Effects of market dynamics on the time-evolving price of second-life electric vehicle batteries

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Abstract

Second-life batteries are defined as those removed from electric vehicles (EVs) when their energy density and power density has degraded below the level required for motive applications but are still performant enough for less demanding stationary applications. They could one day be a plentiful, environmentally benign source of low-cost energy storage. Their price evolution is important to know for designers of and investors in such systems.

A methodology is developed for predicting second-life battery price and sales quantities up to 2050. Although existing data is too scant to draw reliable quantitative conclusions, sensitivity analyses are run to investigate the effects of different EV uptake scenarios, new battery costs, refurbishment costs, recycling net credit, elasticity of supply, and size of demand. No previous work has incorporated all these driving factors in such a transparent way. The second-life price is found to be insensitive to most of these factors, while the quantity sold is sensitive to nearly all of them.

Much work remains to be done in parameterizing the model more accurately. However, this work already elucidates a novel quantitative mode of thinking about what factors influence the long-term price and market size of second-life batteries.

Keywords: second-life, battery, electric vehicle, microeconomics, price, market size

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1. Introduction

The electric vehicle (EV) industry is growing rapidly, driven by falling battery costs [1] and increasing awareness of the harmful impacts of air pollution [2, 3]. Even despite the lagging development of charging infrastructure and the range anxiety of potential customers, current projections of EV uptake indicate that globally, several GWh's of used batteries are likely to be removed from EVs annually by 2030 [4, 5, 6]. The challenge this poses to recycling facilities is immense.

However, this challenge also represents an opportunity. Used batteries are removed from the vehicle when their maximum capacity has degraded to 70-80 % of the original capacity when new [7, 6]. Second-life batteries, as these are called, may still work well in a stationary application which is less restrictive in terms of space and weight than motive applications. Indeed, many demonstration projects and a few commercial ventures exist. Concepts range from off-vehicle storage to buffer EV charging from the grid [8, 9], to modelling studies of home batteries that can save on electricity bills by increasing onsite usage of rooftop PV [10, 6].

A great benefit of using second-life batteries is that they would displace some of the manufacture of new batteries for stationary applications, with their associated environmental impacts [11]. However, the claim that second-life usage postpones the point at which an EV battery must be recycled, while true for an individual battery pack [7], may not be significant for the EV fleet as a whole, as we show later. The theory is that postponing recycling gives time to increase material recovery rates and profitability in future, whether through innovation or simply as a result of increasing scarcity of cobalt and nickel over time [12, 13]. Nonetheless, the environmental benefit of second-life usage, 'reuse before recycle', may in itself be a goal worth pursuing.

The benefits of second-life usage can only be realized once certain drawbacks are addressed: the cost to refurbish a used EV battery (involving testing and voltage-matching the packs [14]); shorter lifetime and decreased efficiency resulting from degradation during the first life [7]; warranty issues and social and regulatory barriers to adoption of second-life batteries [15, 13].

It is clear that second-life batteries will be cheaper than their new counterparts. This presents an opportunity to stakeholders in the stationary applications market [16], to cut costs by using second-life batteries rather than new. At the design stage, it is important to know the price range of the batteries. The usage of cheap second-life batteries could significantly affect design decisions, and expected profits.

Neubauer and Pesaran [17] have attempted to predict the evolution of second-life battery costs by assuming the cost of the battery as new is reduced according to its degraded state of health, reduced again by a 'second-hand discount factor', and with the refurbishment cost subtracted. The second-hand discount factor is arbitrary: they analyzed scenarios 50 % and 75 %. Even after accounting for state of health and refurbishment cost, there is no reason to believe that the second-life price would vary proportionally to the new battery price.

Foster *et al.* [18] have conducted cost-benefit analyses comparing EV battery refurbishment and recycling. They found that for research and development costs of \$50/kWh, refurbishment is profitable if the second-life price exceeds \$114/kWh, the difference being mainly transportation costs. Similarly, Casals *et al.* [14] calculated refurbishment costs under various scenarios to find the minimum viable second-life price. Neither examine whether a second-life market can exist at these prices, or indeed support prices above their calculated minima.

An alternative for potential second-life users is to design the system under a range of different battery cost scenarios, and pick an option passively in response to the market [10, 19]. This may be adequate for a one-off investment, but not if batteries must be replaced over the system lifetime (wind turbines and solar panels may last over 25 years, compared to 15 years or less, even for new batteries).

