge at ≥30 % V2G penetration?	Adversarial-simulation studies coupled with standards development.

A coherent strategy—combining time-bound purchase incentives, fast-tracked bidirectional charging, and binding circular-economy rules—can deliver BEV cost parity and a 60 % life-cycle-emissions reduction within the next decade. Delays in any one domain jeopardise the synergies quantified in this work; synchronised action remains the most robust route to deep transport decarbonisation.

Conflict of Interest Statement

The author must declare that there is no conflict of interest in the study.

CRediT Author Statement

Oğuz Kürşat Demirci: Methodology, Data curation, Formal analysis, Validation, Writing - original draft, Writing - review & editing, Conceptualization, Supervision, Formal analysis, Investigation, Visualization.

References

1. International Energy Agency, Global EV Outlook 2025: Trends in Electric Car Markets. Paris, France: IEA, 2025.
2. International Energy Agency, Global EV Outlook 2025: Executive Summary. Paris, France: IEA, 2025.
3. Diouf, B. (2025). The Second-Hand Market in the Electric Vehicle Transition. World Electric Vehicle Journal, 16(7), 397. https://doi.org/10.3390/wevj16070397
4. Hou, T., Wang, D., Jiang, B., Liu, Y., Kong, J., He, Y., ... & Xu, H. (2025). Ion bridging enables high-voltage polyether electrolytes for quasi-solid-state batteries. Nature Communications, 16(1), 962. https://doi.org/10.1038/s41467-025-56324-9
5. International Organization for Standardization, ISO 15118-20:2022—Road Vehicles—Vehicle-to-Grid Communication Interface—Part 20: 2nd-Generation Network Layer and Application Layer Requirements. Geneva, Switzerland: ISO, 2022.
6. M. J. Page et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," BMJ, vol. 372, p. n71, Mar. 2021, doi: https://doi.org/10.1136/bmj.n71.
7. B. Kitchenham and S. Charters, Guidelines for Performing Systematic Literature Reviews in Software Engineering, EBSE Tech. Rep. EBSE-2007-01, Keele Univ. & Univ. Durham, 2007.
8. N. J. van Eck and L. Waltman, VOSviewer Manual, Version 1.6.20. Leiden, The Netherlands: Leiden Univ., Oct. 2023.
9. M. Aria and C. Cuccurullo, "bibliometrix: An R-tool for comprehensive science-mapping analysis," Journal of Informetrics, vol. 11, no. 4, pp. 959–975, 2017, doi: https://doi.org/10.1016/j.joi.2017.08.007.
10. International Energy Agency, Global EV Outlook 2025: Data Annex. Paris, France: IEA, 2025.
11. BloombergNEF, Battery Pack Prices 2024 Survey (dataset summary), London, U.K., Dec. 2024.
12. International Energy Agency, World Energy Outlook 2024: Stated Policies Scenario Data. Paris, France: IEA, 2024.
13. Argonne National Laboratory, Summary of Expansions and Updates in R&D GREET 2023 (ANL/ESD-23/49). Lemont, IL, USA: ANL, Oct. 2023.
14. International Energy Agency, Global EV Outlook 2025: Battery Demand Trends. Paris, France: IEA, 2025.
15. Regulation (EU) 2023/1804 of 13 Sept. 2023 on the Deployment of Alternative Fuels Infrastructure, Official Journal of the European Union, L 234, pp. 1–98, Sept. 2023.
16. Knobloch, F., Hanssen, S. V., Lam, A., Pollitt, H., Salas, P., Chewpreecha, U., Huijbregts, M. A. J., & Mercure, J.-F. (2020). Net emission reductions from electric cars and heat pumps in 59 world regions over time. Nature Sustainability, 3(6), 437-447. https://doi.org/10.1038/s41893-020-0488-7
17. European Automobile Manufacturers' Association (ACEA), Electric Cars: Tax Benefits and Purchase Incentives 2025 (Fact Sheet). Brussels, Belgium, Mar. 2025.
18. Internal Revenue Service, Instructions for Form 8936 (New Clean Vehicle Credit). Washington, DC, USA, Jan. 2025.
19. Ministry of Finance of the People's Republic of China, State Taxation Administration, and MIIT, "Notice on Extending Purchase-Tax Exemption for New-Energy Vehicles," Jun. 21, 2023.
20. International Energy Agency, "Electric vehicle charging," Global EV Outlook 2025. Paris, France: IEA, 2025.
21. Regulation (EU) 2023/1542 of 12 Jul. 2023 concerning batteries and waste batteries, Official Journal of the European Union, L 191, pp. 1–117, Jul. 2023.
22. U.S. Department of Energy, "Battery Manufacturing and Recycling Grants Program – Overview," Office of Manufacturing & Energy Supply Chains, Oct. 19, 2023.
23. Sederholm, J. G., Li, L., Liu, Z., Lan, K.-W., Cho, E. J., Gurumukhi, Y., Dipto, M. J., Ahmari, A., Yu, J., Haynes, M., Miljkovic, N., Perry, N. H., Wang, P., Braun, P. V., & Hatzell, M. C. (2025). Emerging Trends and Future Opportunities for Battery Recycling. ACS Energy Letters, 10(1), 107-119. https://doi.org/10.1021/acsenergylett.4c02198
24. International Energy Agency, "Trends in charging infrastructure," Global EV Outlook 2023. Paris, France: IEA, 2023.

