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Lag-Based Forecasting Model for the Availability of Second-Life Electric Vehicle Batteries in Energy Applications

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Abstract

This study develops a long-term cohort model for forecasting the residual capacity of electric vehicle batteries that are potentially available for energy applications. New vehicles and used imports are assigned different remaining transport-service lags after national entry. Retirement, collection, technical qualification, and allocation to energy reuse are represented separately through conditional fractions. Ukrainian passenger BEV entry data for 2013–2025 form the historical cohorts, with projections through 2040. Baseline annual capacity inflow is 0.197 GWh in 2025, peaks at 2.242 GWh in 2030, and reaches 1.201 GWh in 2040. The 2025 used-import cohort supplies 98.2% of the 2030 peak. Cumulative inflow is 13.439 GWh, with the three main scenarios spanning 7.696–21.750 GWh. A common nine-year lag reduces cumulative supply through 2030 from 4.865 to 0.900 GWh; a discrete distributed kernel lowers the 2030 peak to 1.515 GWh. A 20,000-run joint input experiment gives 5th–95th design percentiles of 6.917–16.011 GWh for cumulative supply under fixed lags. Longer-lag stress tests shift the peak to 2033 or 2036. A closed-cohort application to independent Norwegian registration data demonstrates the accounting framework across contrasting import structures. Cohort and stage balances connect the timing and scale of potential capacity supply with collection, screening, and repurposing requirements.

Keywords: second-life batteries; electric vehicles; cohort analysis; retirement lag; technical qualification; energy storage; secondary resources; circular economy

1. Introduction

1.1. Battery Resource Formation Across Transport and Energy Applications

The expansion of battery-electric mobility creates a future stream of traction batteries that may retain useful storage capacity after transport use. The scale and composition of this stream depend on the technologies installed in successive vehicle cohorts. Reviews of EV battery technologies and development pathways document a changing mix of chemistries, pack characteristics, and performance requirements [1–3]. The battery technology roadmap further demonstrates that battery development is not a stationary process [4]. Consequently, the future energy-storage resource should be traced to the vehicles and batteries that actually entered service, rather than obtained by multiplying an aggregate fleet projection by one timeless nominal capacity.

Second-life research establishes both the feasibility of retaining battery value and the conditions limiting that opportunity. Critical reviews examine the gap between technical promise and implementation and organise the technological and economic requirements of

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second-life use [5,6]. Broader assessments discuss applications, manufacturing, integration barriers, and business conditions [7,8]. Lifecycle-oriented research also places second-life use within the wider battery lifecycle [9]. These studies support a resource-formation perspective in which transport retirement is an upstream event, followed by access, assessment, and selection for another application. None of these transitions should be assumed to follow automatically from fleet growth.

Resource forecasting is relevant to circularity because battery production embodies energy demand and emissions. Assessments of commercial EV battery production, GWh-scale manufacturing, and the role of recycling illustrate why the battery lifecycle is an important analytical boundary [10–12]. However, an additional GWh of potentially reusable capacity is not itself a quantified environmental benefit. Primary and secondary use must be assessed within a consistent lifecycle, and repurposing requires explicit modelling of the energy flows involved [13,14]. The forecast developed here therefore describes a physical capacity stream; it does not convert that stream directly into avoided emissions.

End-of-life choices also affect the relationship between mobility, stationary storage, and material recovery. Lifecycle studies examine alternative electricity mixes and battery end-of-life strategies [15], the interaction of second-life and recycling [16], and the cost, energy, and carbon implications of second-life use [17]. Uncertainty in the wider vehicle footprint and prospective changes in the battery industry provide additional reasons to avoid a universal benefit factor [18,19]. A transparent supply forecast can provide inputs for these assessments while leaving technology displacement, operating intensity, and environmental allocation to downstream analysis.

From a resource-management perspective, the central question relates to when a battery stock embedded in transport can become a flow of secondary batteries suitable for another use. Retirement releases batteries from one function, whereas collection, technical qualification, and allocation determine the portion entering a potential reuse pathway. The resource quantified here is the residual energy-storage capacity embodied in selected batteries, rather than energy produced by them or the mass of recoverable materials. This boundary connects the timing of product retirement with the preservation of storage functionality across successive uses and makes the intervening selection stages explicit in circular-resource planning.

1.2. Relevance to Ukraine and Import-Dominated Vehicle Markets

A national second-life supply forecast requires a geographical boundary as well as a lifetime assumption. A vehicle entering a country as used brings a battery with an existing service history; its remaining transport life after entry differs from the full service life of a newly purchased vehicle. Domestic resale changes ownership without creating another battery cohort. Conversely, export, deregistration, battery replacement, and salvage can alter the relationship between the registered fleet and batteries that eventually become accessible in that country. The timing of national battery supply therefore depends on vehicle movement and cohort history, not solely on global EV sales.

For Ukraine, a situation analysis of national electric-transport development examines its integration prospects within the power system [20]. A second-life market evaluation identifies the national context in which battery reuse may develop [21]. These studies motivate a dedicated supply forecast linking observed vehicle entries with battery retirement and collection scenarios. In particular, a market supplied substantially by used imports should retain the condition of vehicles at national entry throughout the accounting of subsequent returns.

On the energy side, application studies identify opportunities for battery reuse in renewable-energy integration and stationary storage [22–24]. Planning these applications

calls for estimates of both the volume and the timing of future battery supply. Forecasting the supply calendar is a separate step between identifying an application and planning a deployment programme.

Research on second-life batteries for sustainable and resilient power systems connects reuse with integration requirements [25]. The present study addresses one upstream part of that problem: how successive new-vehicle and used-vehicle entries generate future retirement streams, and how losses after retirement reduce their potential energy-storage contribution.

1.3. Planning Implications of the Supply Calendar

The application literature demonstrates why supply must be expressed in terms relevant to particular storage programmes. Early work linked battery second-life with renewable-energy integration [22], and experimental demonstration examined solar storage and demand-side management [23]. Technical and economic assessments of repurposed batteries in solar applications show that feasibility depends on the characteristics of both the batteries and the receiving system [24]. Residential studies are relevant here as evidence that receiving-application assumptions matter; the present forecasting boundary remains national and does not model household behaviour.

Economic investigations consider the viability of secondary batteries in residential storage [26], charging stations [27], and wind-power systems with degradation [28]. Assessment of distributed photovoltaics with reused batteries likewise relates value to the receiving application [29]. Such findings cannot be transferred directly into national deployment quantities. Nevertheless, they show why annual potential battery capacity is a useful upstream planning input: investment and procurement programmes must match the date of supply with the intended use, testing capacity, and required technical characteristics.

The distinction between supply and deployment is also evident in research on clustered second-life backup storage [30] and KPI-triggered grid integration within the PDCA cycle [31]. These contributions address where or how batteries may be used. The present study complements these deployment approaches by determining when the underlying battery resource forms under specified retirement and selection conditions.

1.4. Objective Scope and Contributions

The objective is to forecast the annual residual storage capacity of EV batteries potentially available for energy applications in a market with heterogeneous vehicle entry. The object of investigation is the process of resource formation through traction retirement in Ukraine, collection, technical qualification, and allocation to energy reuse. The forecasting target is the residual capacity of the selected subset, expressed as GWh entering potential supply in each calendar year. It is distinct from gross retirement counts, cumulative installed capacity, annual electricity delivery, and guaranteed procurement availability. Ukraine provides the application case for an accounting framework intended for markets in which new vehicles and imported used vehicles contribute differently to the timing and composition of future secondary-battery supply.

The study contributes a cohort-consistent formulation that separates vehicles entering as new and used, attaches market shares to the entry year, and treats the lag as remaining transport life after national entry. It then separates the conditional fractions governing collection, technical qualification, and energy-reuse allocation. The numerical experiment compares fixed differentiated lags, a common lag, and an illustrative distributed lag, and examines how stage assumptions change intermediate battery flows and final capacity. Together, these contributions establish a traceable link between heterogeneous vehicle-entry cohorts, post-retirement battery flows, and potential storage-capacity supply. Figure 1

translates the research gap into an implementation sequence: preserve national entry histories, apply category-specific retirement kernels, resolve conditional selection stages, and test the resulting capacity flows. Its eight numbered steps correspond to the calculations in Section 4.

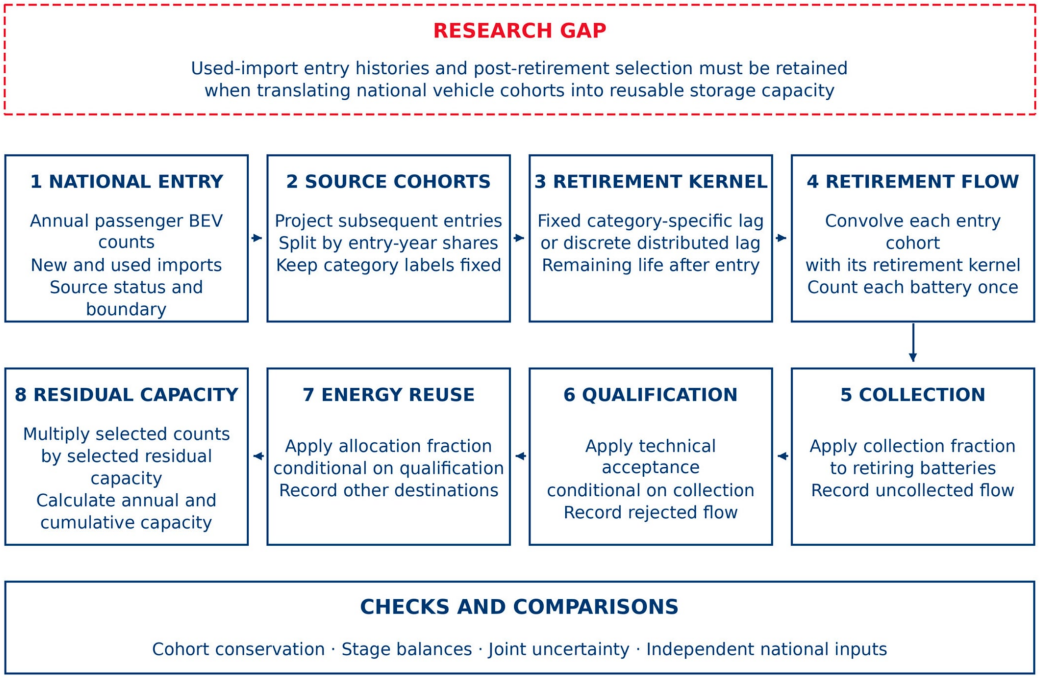


Figure 1. Research gap and implementation sequence for forecasting secondary-battery resource formation.