Here we present a methodology to rationalize the estimation of time-evolving second-life battery price. Principles of microeconomics are used to account for changing supply of and demand for second-life batteries, factoring in the cost of or income available from immediate recycling (without second-life usage), and both niche and mass-market stationary applications. Where Neubauer and Pesaran [17] assume a fixed second-life market and find it would rapidly be saturated by used EV batteries, our methodology attempts to model a more realistic situation, where a larger supply of second-life batteries would reduce the price and thus expand the market for them.

The model setup is explained in Section 2. The model is developed further and parameterized in Section 3. Results are presented in Section 4, followed by discussion in Section 5. The conclusions are in Section 6.

Nomenclature

t	Time (years). $t = 0$ in year 2010.
E_0	Original capacity of EV battery (kWh).
E_b	Capacity when removed from EV (kWh).
$P_{eqm}(t)$	Average equilibrium second-life battery price (\$/kWh).
$Q_{eqm}(t)$	Quantity of second-life batteries sold in year t (kWh).
$P_s(Q,t)$	Price-supply curve (\$/kWh).
$P_d(Q,t)$	Price-demand curve (\$/kWh).
$g_{EV}(t)$	Annual first-time EV battery sales (kWh).
$f_{EV}(t)$	Annual supply of used EV batteries (kWh).
A	All-time total first-time EV battery sales (kWh).
p	Coefficient of innovation (y^{-1}).
q	Coefficient of imitation (y^{-1}).

$Ra(\tau)$ Rayleigh-distributed failure probability of EV battery of age τ years.

i Generation of EV battery replacement purchase.

$\mu(i)$ Mean first lifetime of EV battery (years).

$r_i(t)$ EV battery i^{th}-generation replacement purchases in year t (kWh).

$C_{batt}(t)$ Cost of new stationary battery ($/kWh).

$C_{recyc}(t)$ Net credit from recycling an EV battery, i.e. minus any fee charged ($/kWh).

$C_{refurb}(t)$ Refurbishment cost to prepare used EV battery for second-life use ($/kWh).

n_e Elasticity coefficient, to vary shape of price-supply curve.

C_0 Cost of new stationary battery at $t = 0$ ($/kWh).

C_∞ Eventual minimum cost of new stationary battery ($/kWh).

β Rate of decline of new battery cost (per annum).

$P_{d(niche)}(Q, t)$ Niche-market part of price-demand curve ($/kWh).

$P_{d(mass)}(Q, t)$ Mass-market part of price-demand curve ($/kWh).

$(Q^*(t), P_d^*(t))$ Price-quantity point where niche-market and mass-market segments of price-demand curve meet (kWh,$/kWh).

$N_{batt}(t)$ Global maximum annual demand for second-life batteries (kWh).

A_N Asymptotic value of $N_{batt}(t)$ (kWh).

2. Model Setup

The modeled system and its constituent parts are defined here, with a brief overview of the calculation methodology. This is followed by the assumptions used, with some justification of their validity.

2.1. System Definition

2.1.1. System Boundary

In this work, calculations are done on a global basis. Since battery recycling is a global business, with used batteries being transported to plants in only a few countries, and recycled materials being exported worldwide [14], it stands to reason that battery refurbishment (as the process of preparing a used EV battery for the second-life market will be referred to) would be similarly global.

2.1.2. Sellers

The sellers of second-life batteries would include EV owners but predominantly EV manufacturers, given the trend for battery leasing, where the EV owner does not own the battery outright but pays a monthly fee to rent it from the manufacturer [9, 20]. The results presented in this work are independent of who the sellers are. The competing alternative to selling onto the second-life market is to send the battery to recycling straight away.

2.1.3. Buyers

The buyers of second-life batteries are suppliers of batteries for stationary applications. The competing alternative to buying second-life is to buy new stationary batteries. The supplier may further re-package, market, distribute and install the batteries (new or second-life), with a markup to the end customer. It should be noted that companies specializing in battery refurbishment may be created in future [21]. These companies would act as middlemen between sellers and buyers. This complication is avoided here by attributing the refurbishment costs solely to sellers (as if the refurbishment companies are subsidiaries of the EV manufacturers, for example).