25. Yurdaer, E., & Kocakulak, T. (2021). Comparison of Energy Consumption of Different Electric Vehicle Power Systems Using Fuzzy Logic-Based Regenerative Braking. Engineering Perspective, 1(1), 11-21. https://doi.org/10.29228/sciperspective.47590
26. Bayzou, R., Soloy, A., Bartoli, T., Haidar, F. (2025). Thermal model of Lithium-ion batteries for hybrid electric vehicles. Engineering Perspective, 5 (2), 60-67. http://dx.doi.org/10.29228/eng.pers.76492
27. Do, T. T. (2025). Global Optimization of Hysteresis Energy Management Strategies for Fuel Cell Hybrid Electric Vehicles. International Journal of Automotive Science and Technology, 9(2), 276-283. https://doi.org/10.30939/ijastech..1691411
28. Bousseksou, M.O., Nouri, K., Bartoli, T., Bouzidi, W., Bessais, L., (2025). Magnetocaloric Cooling for Hybrid/ Hydrogen and Electric Vehicle Cabin and Powertrain Components. Engineering Perspective, 4 (1), 9-20. http://dx.doi.org/10.29228/eng.pers.77695
29. Abebe, B. A., Çelebi, S., & Kılıç, R. (2024). A Review on Tribological Considerations in the Transition from IC Engines to Electric Vehicles. International Journal of Automotive Science and Technology, 8(3), 369-380. https://doi.org/10.30939/ijastech..1476366
30. Tosun, E., Keyinci, S., Yakaryılmaz, A. C., Yıldızhan, Ş., & Özcanlı, M. (2024). Evaluation of Lithium-ion Batteries in Electric Vehicles. International Journal of Automotive Science and Technology, 8(3), 332-340. https://doi.org/10.30939/ijastech..1460955
31. Nassar, M., Polat, K., Koçlu, Y., Topaç, M.M., (2025). Design and Optimisation of a Double Wishbone Independent Suspension System for an L6 electric Vehicle: A Response Surface Methodology Based Design Application. Engineering Perspective, 5 (1), 21-30. http://dx.doi.org/10.29228/eng.pers.79569
32. Kilic A., (2023). Charging Techniques, Infrastructure, and Their Influences. Engineering Perspective, 3 (4), 68-74. http://dx.doi.org/10.29228/eng.pers.73000
33. Abdullaev, I., Lin, N., & Rashidov, J. (2024). Electric Vehicles: Manuscript of a Bibliometric Analysis Unveiling Trends, Innovations and Future Pathways. International Journal of Automotive Science and Technology, 8(2), 212-224. https://doi.org/10.30939/ijastech..1424879
34. Can, E. & Demirci, O.K. (2025). Fully Insulated Dual Output DC-DC Converter Battery Charging System with Single Dynamo Input at the Electric Vehicle. Tehnički vjesnik, 32 (4), 1283-1290. https://doi.org/10.17559/TV-20250112002261
35. Karaman, M., & Korucu, S. (2023). Modeling the Vehicle Movement and Braking Effect of the Hydrostatic Regenerative Braking System. Engineering Perspective, 3(2), 18-26. https://doi.org/10.29228/eng.pers.69826
36. Haidar, F., Laıb, A., Ajwad, S. A., Guılbert, G. (2024). Integrated Vehicle Dynamics Modeling, Path Tracking, and Simulation: A MATLAB Implementation Approach. Engineering Perspective, 3(1), 7-16. https://doi.org/10.29228/eng.pers.75106
37. Nagareddy, S., Rajeswaran, S. S., Jaganathan, D., … Bala Subramanian, V. P. (n.d.). Turbocharged Six-Cylinder Direct Injection Hydrogen Fueled Spark Ignition Engine Combustion and NOx Control Model. Engineering Perspective, 4(3), 100-110. https://doi.org/10.29228/eng.pers.82203
38. Altun, K. (2025). A Proof-of-Concept for Parameter Manipulation in TRIZ: Automotive Case Stud. International Journal of Automotive Science and Technology, 9(2), 166-173. https://doi.org/10.30939/ijastech..1592053
39. Nahian Samin, S. A., Hossen, S., Rahman, K. M. M., Gosh, U. (2024). Lightweighting of a Vehicle Steering Uprights via Structural-Based Design and FEA Analysis. Engineering Perspective, 3(4), 157-170. https://doi.org/10.29228/eng.pers.78029
40. Djebbar, A. M., & Amina, K. (2025). A Hybrid Approach for Solving the Capacitated Vehicle Routing Problem. International Journal of Automotive Science and Technology, 9(2), 249-258. https://doi.org/10.30939/ijastech..1663305
41. Serarslan, B. (2025). The Impact of Temperature and Ageing on LFP Electric Vehicle Batteries: A Comprehensive Modelling Study. International Journal of Automotive Science and Technology, 9(1), 12-25. https://doi.org/10.30939/ijastech..1519778