2. Related Research and Modelling Requirements

2.1. Review Scope and Analytical Comparison

The literature is organised as a focused narrative review of the steps needed to connect vehicle entry with potential second-life storage capacity. The comparison distinguishes the entry boundary, retirement representation, treatment of used vehicles, post-retirement selection, capacity definition, and empirical data requirements. Technology reviews and application studies provide context, while explicit battery-flow and return-volume models provide the closest methodological comparators.

The central distinction is between predicting that batteries leave transport service and predicting that an accessible, technically acceptable subset is directed to energy reuse. Studies may address one or several of these processes. Comparison should therefore concern the output actually modelled, rather than infer that a forecast of retired vehicles, recyclable materials, reusable packs, or installed capacity measures the same resource. The following subsections compare representative approaches and derive the requirements for the present formulation.

2.2. Cohort Models Material Flows and Retirement Distributions

A material-flow model for traction batteries in Europe links second use with stocks and flows over time [32]. This work establishes that extending battery use changes the timing and composition of downstream flows. It is a methodological foundation for distinguishing incoming secondary capacity from capacity retained in a second-life stock. The present model follows that accounting principle while concentrating on the national entry of new and used vehicles and the selection boundary preceding energy applications.

Dynamic estimation of end-of-life batteries in the EU-27 considers reuse, remanufacturing, and recycling options [33], incorporating lifetime variation and alternative end-of-life pathways. Building on these approaches, the present study integrates remaining transport life after national entry of used vehicles with explicitly defined post-retirement selection stages to forecast the formation of secondary-battery resources for energy applications.

A lifetime-based approach estimates battery return volumes for remanufacturing, reuse, and recycling [34], while global material-flow forecasting quantifies the corresponding streams of battery materials [35]. These studies reinforce the need to specify what returns: batteries, embedded materials, or storage capacity. A return forecast intended for reverse-logistics infrastructure can use pack counts, whereas energy planning additionally requires a residual-capacity estimate for the subset that is selected. Converting between these quantities requires stated battery-size and condition assumptions.

Forecasting of usable retired-battery capacity explicitly considers battery chemistry and recycling requirements [36]. This directly challenges any broad claim that previous work ignores usable capacity or alternative allocation. Dynamic material-flow analysis also connects vehicle-to-grid and second-life pathways with stationary-storage and material requirements [37]. This comparison illustrates how transport and stationary services can share a battery resource while remaining different lifecycle pathways. A national second-life forecast should consequently distinguish batteries still performing traction service from batteries released for another use.

Industry forecasting methodology also recognises product movements and trade in geographically differentiated battery flows [38]. This matters because the country in which a vehicle is first sold need not be the country in which its battery retires. The parsimonious representation used here divides national entry into new and used vehicles. It is a tractable approximation under limited information, rather than a replacement for detailed age-at-import distributions, cross-border vehicle histories, or chemistry-resolved material-flow models.

A fixed lag places all batteries in a cohort into one retirement year and makes the source of each annual supply wave transparent. A distributed lag spreads the same source cohort across several years and can represent heterogeneity in use and retirement decisions. The appropriate choice depends on available observations and the planning resolution. A smoother trajectory is not necessarily a more accurate one, and a concentrated peak is not necessarily evidence of a real synchronised return event. Both must be interpreted in relation to cohort size and the assumed retirement kernel.

2.3. Remaining Transport Life Degradation and Retirement Thresholds

Battery retirement is not determined by chronological age alone. Degradation studies distinguish the effects of driving and vehicle-to-grid services [39] and examine dependence on the sequence of operating conditions [40]. These studies explain why identical vehicle-entry dates need not imply identical battery condition at withdrawal. For used imports, the unavailable portion of the operating history is particularly relevant to the remaining transport period.

Calendar-ageing prognostics and second-life lifespan analysis provide additional perspectives on the time boundary [41,42]. Ageing-based assessment further examines the technical viability of battery second-life [43]. Together, these works support distinguishing an assumed national-entry lag from a measured remaining useful life for an individual pack. A population lag aggregates many technical and behavioural processes; it should not be interpreted as a universal state-of-health retirement threshold.

Empirical age–mileage analysis linked to observed battery health trends shows that vehicle retirement and a fixed battery state-of-health threshold need not coincide [44]. Real-

world telematics covering more than 22,700 EVs reports average annual capacity degradation of 2.3%, with substantial variation by charging behaviour and operating conditions [45]. These observations support treating retirement timing and selected residual capacity as separate inputs. They also motivate the longer-service stress tests introduced here, rather than interpreting nine years as a universal battery lifetime.

Analysis of calendar and cyclic ageing in diagnostic and prognostic models relates these mechanisms to second-life battery assessment [46]. This complements the aggregate forecasting model by identifying information that would be needed to condition retirement and residual-capacity assumptions on actual battery use. Age at import, recorded battery replacement, usage intensity, and condition measurements provide complementary information for specifying cohort-dependent retirement parameters.

The numerical model therefore separates a retirement kernel from post-retirement qualification. Moving a lag changes when a battery is expected to leave transport; changing qualification alters which collected batteries can proceed to energy reuse. Treating these as one coefficient would obscure whether a forecast shortfall arises from later retirement or a smaller acceptable fraction. The staged representation also provides a basis for incorporating degradation models as cohort-specific condition data become available.

2.4. Technical Qualification and Residual Capacity of Selected Batteries

The transition from vehicles to stationary storage requires targeted diagnostics rather than a direct transfer of rated pack capacity. Reviews of diagnostic requirements [47] and research on classification for secondary uses of retired traction batteries [48] support an explicit screening stage between collection and reuse. The relevant acceptance criteria must be tied to the intended application class and battery condition; qualification is not established merely by a positive remaining capacity.

State-estimation research provides methods that can inform screening but also highlights the information required for reliable inference [49]. Differential voltage analysis [50], voltage relaxation assessment [51], and impedance measurements across ageing states [52] represent different diagnostic approaches. Their measurements address pack or cell condition; they do not directly estimate how many retired batteries are collected nationally. A forecasting framework must keep these technical observations separate from the denominator used for collection efficiency.

Prognostic methods using incremental capacity information and Gaussian process regression illustrate how partial measurements can support health inference [53]. Technical evaluation and design-oriented second-life studies connect assessment to receiving-system requirements [54]. At the national level, these methods justify defining the residual-capacity parameter as the mean for batteries that pass the stated screening and allocation stages. They do not justify assigning one experimental dataset's capacity distribution to every national cohort without checking chemistry, pack size, age, and selection bias.

This leads to two separate quantities: the fraction of collected batteries accepted and the mean residual capacity of the batteries eventually selected. The first changes the expected count; the second converts that count into storage capacity. A state-of-health multiplier can convert nominal capacity into residual capacity, but the same rejection fraction must not be applied again within a parameter already defined for the accepted subset. Where the condition varies across retirement ages, both the qualification fraction and selected-capacity mean should be calculated inside the cohort sum.

2.5. Collection Allocation and the Institutional Boundary of Availability

Legal and institutional arrangements affect which batteries can enter a repurposing chain. Comparative analysis of legislative approaches addresses conditions relevant to

second-life energy use [55]. Research examines reuse and recycling as alternative end-of-life routes [56] and situates these choices within the circular economy [57]. These works motivate explicit access and allocation assumptions. Collection and allocation fractions represent the national organisation of these pathways, while qualification describes acceptance for the specified technical application.

A scientometric analysis of second-life use and recycling identifies the breadth of the research field [58]. Work on battery circularity links business model choices with collaboration in the battery ecosystem [59], and exploration of second-life applications identifies different receiving uses [60]. The methodological implication is that collection and reuse allocation are organised processes involving several actors. A model can represent them as conditional fractions, but those fractions should be estimated from flow records or retained as explicit scenarios.

Critical reviews examine sustainable business models for battery second use [61], while market analysis explicitly addresses second-life price and quantity in a changing supply-and-demand setting [62]. This is the basis for retaining a careful distinction between potential supply for energy applications and availability for procurement. The latter involves prices, competing buyers, ownership, contracting, and alternative recycling value. The present model does not solve that market-allocation problem and therefore uses a scenario fraction for energy-reuse allocation rather than a predicted transaction volume.

For staged flow accounting, collection is measured relative to traction retirements, technical qualification relative to collected batteries, and energy-reuse allocation relative to qualified batteries. Multiplying these conditional fractions follows their nested denominators and does not require them to be statistically independent. Nevertheless, the factors can change together: extending collection to a wider set of owners may change the age and condition of collected packs, and a change in receiving applications may change qualification criteria. One-at-a-time sensitivities are therefore conditional experiments rather than causal intervention estimates.

2.6. Data Requirements and Uncertainty

The available evidence has different scales: registration histories describe vehicles; collection and screening records describe batteries entering particular channels; experimental datasets describe condition and degradation under specified tests. Reviews of open lithium-ion battery datasets assess their relevance to degradation modelling and lifecycle management [63]. These datasets support condition modelling, while national battery-flow accounting draws on registration, collection, and screening records. Matching data to the corresponding stage preserves a consistent link between measurement scale and model parameter.

The distinction between conditional scenarios and calibrated forecasts is also relevant to energy-system decision support. Research on forecasting stochasticity in power-system optimisation treats uncertainty as an explicit part of planning [64]. This motivates the decision to carry supply uncertainty into subsequent decisions and examine the effects of alternative retirement, collection, and qualification assumptions through explicitly defined scenarios.