2.1.4. Calculation Methodology

The higher the price of second-life batteries, the greater the incentive to sell. The lower the price, the greater the incentive to buy. These tendencies are quantified respectively in the price-supply and price-demand curves, which change from year to year in response to the changing supply of used EV batteries, developments in battery recycling, etc. Quasi-static equilibrium is assumed, whereby the price-quantity equilibrium is converged upon each year. Equilibrium is the crossing point of the price-supply and price-demand curves: an above-equilibrium price would be lowered by sellers competing to attract more buyers, and a below-equilibrium price would be bid upwards by competing buyers [22]. Price-quantity equilibria are found for every year from 2017 to 2050, giving the time evolution of second-life price and total quantity sold, under given scenarios. These are explored in the Results and Discussion sections.

2.2. Assumptions

2.2.1. No Stockpiling

The stockpiling of used batteries is neglected. However, this assumption may not hold under some circumstances: for example, if the batteries' value as material for recycling increases faster than the annual warehouse costs. Such analysis is outside the scope of this work. We assume the only two choices available to the owner of a used EV battery are to recycle immediately, or sell into second-life. Illegal dumping is ruled out [23, 24].

2.2.2. Frictionless International Trade

Import/export tariff barriers are neglected, as are subsidies and taxes which may vary between countries unless an international agreement can be reached. The current political climate would suggest that this cannot be taken for granted, but detailed analysis is outside the scope of this work.

2.2.3. Perfect Competition

The assumption of quasi-static equilibrium is valid under perfect competition: large numbers of buyers and sellers (no monopoly) with perfect knowledge of the market, operating rationally and freely with no collusion to fix prices [22]. While there are many EV manufacturers and potential second-life battery users, today's situation is far from perfect competition. However, new electronic trading platforms and future regulations may improve knowledge availability to buyers and sellers [21].

As long as changes in new battery price, recycling income, supply of used EV batteries, etc., are slow compared to the timescale on which second-life prices converge to equilibrium, quasi-static equilibrium may be reasonably assumed. However, with a yearly time step, some features will not be captured in this work: sub-yearly dynamics such as new product launches and seasonal variations, economic boom-and-bust cycles, sudden leaps and step changes in technology.

2.2.4. EV Sales unaffected by Second-life Market

Some pose the question of whether the second-life sale of used EV batteries can allow a discount on new EV batteries, thus driving EV sales. The conclusion is most commonly that the second-life price would be insufficient to bring this about [17]. Therefore, the feedback is not modelled here, but nonetheless a number of different EV uptake scenarios are investigated.

2.2.5. Sufficient Battery Refurbishing Capacity

It is assumed that the processing capacity of battery refurbishing plants will be sufficient at every time step. Good market research and forecasting should ensure that adequate investment is made in refurbishing capacity. In such a case, second-life sales quantities are driven by market dynamics rather than ignorance, poor analysis, or poor decision-making.

2.2.6. Second-Life Price Variance

The same price per kWh is unlikely to be paid for every second-life battery. Even if all EV batteries are removed once they degrade to 80 % of their original capacity, there may still be variations in performance and remaining life. These could be due to differences in battery chemistry and first-life usage patterns [25], while the second-life application will affect the remaining second lifetime [7]. It is beyond the scope of this work to account for the variance in second-life price likely to come about due to all these differences.

The degraded capacity relative to the original capacity (E_b/E_0) is approximated here as uniformly 75 % for all batteries entering the second-life market. All prices will be quoted in \$/kWh. While $E_b/E_0 = 80$ % is more common in the literature [7, 21, 26], there is some evidence that EV performance is still good when the battery is used beyond this point [27]. As the cost per mile to run an EV decreases with mileage [17], it is likely the industry standard would converge to below 80 %, which is why $E_b/E_0 = 75$ % is taken here. Thus the price found, $P_{eqm}(t)$, would be not *the* equilibrium second-life price, but the *average* equilibrium second-life price.

3. Model Development

The aim is to find the equilibrium second-life price $P_{eqm}(t)$ for each year from 2017 to 2050. To do this, the price-supply curve $P_s(Q, t)$ and price-demand curve $P_d(Q, t)$ for each year must be found, $(Q_{eqm}(t), P_{eqm}(t))$ being their crossing point. This section explains how the price-supply and price-demand curves are constructed and parameterized. The price-supply curve depends on the rate at which used batteries are removed from EVs, and so the problem of determining this rate is addressed first.

3.1. Determining Supply of Used EV Batteries

The rate at which used batteries are removed from EVs is denoted here by $f_{EV}(t)$ (in kWh). An adaptation of the Bass model of innovation diffusion [28] is used to estimate $f_{EV}(t)$. EV sales data are used to parameterize the model.