A staged model requires at least four independent types of observations for meaningful calibration: battery retirement or replacement histories, collection counts linked to the retirement population, screening outcomes for collected batteries, and destinations and capacities of the selected subset. Registration data can constrain source cohorts, but cannot identify all downstream fractions. If only final capacity is observed, several combinations of collection, qualification, and allocation can produce the same output. This identifiability

problem remains even when the calculation is dimensionally correct and all transition fractions lie within admissible limits.

Further empirical refinement can follow the same stage structure. Vehicle and battery histories describe transport retirement, collection records describe intake to the assessment chain, screening outcomes describe conditional technical acceptance, and allocation records identify subsequent reuse. Linking these records preserves the distinction between vehicle deregistration, battery replacement, export, and national collection. This structure supports progressive updating of model parameters as cohorts pass through the relevant stages.

2.7. Research Gap and Requirements Addressed by the Model

The reviewed literature provides the foundations for material-flow accounting, probabilistic battery lifetimes, technical screening, usable-capacity estimation, and economic allocation. The research gap addressed here is their integration in a national forecasting framework that retains the entry history of imported used vehicles and resolves the successive stages of secondary-resource formation. In a market dominated by used imports, a transparent national forecast must connect entry condition and remaining traction life with separately defined post-retirement selection stages. It must also show which quantities are observed, which are proxies, and which remain scenario assumptions.

The present model addresses this requirement through a common accounting chain from national vehicle entry to retirement, collection, qualification, allocation, and selected residual capacity. Its reduced form remains compatible with aggregate transition fractions when stage observations are unavailable, while the expanded form exposes the intermediate counts and the data needed to identify them. The comparison of lag representations examines the supply calendar under matched assumptions; the stage illustration examines how a given retirement stream is reduced before entering potential energy reuse. These are the methodological questions tested in the following sections.

3. Data and Scenario Assumptions

3.1. National Entry Accounting

The study is a long-term resource-supply forecast through 2040, evaluated at one-calendar-year resolution. The boundary is passenger battery-electric vehicles entering Ukraine as new or imported used vehicles. Plug-in hybrids, commercial vehicles, buses, domestic resale, and temporary registrations are excluded. Annual aggregation matches the planning target and the available historical series. Quarterly entry data would support a finer model only together with subannual retirement and processing kernels; dividing annual counts into assumed quarters would add temporal detail without additional evidence.

Let $I(t)$ denote annual national vehicle entry. Reported first registrations and registrations of imported passenger BEVs are used directly where available. The stock balance remains a consistency relation, rather than the estimator used to construct the revised historical series:

$$I(t) = S(t) - S(t - 1) + X(t). \quad (1)$$

Here, $S(t)$ denotes the active stock and $X(t)$ its departures. Stock differences equal gross entry only if departures are absent. The revised input series uses registration reports rather than treating net stock increments as observed inflows; vehicle-stock and battery retirement balances remain distinct.

The historical registration totals for 2013–2021 are taken from the national automotive federation's MIA-based annual review [65]; its later review supplies the 2022–2023 totals [66]. The federation defines its passenger BEV series as first registrations and registrations of vehicles imported under customs documentation, excluding re-registrations and temporary registrations [67,68]. For 2024–2025, rounded passenger-entry reports give

10,200 new and 41,200 used vehicles in 2024 [69], and 22,800 new and 84,400 used vehicles in 2025 [70]. These reports provide the category split directly.

Table 1 combines the annual entry totals with their new and used shares and records the evidential status of the split. Shares for 2013–2015 are explicit working assumptions, not recovered observations. Values for 2016–2019 transfer rounded market proportions from another reporting series [71–73] and are treated as proxies. The 2020–2021 shares are reported in the federation's passenger series [67]; the 2022 value is a rounded structural assumption, while the 2023 share is directly reported [68]. Future shares remain scenarios. This distinction prevents an approximate historical reconstruction from being presented as a fully linked registration database.

Table 1. Passenger BEV entry cohorts, market shares, and input status.

Entry Year	Annual Entry, Vehicles	New, %	Used, %	Source and Status
2013	50	40.00	60.00	Total [65]; assumed split
2014	77	35.00	65.00	Total [65]; assumed split
2015	488	25.00	75.00	Total [65]; assumed split
2016	1664	49.00	51.00	Total [65]; proxy split [71]
2017	3203	15.00	85.00	Total [65]; approximate proxy [71]
2018	5545	16.50	83.50	Total [65]; proxy split [72]
2019	7181	8.00	92.00	Total [65]; proxy split [73]
2020	7186	8.90	91.10	Total [65]; split [67]
2021	8541	14.20	85.80	Total [65]; split [67]
2022	13,318	17.00	83.00	Total [66]; assumed rounded split
2023	37,334	19.40	80.60	Total [66]; split [68]
2024	51,400	19.84	80.16	Rounded counts and split [69]
2025	107,200	21.27	78.73	Rounded counts and split [70]
2026–2030	Projected	30.00	70.00	Structural scenario
2031–2035	Projected	45.00	55.00	Structural scenario
2036–2040	Projected	60.00	40.00	Structural scenario

Figure 2 shows the cohort sizes and their new/used decomposition from Table 1; proxy or assumed shares affect the bar composition, not the reported annual totals.

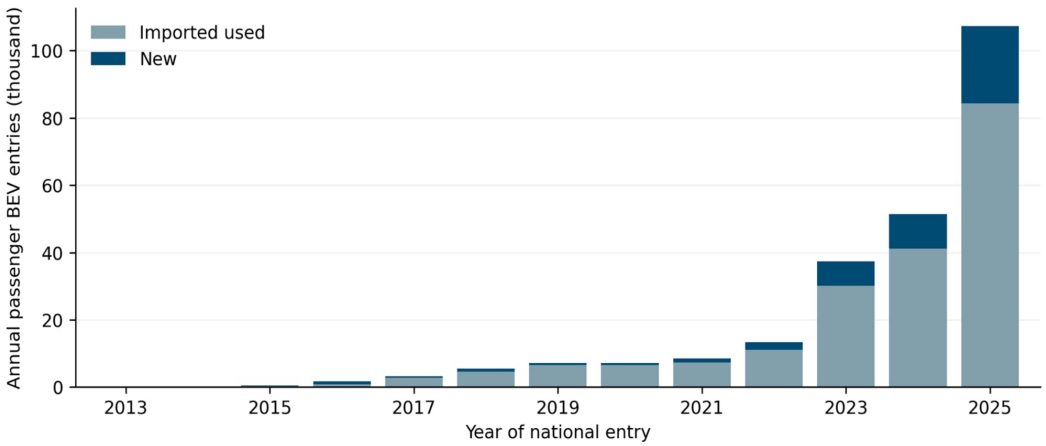


Figure 2. Annual national entry series used to form battery cohorts.

The annual totals are reported registration inputs; the status of each new/used split is specified in Table 1.

3.2. Battery Heterogeneity and Post-Retirement Selection

The entry year and the manufacture year are different attributes, particularly for used imports. Market reports show a changing model mix: the older market was strongly associated with Nissan Leaf, whereas recent new and used registrations include a broader range of manufacturers and battery generations [72–75]. A model name alone does not identify cathode chemistry, pack capacity, cell supplier, or cooling configuration across all model years. Technology reviews and targeted diagnostics support retaining this heterogeneity without assigning one lifetime or acceptance rate to an entire brand [1,2,47]. Table 2 translates the relevant battery characteristics into information requirements for the staged forecast.

Table 2. Battery characteristics and their implications for resource forecasting.

Characteristic	Information Required	Implication for the Staged Forecast
Chemistry and cell design	LMO-based, NMC/NCA, and LFP families; verify the actual battery version	Condition-dependent retirement and qualification; no universal chemistry-specific lag [1–4,47]
Pack size and age at national entry	Nominal capacity, manufacture year, age at import, battery replacements	Cohort-specific residual-capacity mean and remaining transport lag
Operating and thermal history	Usage intensity, temperature exposure, cooling-system condition, incident records	Retirement kernel and technical qualification conditional on collection [39–43,46,47]
Pack architecture and interfaces	Module accessibility, electrical configuration, BMS communication, insulation	Qualification for the intended reuse configuration; adaptation effort and allocation [47,54]
Condition of the selected subset	Measured capacity, resistance, imbalance, safety and service requirements	Selected-battery residual capacity after screening; avoid double rejection discounts [47–54]

Technical qualification and economic allocation must not be conflated. A battery can satisfy an application's technical criteria, yet remain unattractive because acquisition, testing, BMS adaptation, mechanical integration, cooling, or warranty costs exceed its expected value. The qualification fraction concerns a stated technical configuration; the subsequent allocation fraction accounts for competing destinations at the scenario level [61,62]. A synthesis of global reuse and recycling strategies likewise treats technologies, infrastructure, and regulation as complementary requirements [76].

Technology characteristics inform scenario design but do not independently identify national transition rates. The application retains common selected-capacity values of 37.5–49.0 kWh as scenario assumptions, because a cohort-weighted distribution of battery

versions and measured retirement condition is unavailable. The existing cohort-dependent formulation can accommodate such data when they become available.

Reporting boundaries also differ across providers. For example, one 2024 report gives 50,458 passenger BEVs and a larger all-vehicle BEV total [74]; the corresponding 2025 passenger count is 107,470, while the all-vehicle total exceeds 110,200 [75]. Commercial vehicles and buses are not added to the passenger model. Section 5.4 tests replacement of the two recent passenger totals while keeping the main category-share assumptions fixed.

3.3. Development and Battery Assumptions

Three cases are designated pessimistic, baseline, and optimistic scenarios. They vary the vehicle-entry development path, aggregate transition fractions, and selected-battery residual capacity. All three use the same remaining transport-life lags: nine years for new entries and five years for used entries. The scenario names describe resource-formation conditions; they do not rank battery longevity. Retirement timing is varied separately in the baseline sensitivity analysis in Section 5.4.

For reproducible entry accounting, $A(t)$ is cumulative modelled passenger BEV entry since 2013. Summing the annual historical entries in Table 1 gives $A(2025) = 243{,}187$ vehicles. This is an entry-accounting index, not the active fleet. The 2040 endpoints of 600,000, 900,000, and 1,300,000 remain cumulative-entry scenario targets, rather than externally validated forecasts or policy commitments.

The battery parameters define conditional resource-formation scenarios. The nine- and five-year lags refer to remaining transport service after national entry. Their four-year difference represents a stylised prior-service offset for used imports, rather than an observed Ukrainian import-age estimate. The main scenarios retain these lags to isolate quantity effects. Timing tests cover 8/4, 10/6, 12/8, and 15/11 years for new/used entries. The latter cases examine longer transport use consistent with evidence that batteries may remain serviceable beyond early replacement assumptions [44,45]. Aggregate transition fractions equal collection × qualification given collection × allocation given qualification. They are scenario parameters, not estimates recoverable from registration totals. The baseline decomposition in Section 5.5 exposes their implied intermediate flows. The 37.5–49.0 kWh values describe residual capacity of selected batteries; as an illustrative scale check, they correspond to nominal capacities of 50.0–65.3 kWh at 75% capacity retention. This conversion provides context, while the calculations use residual capacity directly and apply no additional state-of-health multiplier.

Independent second-use records provide context for the selection stages. The Dutch collection scheme reports both whole packs and modules and records their subsequent routes [77,78]. These records support separating collection from reuse, but their mass-based routing shares have a different denominator from the pack-count fractions used here. Section 5.7 therefore evaluates them as an external boundary check and discusses the relatively favourable capture and selection conditions represented by the main scenarios.

4. Lag-Based Model of Retirement and Resource Formation

4.1. Entry Projection and Cohort Decomposition

The implementation follows Figure 1. Steps 1–2 establish annual entries and split each cohort using its entry-year new/used share, Equations (1)–(5). Steps 3–4 select and apply the retirement kernel, Equation (6) or (13). Steps 5–7 apply the conditional collection, qualification, and allocation fractions, Equations (7)–(10). Step 8 converts selected counts into residual capacity, Equations (11) and (12), and accumulates annual inflows using Equation (15). Each run then checks cohort conservation and stage balances before producing the comparative results.

$A(t)$ denotes cumulative modelled passenger BEV entry since 2013. With $A(2025) = 243{,}187$, a constant compound continuation connects the historical input series with each assumed 2040 endpoint. This transparent construction can be replaced by an independently developed annual entry scenario:

$$A(t) = A(2025)(1+r)^{t-2025},\ 2026 \le t \le 2040; \tag{2}$$

$$r = \left[\frac{A(2040)}{A(2025)}\right]^{1/15} - 1; \tag{3}$$

$$I(t) = A(t) - A(t-1); \tag{4}$$

$$I_n(t) = w_n(t)I(t),\ I_u(t) = w_u(t)I(t). \tag{5}$$

Here, $w_n(t) + w_u(t) = 1$. Reported annual entry totals are used through 2025, with observed, proxy, or assumed shares as identified in Table 1; Equations (2)–(4) specify subsequent entry. Entries before 2013 are set to zero as a calculation boundary. Later export and transport losses are not separately simulated; the retirement forecast remains conditional on national retention of each cohort.

4.2. Retirement from Traction Service in Ukraine

Each entering vehicle is associated with one traction-battery cohort and one end of its traction use in Ukraine. New and used categories describe the vehicle at national entry. A used import has already undergone transport use abroad; its lag therefore measures the remaining traction period after import, not the battery's age since manufacture. Replacement packs, independent battery imports, salvage returns, and later transport reuse outside Ukraine are excluded from the numerical example.

$$N_{ret,v}(t) = I_v(t - \tau_v),\ v = n, u. \tag{6}$$

$N_{\mathrm{ret},v}(t)$ is the expected number of batteries leaving traction use in category v during year t. Multiplying a cohort by a fraction may yield a non-integer expected count. Under fixed lags, each cohort retires in a single year. In expanded form, $I_v(t - \tau_v) = w_v(t - \tau_v)I(t - \tau_v)$: market shares must be evaluated in the entry year. Using $w_v(t)$ would reassign the retiring battery to the market structure of a different year.

4.3. Collection Technical Qualification and Allocation to Energy Reuse

Traction retirement is followed by three distinct selection stages. Collection denotes physical access to batteries through the collection and assessment chain. Qualification denotes acceptance against specified technical criteria for the intended class of energy application. Allocation denotes the fraction of qualified batteries directed to energy reuse, taking account of alternative destinations at the scenario level:

$$N_{col,v}(t) = k_{col,v}(t)N_{ret,v}(t); \tag{7}$$

$$N_{qual,v}(t) = k_{qual|col,v}(t)N_{col,v}(t); \tag{8}$$

$$N_{reuse,v}(t) = k_{reuse|qual,v}(t)N_{qual,v}(t). \tag{9}$$

All fractions lie between zero and one. The qualification fraction is conditional on collection, and the energy-reuse fraction is conditional on qualification. Hence the aggregate fraction is given by the chain of conditional fractions, without assuming statistical independence:

$$k_{avail,v}(t) = k_{col,v}(t)k_{qual|col,v}(t)k_{reuse|qual,v}(t). \tag{10}$$

In this annual model, collection, assessment, and allocation are assumed to occur within the retirement year. No additional processing delay or intermediate inventory is included. Thus $N_{\mathrm{ret},v} \geq N_{\mathrm{col},v} \geq N_{\mathrm{qual},v} \geq N_{\mathrm{reuse},v}$ for each year and category. Where processing extends across years, stage-specific delay distributions and inventory balances must replace the same-year products. Batteries not advancing at a stage are residual flows to other destinations or deferred processing; their subsequent fate is outside this calculation.

The aggregate fractions in Table 3 determine the main scenario outputs, while the separate fractions explain their composition. An observed aggregate alone cannot identify its three factors. Stage separation therefore makes the intermediate battery flows explicit and allows for the contribution of each conditional fraction to final capacity to be examined separately.

Table 3. Scenario parameters and implied annual growth of the entry index.

Parameter	Pessimistic	Baseline	Optimistic
$A(2040)$, vehicles	600,000	900,000	1,300,000
New-entry retirement lag, years	9	9	9
Used-entry retirement lag, years	5	5	5
Aggregate transition fraction, new entries	0.65	0.75	0.85
Aggregate transition fraction, used entries	0.50	0.60	0.70
Mean residual capacity of selected batteries, kWh	37.5	43.5	49.0
Annual entry-index growth, %	6.206	9.116	11.824

4.4. Residual Capacity Potentially Available for Energy Applications

The final forecast is the residual energy-storage capacity of the batteries selected for energy reuse during each calendar year. Capacity is evaluated for this selected subset:

$$B_{avail}(t) \;=\; 10^{-6} \sum\nolimits_{v=n,u} N_{reuse,v}(t) C_{res|reuse,v}(t). \tag{11}$$

(t) is the mean residual capacity, in kWh per selected battery, and $B_{\mathrm{avail}}(t)$ is the GWh of storage capacity entering potential energy-reuse supply during year t. This is a capacity inflow, not electricity generated or delivered during that year. A common selected-battery mean is used within each numerical scenario. It can be replaced with category-, age-, or cohort-specific values when corresponding data are available.

Technical rejection is accounted for in $k_{\mathrm{qual|col}}$. The residual-capacity mean must therefore describe the accepted and allocated batteries. It must not incorporate a second rejection fraction. A state-of-health multiplier is appropriate when converting nominal pack capacity to residual capacity, but it must not be applied again if the input is already residual capacity.

$$B_{avail}(t) = 10^{-6} C_{res|reuse} \sum\nolimits_{v=n,u} k_{avail,v} I_v(t - \tau_v). \tag{12}$$

Equation (12) is the reduced numerical form under constant aggregate fractions and a common residual capacity. It preserves the scenario capacity totals while making their selection boundary explicit. "Potentially available for energy applications" means scenario-estimated supply following the specified selection stages. It does not mean guaranteed

availability for procurement: no price, contract, ownership-transfer, or market-clearing model is included.

4.5. Distributed Retirement and Cohort-Specific Selection

A discrete kernel $p_v(a)$ describes the probability that a battery leaves traction service a years after national entry, with nonnegative probabilities summing to one. The retirement count then becomes

$$N_{ret,v}(t) = \sum_{a \geq 0} p_v(a) I_v(t-a). \tag{13}$$

The fixed-lag model is recovered by concentrating the kernel at τ_v. The numerical sensitivity illustration assigns 0.25, 0.50, and 0.25 to ages $\tau_v - 1$, τ_v, and $\tau_v + 1$. This preserves the mean lag and spreads the returns across three years; the kernel is not fitted to lifetime observations. Equations (7)–(11) apply after retirement aggregation if the fractions and selected-battery capacity means represent the corresponding retirement-year mixture.

For the fixed-lag calculation, the kernel is a discrete point mass: the probability is one at the category lag and zero at every other age. For the distributed calculation, retirement age is the category lag minus one year plus a binomial random variable with two trials and a success probability of 0.5. Its probability masses are therefore 0.25, 0.50, and 0.25 at one year before, at, and one year after the category lag. The mean equals the fixed lag and the variance is 0.5 year^2. This is a specified discrete binomial kernel used in the deterministic convolution in Equation (13); no random retirement draw is needed for the expected flow. Both kernels sum to one. Equations (7)–(11) apply after retirement aggregation when selection fractions and selected-capacity means describe the corresponding retirement-year mixture.

$$A_v = \tau_v - 1 + X,\ X \sim Binomial(2,\ 0.5)$$

Here, A denotes retirement age after national entry and τ the category-specific central lag. The term distributed lag refers to dispersion of cohort returns across years; it does not denote a trained time-varying regression or an estimated Weibull lifetime distribution.