3.1.1. Bass Model

The original Bass model considers the rate of uptake of a new technology, $\dot{F}(t)$, relative to the population yet to adopt it, $1 - F(t)$, to vary linearly with the fraction of the population that has already adopted it, $F(t)$ (the integral of $\dot{F}(t)$):

$$\frac{\dot{F}(t)}{1 - F(t)} = p + qF(t). \tag{1}$$

The parameters p and q have natural interpretations as the spontaneous uptake of the technology by early adopters (the 'coefficient of innovation'), and the influence of those who have already become users of the technology on those who have not yet ('coefficient of imitation'), respectively [28].

Solving (1), the adoption rate $\dot{F}(t)$ follows the form given in (2), growing as the technology gains popularity, then peaking and declining as the market saturates [28]. Though conceived to model populations adopting a technology, the Bass model was found to be valid for sales figures for numerous products.

Olson and Choi [29] adapted the Bass model to include replacement purchases of durable goods with finite lifetimes, finding their version predicted sales figures for televisions and fridges with better accuracy than the Bass model alone. Their methods should be applicable to EV battery replacement purchases: EVs may soon go from novelty to essential commodity, where nearly all purchases now are first-time purchases, but in future nearly all may be replacement purchases.

First we define $g_{EV}(t)$, the annual first-time sales of EVs (specifically their batteries, in kWh):

$$g_{EV}(t) = A\frac{(p+q)^2 \exp\left(-(p+q)t\right)}{p(1+\frac{q}{p}\exp\left(-(p+q)t\right))^2} \tag{2}$$

where A is the all-time total of first-time EV sales (in kWh), and p and q are as in (1). Equation (2) is the solution to (1), but multiplied by A to give $g_{EV}(t)$ in kWh.

Next, the parameter values A, p, q must be chosen. Then the replacement purchases are calculated, taking account of variation in the battery first-lifetime. Since removal of a used EV battery must be quickly followed by a replacement (of the battery or the entire vehicle, but in either case a new battery replaces a used one), the quantity of used batteries (kWh) removed in a given year equals the sum of all replacement purchases in that year.

3.1.2. *Choosing Parameters A, p, q*

The International Energy Agency has published statistics [30] on the cumulative global fleet of battery electric vehicles (BEV - that is, with no internal combustion engine, or ICE) and plug-in hybrid electric vehicles (PHEV - typically diesel vehicles with an onboard battery to power most driving except long stretches of cruising). Battery capacity varies between different makes of BEVs and PHEVs. Therefore, sales data from EV Volumes [31, 32, 33] were used to estimate their average capacities from 2013-2016, and a linear extrapolation was assumed for previous years to 2010, the first year for which complete unit sales data are available [30].

Total annual EV battery sales are given as BEV annual sales multiplied by the respective average battery capacity for that year, added to the same for PHEVs. Finding the battery sales in kWh obviates the need to extrapolate separately the sales figures for BEV and PHEV units and average battery capacities (see Supplementary Table S3). Thus only the total kWh data need be extrapolated.

The Bass model curve $g_{EV}(t)$ (2) was fit to the total annual (kWh) sales data by a least-squares regression. As there are so few data points, the coefficient of determination R^2 can exceed 0.999 for extremely different outcomes depending on the initial parameters given to the fitting procedure. This indicates an underconstrained problem. Due to heteroskedasticity in the system, it is not well suited to least-squares regression in the first place [29]. We stress that the impossible task of making accurate predictions 40 years into the future is not the aim of this work; rather, plausible scenarios are sought in order to explore the dependence of second-life price on different driving factors such as EV uptake.

The fit parameters are given in Table 1 along with R^2, and long-term outcomes, for ‘Low’, ‘Medium’ and ‘High’ EV uptake scenarios. ‘Low’ is defined as the set of parameters that maximizes R^2. The result is eventual EV penetration of around 0.75 %. This is even less than the current EV penetration of 2 %, assuming all-time average battery capacity 40 kWh (the trend is for increasing

EV Uptake	A (kWh)	p	q	R^2	Total EV fleet
Low	6.05×10^8	0.0112	0.6039	0.99921	15 million
Medium	3.60×10^{10}	2.11×10^{-5}	0.5645	0.99899	900 million
High	8.00×10^{10}	9.50×10^{-6}	0.5641	0.99899	2 billion

Table 1: Best-fit parameters, and R^2 and resultant total sales implied (integrating the curve, and assuming all-time average EV capacity 40 kWh), for Low, Medium and High EV uptake scenarios.

capacity). For reference, the global car fleet today is roughly 1 billion, and is expected to double by 2040 [34]. 'Medium' corresponds to an eventual EV penetration of 45 %, guided by the projections of Wills [35]. It is taken as the most likely future scenario. 'High' is defined as resulting in all 2 billion cars being electric, each with a 40 kWh battery. The first-time annual sales $g_{EV}(t)$ for the 'Low' scenario is shown in Fig. 1.