If the battery condition, collection, or allocation depends on cohort age, selection must instead be applied inside the cohort sum. When $K_v(t,a)$ denotes the product of the three conditional fractions for age a at retirement year t and $C_v(t,a)$ denotes the mean residual capacity of that selected subset, the general form is

$$B_{avail}(t) = 10^{-6} \sum_{v=n,u} \sum_{a \geq 0} I_v(t-a) p_v(a) K_v(t,a) C_v(t,a). \tag{14}$$

This form allows for the joint influence of retirement age and selected residual capacity to be represented without assuming that these quantities are independent. The numerical application uses constant category-specific K and a common capacity mean because age-resolved return and assessment data are not available.

4.6. Cumulative Supply and Downstream Deployment

$$B_{cum}(t) = \sum_{j=2025}^{t} B_{avail}(j). \tag{15}$$

B_{cum} is gross accumulated potential capacity inflow during 2025 − t. It excludes supplies before 2025 and does not subtract ageing, second-life retirement, export, stockpiling, or non-deployment. It is not the installed capacity available in operation. If $D(j)$ is capacity actually deployed from supply year j, a separate operational balance is

$$E_{op}(t) = \sum_{j \leq t} D(j) q(t-j) d(t-j),\ 0 \leq D(j) \leq B_{avail}(j). \tag{16}$$

Here, q is the surviving fraction of deployed capacity and d is the retained capacity conditional on survival. This expression assumes deployment in the supply year; delayed

deployment requires separate supply and commissioning dates. Neither deployment nor second-life survival is calculated here. Converter power, state-of-charge restrictions, efficiency, connection constraints, and dispatch are additionally required to estimate MW of reserve or annual energy delivery.

4.7. Sensitivity and Identifiability

With other variables held fixed, annual potential supply is linear in common residual capacity and in each selection fraction. For category v and a positive collection fraction, the marginal collection effect is

$$\frac{\partial B_{avail}(t)}{\partial k_{col,v}(t)} = 10^{-6} C_{res|reuse,v}(t) N_{ret,v}(t) k_{qual|col,v}(t) k_{reuse|qual,v}(t). \quad (17)$$

Analogous expressions follow for qualification and reuse allocation by retaining the other two factors. A proportional change in any one factor produces the same proportional change in that category's capacity contribution. Its effect on total supply is weighted by the category's share. These are conditional sensitivities: in practice, expanding collection may also change the quality distribution of collected batteries.

Different decompositions with the same product and the same selected-capacity mean produce identical final capacity. Therefore, final capacity observations alone cannot identify the three fractions. Retirement, collection, screening, and allocation records are needed to estimate them separately. By contrast, a change in retirement lag selects another source cohort and can move a supply wave to a different calendar year.

4.8. Numerical Checks and Joint Uncertainty Analysis

Verification covers three accounting properties: each closed entry cohort contributes once over the complete retirement-kernel support; annual counts are non-increasing through collection, qualification, and allocation; and the initial retirement flow equals selected batteries plus the three non-advancing flows. Capacity is computed only after selection. A separate 2019–2025 closed-cohort experiment uses official Norwegian electricity-powered private-car registrations, distinguishing new and second-hand imported vehicles and summing all Euro classes once [79]. Identical illustrative kernels isolate the effect of entry composition across markets; no Ukrainian selection coefficient or residual-capacity mean is transferred to Norway. Additional checks reproduce the baseline cumulative inflow of 13.4392156129497 GWh, retain the annual ordering of the three main scenarios, and confirm that a 100-battery impulse produces distributed returns of 25, 50, and 25 batteries. Doubling the selected residual-capacity mean doubles capacity, and all sampled stage fractions and outputs remain admissible. Full-support cohort conservation is checked through 2057.

Joint uncertainty is explored using 20,000 Latin-hypercube runs with seed 4688583 and uniform marginal design ranges. The entry-index endpoint varies from 600,000 to 1,300,000 and selected residual capacity from 34.8 to 52.2 kWh. For new entries, collection, qualification, and allocation range over 0.80–0.98, 0.75–0.98, and 0.70–0.99; corresponding used-entry ranges are 0.65–0.98, 0.60–0.95, and 0.50–0.95. Each future new-share block varies by ± 10 percentage points. Assumed historical shares vary by ± 10 points and proxy shares by ± 5 points; directly reported shares are retained. Recent rounded category counts vary by ± 50 vehicles each. These are transparent exploration bounds, not fitted probability distributions.

The sampling design has 24 dimensions: the endpoint, residual capacity, six stage fractions, four assumed shares (2013, 2014, 2015, and 2022), four proxy shares (2016–2019), four rounded category counts (new and used in 2024 and 2025), three future-share blocks, and one lag-shift dimension. The last dimension is unused in the fixed-lag experiment. Shares are clipped to $[0, 1]$; the 2020, 2021, and 2023 reported shares remain fixed. Future

new-share ranges are 0.20–0.40, 0.35–0.55, and 0.50–0.70 for 2026–2030, 2031–2035, and 2036–2040, respectively. The compound continuation is re-anchored to each run's perturbed cumulative historical entry and 2040 endpoint. The principal design samples dimensions independently using scipy.stats.qmc.LatinHypercube (SciPy 1.17.0); the seed and dimension order above define the numerical design.

The principal ensemble keeps lags at 9/5 years. A second ensemble adds an equally weighted common integer shift from −1 to +6 years, preserving the four-year category gap. A historical-input-only experiment holds all subsequent assumptions at baseline values. Spearman rank correlations describe sensitivity within the principal design. A dependence stress test preserves the sampled marginal values but inversely ranks collection and qualification within each category. Sampling assumptions concern uncertain parameter combinations; they do not change the conditional-event accounting in Equation (10). Reported percentiles describe these numerical designs. A numerical sampling check compares the first 10,000 points with all 20,000: cumulative 5th, 50th, and 95th percentiles change from 6.927, 10.571, and 15.984 GWh to 6.917, 10.551, and 16.011 GWh, respectively; the largest relative change is 0.183%.

5. Results

5.1. Scenario Supply Trajectories

The calculation produces the annual and cumulative trajectories in Figure 3. Table 4 lists the complete annual output for 2025–2040. Gross cumulative potential supply is 7.696, 13.439, and 21.750 GWh in the pessimistic, baseline, and optimistic cases, respectively. Their annual 2040 inflows are 0.491, 1.201, and 2.425 GWh. These are scenario outputs after the specified selection losses, rather than observed battery returns or guaranteed purchases.

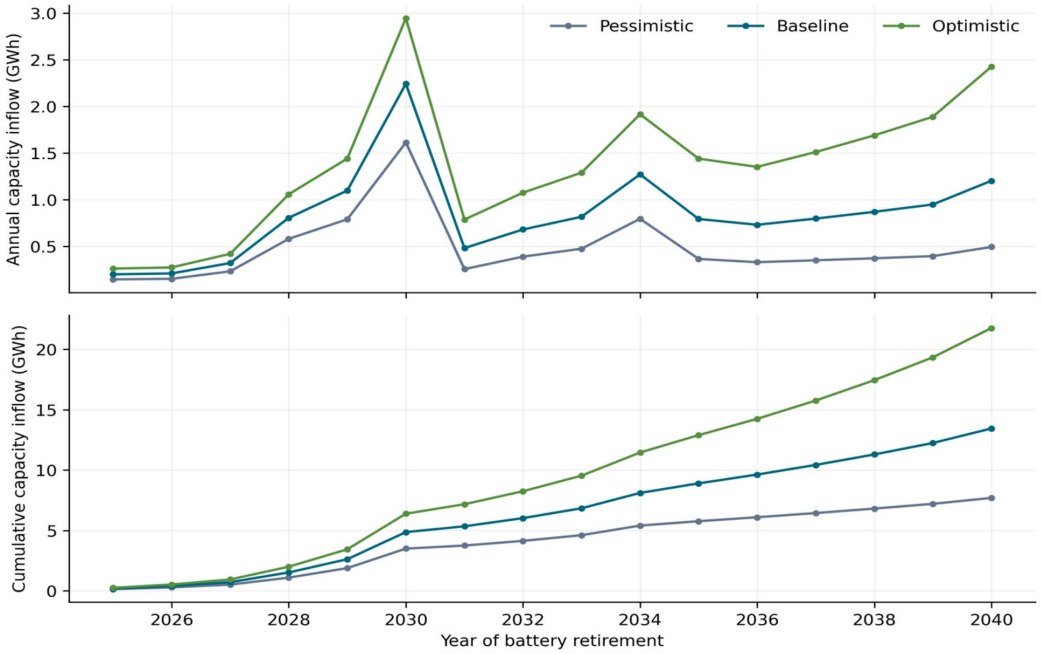


Figure 3. Annual residual-capacity inflow (**a**) and cumulative supply (**b**) over 2025–2040 under the pessimistic, baseline, and optimistic scenarios.

Table 4. Annual potential capacity and cumulative supply calculated from the cohort model.

Year	Annual Pessimistic	Annual Baseline	Annual Optimistic	Cumulative Pessimistic	Cumulative Baseline	Cumulative Optimistic
2025	0.143	0.197	0.259	0.143	0.197	0.259
2026	0.149	0.207	0.271	0.292	0.404	0.530
2027	0.230	0.318	0.417	0.521	0.723	0.947
2028	0.578	0.804	1.056	1.100	1.527	2.003
2029	0.788	1.096	1.440	1.888	2.623	3.443
2030	1.612	2.242	2.945	3.500	4.865	6.388
2031	0.253	0.479	0.785	3.753	5.344	7.173
2032	0.387	0.678	1.074	4.140	6.023	8.247
2033	0.472	0.815	1.288	4.612	6.838	9.535
2034	0.793	1.270	1.915	5.405	8.108	11.450
2035	0.362	0.791	1.439	5.767	8.899	12.889
2036	0.327	0.729	1.350	6.095	9.628	14.239
2037	0.348	0.795	1.510	6.443	10.423	15.749
2038	0.369	0.868	1.688	6.812	11.291	17.437
2039	0.392	0.947	1.888	7.204	12.238	19.325
2040	0.491	1.201	2.425	7.696	13.439	21.750

All three main scenarios use identical retirement lags; lag sensitivity is assessed separately. Table 4 reports the annual model outputs and their cumulative sums for all three scenarios, providing the numerical basis for the trajectories in Figure 3.

All capacity values in Table 4 are GWh. Cumulative values are calculated from unrounded annual outputs; small differences from sums of displayed values arise from rounding.

The baseline annual inflow is 0.197 GWh in 2025 and peaks at 2.242 GWh in 2030, when the large 2025 used-entry cohort retires under the five-year lag. The pessimistic and optimistic scenarios also peak in 2030, at 1.612 and 2.945 GWh, respectively. The common lags preserve the timing of this historical-cohort wave, while the resource-formation assumptions determine its magnitude. Annual and cumulative outputs remain ordered across the three main scenarios throughout the calculation horizon.

5.2. Origin of the Baseline Supply Peak

The baseline 2030 output combines 84,400 used entries from 2025 with $8541 \times 0.142 = 1212.822$ expected new-entry batteries from 2021. The used contribution is 2.20284 GWh and the new contribution is 0.03957 GWh after their respective aggregate fractions of 0.60 and 0.75 and the selected-capacity mean of 43.5 kWh are applied. Their sum is 2.24241 GWh; used entries provide 98.2%. The peak has an identifiable source cohort, but its magnitude depends on selection and residual-capacity assumptions.

The illustrative three-year retirement kernel lowers the baseline 2030 output to 1.515 GWh, a reduction of 32.4%. Cumulative supply through 2040 changes from 13.439 to 13.409 GWh. The cumulative difference reflects movement across the calculation-window boundaries; it is not a general equivalence between fixed and distributed retirement.

5.3. Comparison with Simplified Accounting

Figure 4 compares differentiated fixed lags, a common nine-year lag, and illustrative distributed lags under the baseline assumptions. Applying nine years to both categories while retaining their cohort shares and transition fractions gives 0.900 GWh of cumulative supply through 2030 compared with 4.865 GWh under differentiated lags, a reduction of 81.5%. This quantifies the change in the near-term supply calendar caused by replacing category-specific remaining transport lives with a single lag.

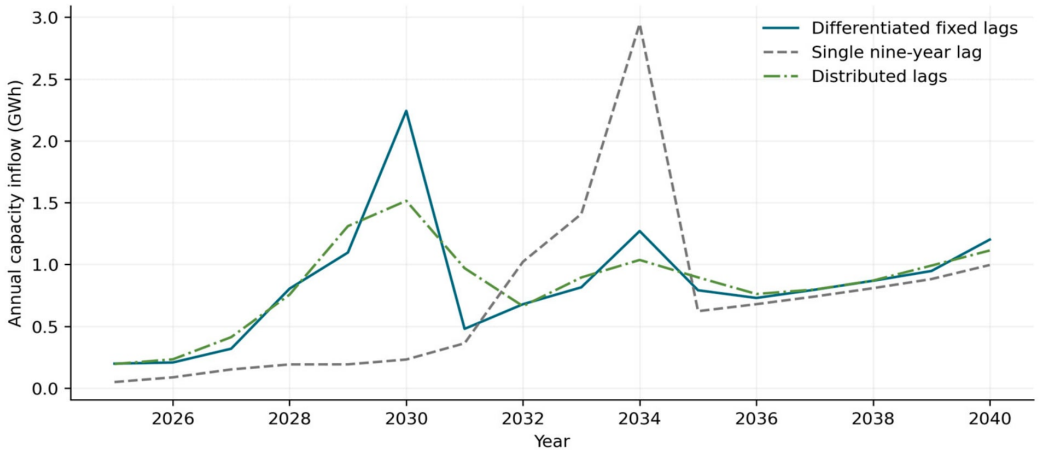


Figure 4. Baseline-scenario annual supply with differentiated fixed lags, a single nine-year lag, and illustrative distributed lags.

Using current-year shares with lagged entry counts instead of cohort-year shares gives 2.042 GWh in 2030 and 14.742 GWh cumulatively through 2040, compared with 2.242 and 13.439 GWh under correct indexing. The selected annual value changes by −8.9% and the cumulative value by +9.7%. The direction depends on market-share changes and the observation window.

5.4. Sensitivity of Supply Timing and Quantity

Table 5 compares lag representations and varies one assumption at a time around the baseline case. The ±1-year changes move both category lags together. Capacity changes affect only the residual-capacity mean. Data sensitivities replace the recent passenger totals, restore the earlier piecewise historical shares, or lower the 2016 new-share proxy while keeping other settings fixed. Alternative totals re-anchor the cumulative-entry path to the same 2040 endpoint.

Bringing both lags forward moves the main used-entry wave to 2029: the 2030 annual value becomes 0.479 GWh, while cumulative supply through 2030 becomes 5.147 GWh. Delaying both lags gives 2.799 GWh cumulatively through 2030. Calendar-specific resource planning therefore requires the full supply trajectory rather than only a cumulative total.

A ±20% change in the selected residual-capacity mean gives 10.751–16.127 GWh cumulatively through 2040. At the 2030 peak, an absolute increase of 0.10 in the aggregate used-entry transition fraction adds 0.367 GWh; the corresponding new-entry increase adds 0.005 GWh. Section 5.5 isolates the component stages.

Table 5. Baseline-case sensitivity and accounting comparisons.

Case	Annual 2030, GWh	Cumulative to 2030, GWh	Cumulative to 2040, GWh
Baseline	2.242	4.865	13.439
Distributed lag	1.515	4.419	13.409
Both lags −1 year	0.479	5.147	14.345
Both lags +1 year	1.096	2.799	12.414
Single nine-year lag	0.231	0.900	11.365
Current-year shares	2.042	4.448	14.742
Residual capacity −20%	1.794	3.892	10.751
Residual capacity +20%	2.691	5.839	16.127
Alternative 2024–2025 passenger totals	2.248	4.851	13.423
Earlier piecewise historical shares	2.273	4.784	13.461
2016 new-share proxy reduced to 15%	2.242	4.847	13.421
New/used lags 12/8 years	0.318	1.093	10.793
New/used lags 15/11 years	0.176	0.403	8.510

Replacing only the 2024–2025 passenger totals with the alternative reported values changes cumulative baseline supply to 13.423 GWh (−0.12%). Restoring the earlier piecewise historical shares gives 13.461 GWh. Changing the 2016 new-share proxy from 49% to 15% changes the 2025 inflow from 0.197 to 0.179 GWh, illustrating why uncertain early splits matter for near-term supply. These experiments quantify how reporting choices and historical market-share reconstruction propagate into the forecast.

Extending new/used lags to 12/8 years shifts the peak to 2033 and reduces cumulative inflow through 2040 to 10.793 GWh. At 15/11 years, the peak occurs in 2036 and cumulative inflow is 8.510 GWh. Thus, the calendar concentration persists under longer service, while its year and the amount entering the assessment window change substantially.

5.5. Stage-Resolved Formation of Potential Energy Resources

To demonstrate the intermediate balances, Table 6 specifies one hypothetical decomposition of the baseline aggregate fractions. Both categories have a collection fraction of 0.90. Qualification conditional on collection is 0.90 for new entries and 0.80 for used entries. Energy-reuse allocation conditional on qualification is 25/27 for new entries and 5/6 for used entries. These choices reproduce aggregate fractions of exactly 0.75 and 0.60. This illustrative decomposition holds the aggregate baseline fractions constant while exposing the separate collection, qualification, and allocation balances.

Table 6. Hypothetical baseline-case transition fractions preserving the aggregate scenario.

Category at Entry	Collection	Qualification Given Collection	Energy Reuse Given Qualification	Product
New	0.90	0.90	25/27 ≈ 0.925926	0.75
Used	0.90	0.80	5/6 ≈ 0.833333	0.60

Table 7 reports the resulting stage balances. In 2030, approximately 85,613 batteries retire, 77,052 are collected, 61,750 qualify, and 51,550 are allocated to energy reuse. The selected mean of 43.5 kWh yields 2.242 GWh. Stage losses change the selected count, rather than discounting residual capacity repeatedly.

Table 7. Illustrative baseline-case annual stage flows and residual capacity.

Year	Retired Batteries	Collected Batteries	Qualified Batteries	Selected for Energy Reuse	Potential Capacity, GWh
2025	7362	6626	5374	4539	0.197
2030	85,613	77,052	61,750	51,550	2.242
2035	28,648	25,783	21,225	18,186	0.791
2040	42,165	37,948	31,747	27,613	1.201

Counts in Table 7 are rounded expected annual flows; all stage products are calculated before rounding. The selected counts refer to potential allocation under the assumed fractions, not observed collections or completed installations.

Holding other baseline settings fixed, lowering used-entry collection from 0.90 to 0.80 changes the aggregate fraction from 0.60 to 0.5333 and reduces 2030 potential capacity from 2.242 to 1.998 GWh. Lowering qualification conditional on collection from 0.80 to 0.70 instead gives an aggregate fraction of 0.525 and 1.967 GWh. The calculations isolate the capacity response to each stage fraction with collected-battery condition and receiving-application assumptions held fixed.

The pessimistic and optimistic cases retain their aggregate fractions without assigning unique stage decompositions. Many combinations can yield the same final capacity, so the aggregate scenario envelope does not identify intermediate flows. Separate stage observations would allow that ambiguity to be reduced and collection or screening interventions to be assessed on an empirical basis.

Figure 5 extends the four-year tabulation to the complete annual stage trajectories and summarises parameter sensitivity under the joint design. At the 2030 baseline peak, 8561 batteries remain outside collection, 15,302 are not technically accepted, and 10,200 qualified batteries are not allocated to energy reuse; approximately 51,550 are selected. These mutually exclusive flows sum to the retirement input before rounding. Across the full cohort support, conservation error is below 10^{-8} battery in floating-point arithmetic, and the annual stage-balance residual is zero.

5.6. Joint Uncertainty and Robustness of the Supply Calendar

Figure 6 compares the joint input experiment with explicit longer-service cases. With fixed 9/5-year lags, the 5th–95th design percentiles of cumulative supply through 2040 are 6.917–16.011 GWh, with a median of 10.551 GWh. The corresponding 2030 annual range is 1.044–2.583 GWh. The design median differs from the baseline because all six stage fractions vary over ranges whose products differ from the baseline aggregate fractions. In 19,495 of 20,000 runs (97.5%), the annual maximum remains in 2030. This persistence is conditional on the fixed timing assumptions.

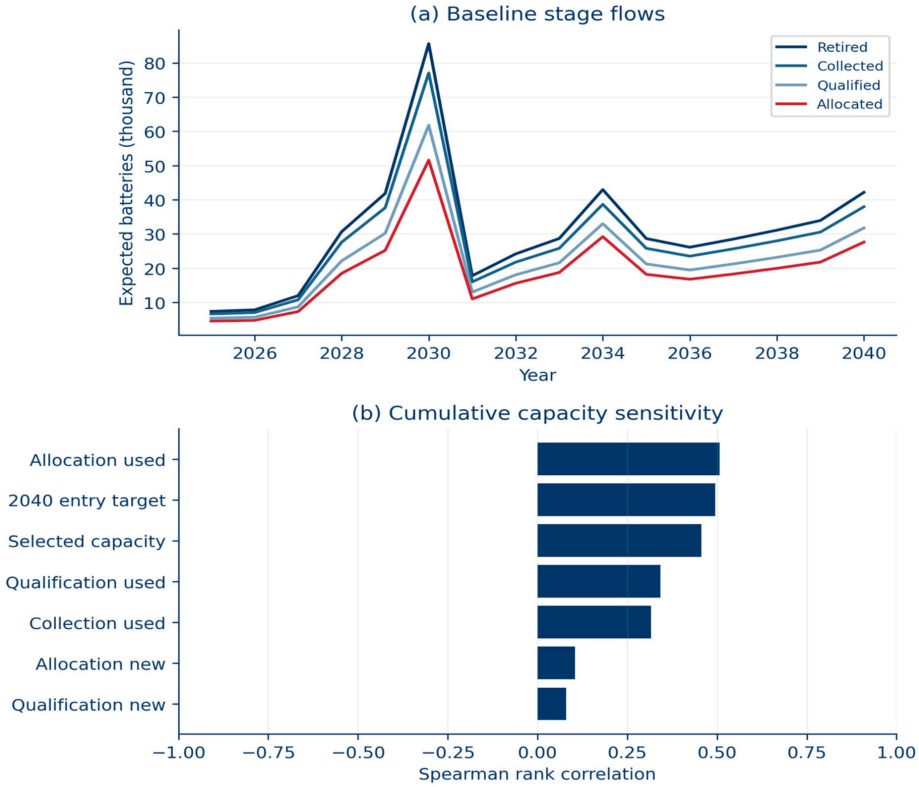


Figure 5. Baseline annual battery flows at successive selection stages (**a**) and rank sensitivity of cumulative capacity in the joint parameter design (**b**).

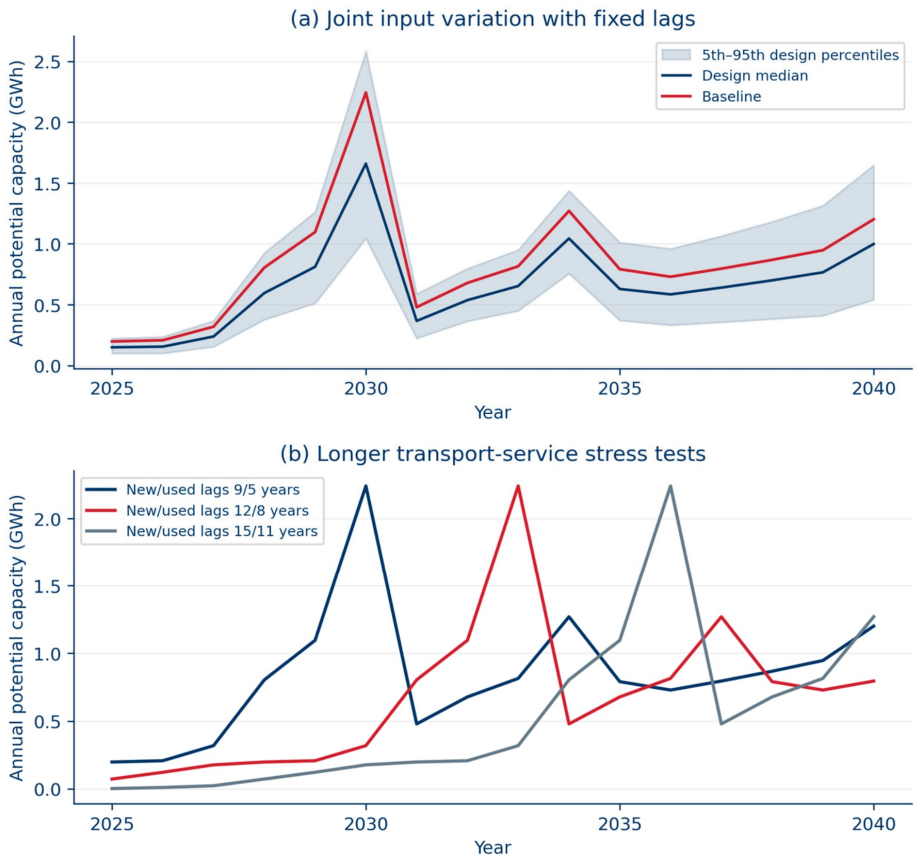


Figure 6. Annual potential capacity under (**a**) joint input variation with fixed retirement lags and (**b**) stress tests with longer remaining transport service.

Varying only historical input splits and rounding gives cumulative percentiles of 13.422–13.457 GWh, with the peak in 2030 in every run. This narrow range concerns the specified historical input perturbations; it does not cover future market development or battery return conditions. Adding the broader lag shifts to the joint experiment gives cumulative percentiles of 5.246–14.317 GWh, and moves the principal supply wave across 2029–2036. Inversely ranking collection and qualification gives a cumulative range of 7.236–15.023 GWh. The results distinguish relatively small entry-reconstruction effects from the larger uncertainty in retirement timing and subsequent resource capture.

5.7. Independent National Inputs and Observed Routing Boundaries

Table 8 compares the same closed entry period, 2019–2025, in Ukraine and Norway. The Norwegian inputs are directly reported electricity-powered private-car registrations [79]; hydrogen, hybrids, commercial vehicles, and later entries are excluded. The 828,308 Norwegian entries include 48,103 used imports (5.8%), compared with an 80.6% used share in the Ukrainian cohorts. Applying the same 9/5-year kernels yields 298,855 Norwegian cohort retirements cumulatively through 2030 versus 273,466 with a common nine-year lag. The corresponding Ukrainian counts are 189,653 and 22,908. These are closed-cohort scenario counts, not observed retirements or complete national forecasts.

Table 8. Closed-cohort comparison using national entry data for 2019–2025.

Market	Entries	Used share, %	Retired Through 2030, 9/5 Years	Retired Through 2030, Common 9 Years
Ukraine	232,160	80.65	189,653	22,908
Norway	828,308	5.81	298,855	273,466

The Norwegian extraction uses Statistics Norway Table 12906 [79], API https://data.ssb.no/api/v0/en/table/12906, with Region = 0 (whole country), TypeRegistrering = N/B (new/second-hand imported), DrivstoffType = 5 (electricity), ContentsCode = Personbil1 (private cars), EuroKlasser = 00–07 (summed once), and Tid = 2019–2025; accessed 3 November 2026. Annual new/used-import counts are 60,246/6803 (2019), 76,791/5434 (2020), 113,715/10,477 (2021), 138,283/14,473 (2022), 104,576/1733 (2023), 114,377/3774 (2024), and 172,217/5409 (2025). Returns are tracked over 2024–2040, with all entries outside 2019–2025 excluded. Ukrainian comparison inputs are the corresponding rows of Table 1.

Figure 7 shows the cumulative return profiles normalised by the size of each market's input cohorts. Both representations conserve all cohort members by 2034, but differentiated timing brings a much larger proportion forward in the import-dominated Ukrainian case. This independent-input application demonstrates the portability of the cohort accounting and the role of market composition. The shared lags are experimental controls, rather than Norwegian lifetime estimates.

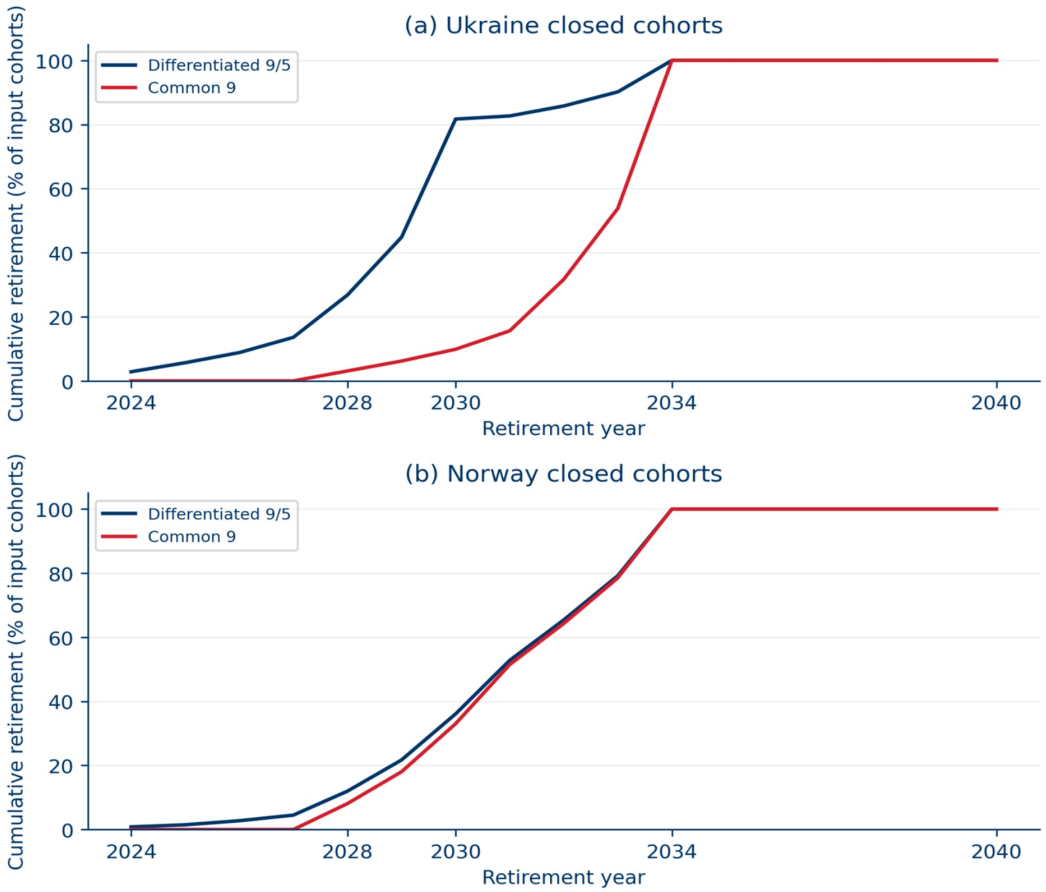


Figure 7. Normalised cumulative retirement of the 2019–2025 entry cohorts in (**a**) Ukraine and (**b**) Norway under differentiated and common retirement lags.

Observed destination records provide a complementary check on the downstream boundary. The Dutch scheme reports 263,373 kg collected in 2023, of which 70,071 kg (26.60%) entered second use; for 2024, the corresponding values are 362,869 and 55,855 kg (15.39%) [77,78]. Recycling accounts for 193,302 kg in 2023 and 306,642 kg in 2024; the latter year's published destinations leave 372 kg unreconciled, for which no destination is imputed. These mass flows combine packs and modules and include replacement-related returns. They therefore inform the selection boundary without identifying separate pack-count collection, qualification, or allocation fractions. In particular, the baseline's favourable capture and routing assumptions should be interpreted as organised-reuse scenarios, rather than as measured current Ukrainian practice.

6. Discussion

The model connects vehicle entry structure with the calendar of battery retirement and then with losses between retirement and potential energy reuse. This permits the source of a supply restriction to be identified within a scenario: delayed retirement, incomplete collection, low technical eligibility, or diversion to other destinations. The baseline illustration demonstrates that identical final totals can coexist with different intermediate burdens on collection and screening. It can inform the timing of assessment facilities and resource-development programmes, while procurement budgets require an additional market-access and cost analysis.

For secondary-resource planning, each intermediate flow corresponds to a different infrastructure requirement. Retirement counts indicate the potential scale of batteries leaving transport use, collection counts indicate expected intake to the assessment chain, qualified

counts indicate the volume passing the specified technical criteria, and allocated counts and residual capacity indicate the potential feedstock for energy-oriented repurposing. Table 7 therefore informs more than a final capacity estimate: it distinguishes the expected annual numbers handled at successive stages. These quantities can support initial planning of collection coverage, diagnostic throughput, and repurposing intake. Converting annual counts into facility capacities would additionally require processing times, logistics, pack characteristics, and operating schedules.

Supply forecasting and operational qualification address different decisions. The annual potential capacity $B_{\text{avail}}(t)$ can inform how much battery material might become accessible to a deployment programme. It does not confirm that a specific storage system can meet a reserve request. That decision requires pack-level assessment, remaining-life estimation, electrical integration, and service-specific operating limits. A KPI-triggered deployment and control framework [31] can use supply estimates as upstream information while retaining its own technical and operational admission criteria. A high cumulative total does not by itself demonstrate economic or environmental superiority. Acquisition costs, testing, adaptation, utilisation, replacement, and the value of recycling must be assessed separately. Likewise, a capacity inflow cannot be converted directly into avoided emissions without a lifecycle boundary and a displaced-technology baseline. Resource formation is an enabling input to these assessments, not a substitute for them.

Comparison with new stationary batteries requires a matched service, delivered-energy functional unit, and assessment horizon. For each alternative, LCOS includes discounted acquisition, refurbishment where applicable, integration, maintenance, charging, replacement, and end-of-life costs divided by discounted delivered energy. Degradation and residual life determine that denominator and replacement schedule. An environmental comparison likewise requires refurbishment and transport inventories, use-phase losses, allocation of first-life impacts, and a consistent recycling counterfactual [13–17,24,26–29]. The forecast supplies the annual residual-capacity input to such comparisons; it leaves their service-specific cost and impact parameters to the receiving-system assessment. Consequently, no universal economic or environmental preference is assigned to the capacity trajectories.

The main scenarios separate resource-formation conditions from retirement timing. Their common lags allow the effects for of vehicle-entry development, aggregate transition fractions, and selected residual capacity to be compared without simultaneously advancing or delaying retirement. In this experiment the pessimistic, baseline, and optimistic trajectories remain ordered in every year. The separate lag sensitivity shows that earlier retirement can move a supply wave away from a particular planning year even when cumulative supply increases. A shorter lag therefore has no intrinsically optimistic interpretation, and longer transport use does not by itself imply poorer battery performance. Planning decisions should consider both the full supply trajectory and the independently assessed uncertainty in retirement timing.

The model can be extended by vehicle class, battery chemistry, original pack size, age at import, and condition. Category labels remain tied to entry, but retirement kernels and selection fractions can depend on cohort age. Processing delays require intermediate inventories and separate collection, assessment, allocation, and commissioning dates. These extensions provide a route to greater technological and operational detail as the corresponding cohort and processing data become available.

The transferable element is the cohort and stage accounting, rather than the numerical Ukrainian parameter values. Applying the framework elsewhere requires a consistent national-entry series, identification of new and used entries, and retirement and selection assumptions matched to that geographical boundary. Retaining entry-year category shares prevents subsequent changes in the market mix from being imposed on older cohorts.

Separating collection, qualification, and allocation then allows countries with different reuse infrastructures to represent different routes from the same retirement potential to accessible secondary-battery supply.

7. Scope and Directions for Model Development

The forecast describes annual potential secondary-battery supply within a national passenger BEV boundary. Joint parameter experiments and longer-service stress tests quantify the effects of the chosen temporal and technological resolution. The independent Norwegian input application checks transfer of the cohort accounting across market structures, while the Dutch routing records expose the distinction between collected mass and selected pack counts. Direct estimation of retirement and conditional selection rates requires linked battery histories with matching denominators. The present results support scenario-based infrastructure planning at this stated resolution.

Consistent registration boundaries support comparable cohort inputs. For 2020, an alternative report gives 7095 passenger BEVs [80], compared with 7186 in the federation's annual series [65]. The sensitivity calculations quantify the implications of alternative reporting series. Further harmonisation can reconcile registration dates, revisions, and classification rules through vehicle-level records.

Further development can combine age-at-import distributions, battery replacements, chemistry and pack-size information, and measured condition at retirement. Linked collection, screening, and reuse records would support stage-specific parameter estimation and updating. Separate processing dates and inventories would extend the model to delayed collection and repurposing. The post-2025 entry paths can likewise be replaced with market scenarios incorporating policy, income, charging infrastructure, and wartime changes. These extensions retain the cohort-consistent accounting structure while adapting its detail to the planning question and available information.

8. Conclusions

A stage-resolved lag-based cohort model has been formulated for forecasting the residual capacity of EV batteries potentially available for energy applications. It distinguishes new- and used-vehicle entry, remaining traction-service duration, collection, technical qualification, and energy-reuse allocation. Conditional transition fractions preserve the dependence of each stage on the preceding one. Residual capacity is evaluated for the selected subset, avoiding duplicate technical-rejection discounts.

The revised passenger BEV illustration gives cumulative residual-capacity supply of 7.696–21.750 GWh over 2025–2040. The baseline case yields 13.439 GWh, with an annual peak of 2.242 GWh in 2030, 98.2% attributable to the 2025 used-entry cohort. Reported registrations, proxy market shares, and battery-selection assumptions remain explicitly distinguished.

The common nine-year lag reduces cumulative supply through 2030 from 4.865 to 0.900 GWh, while the illustrative distributed kernel reduces the 2030 peak to 1.515 GWh. Additional sensitivities quantify the effects of reporting differences and historical market-share assumptions. The comparisons establish how retirement representation changes the timing and concentration of supply, while the source and market-share sensitivities quantify the influence of historical cohort construction.

The joint input experiment produces cumulative 5th–95th design percentiles of 6.917–16.011 GWh under fixed lags, whereas historical split and rounding variations alone give 13.422–13.457 GWh. Longer remaining transport service shifts the main wave to 2033 or 2036. Independent Norwegian entry data reproduce the expected dependence of the timing comparison on the used-import share. These experiments identify which parts of

the supply calendar follow from observed cohort composition and which depend on future retirement and resource-capture conditions.

Stage-resolved accounting explains how collection, technical qualification, and allocation shape the potential resource. The illustrative decomposition preserves the baseline aggregate fractions, demonstrates consistent intermediate counts, and permits individual stage sensitivities to be calculated. Annual capacity inflow, cumulative potential supply, and surviving installed capacity remain separate quantities. The resulting stage balances existingpotential capacity supply to the annual volumes passing through collection, assessment, and allocation, supporting coordinated planning of the secondary-battery chain.

For circular-resource management, the main contribution is a traceable connection between transport cohorts and the calendar of potential secondary storage-capacity supply. The intermediate battery flows provide a basis for coordinating collection, diagnostic assessment, and repurposing infrastructure, while the final capacity trajectory supports comparison with prospective stationary-storage programmes. The accounting structure can be transferred to other used-import markets with locally specified inputs, enabling the formation of reusable battery resources to be analysed separately from subsequent deployment and material recovery.

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Abbreviations

The following abbreviations are used in this manuscript:

BEV	Battery electric vehicle
BMS	Battery management system
EV	Electric vehicle
KPI	Key performance indicator
LFP	Lithium iron phosphate
LMO	Lithium manganese oxide
NCA	Lithium nickel cobalt aluminium oxide
NMC	Lithium nickel manganese cobalt oxide
PDCA	Plan–Do–Check–Act
LCOS	Levelized cost of storage

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