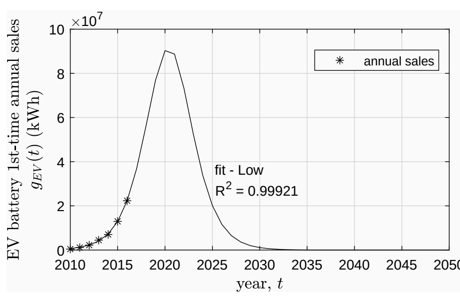

Figure 1: Total EV annual sales and extrapolated Low scenario. It peaks in 2020 at 91 GWh. The Medium and High scenarios (not shown) peak respectively in 2028 and 2029, at 5 TWh and 11 TWh.

EV uptake will depend on many factors: battery costs, charging infrastructure and electricity network development, oil prices, government policy, consumer preferences [3]. The 'Low' and 'High' scenarios define the range over which EV uptake may vary.

3.1.3. Calculating Removal Rate of Used EV Batteries

Following Olson and Choi, a Rayleigh distribution $Ra(\tau)$ is used for the distribution of product lifetime, as it requires only one parameter (the mean lifetime, μ): [29]

$$Ra(\tau) = \frac{\pi}{2\mu^2} \tau \exp\left(-\frac{\pi\tau^2}{4\mu^2}\right). \tag{3}$$

They found distribution choice to have little influence on results [29]. The lifetime before removal and replacement of an EV battery is influenced by mileage, ambient temperature, driver aggression, usage in vehicle-to-grid, amongst other factors [25]. Thus it is reasonable to expect a spread around the mean lifetime, as shown in Fig. 2.

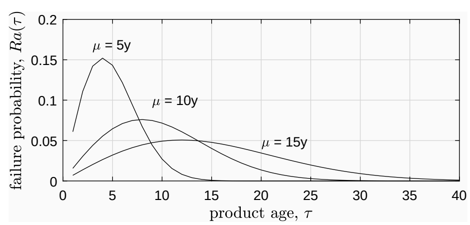

Figure 2: Rayleigh distributions of battery failure probability in year τ, for various mean lifetimes μ.

Neubauer and Pesaran [17] use 8 years (no spread) as the EV battery's first lifetime, while Foster *et al.* [18] use a uniform distribution between 3 to 10 years. With improvements in understanding of battery chemistry and battery management systems, further increases in lifetime may be achieved.

The removal rate of used EV batteries, $f_{EV}(t)$, is given by the sum of all replacement purchases. Let us call the replacement of the first-time sales the 'first-generation replacement'. The eventual replacement of these replacement purchases is the 'second-generation replacement', and so on ad infinitum. Replacement of EVs themselves occurs too, but the focus is on their batteries. The amount (kWh) of batteries removed and replaced in year t of generation i is given by the sum from the beginning of the time series up to year t, of the previous generation's sales in year τ multiplied by the failure probability of a battery of that age, $(t-\tau)$ years: [29]

$$r_i(t) = \sum_{\tau=0}^{t} r_{i-1}(\tau) \cdot Ra(t-\tau). \tag{4}$$

The generation previous to the first-generation replacement is the first-time sales, $r_0(t) = g_{EV}(t)$. As $r_i(t)$ cannot be summed to $i \to \infty$, the sum is truncated at $i = 14$. The reason for this is that even for a mean lifetime as low as $\mu = 5$ years, the sum of replacement purchases up to $i = 14$ is indistinguishable from the sum to $i = 13$ over the time period considered, 2017 to 2050, as increasingly few units reach their i^{th} replacement before 2050 as i is increased. Specifically, the root-mean-square difference between the sums to $i = 13$ and to $i = 14$ is 107 kWh, less than 0.1 % of the sum's plateau, around 150 GWh. For longer mean lifetime, even fewer generations would need to be summed to achieve an adequate approximation of the sum to infinity. As computational run-time was so short as to not be an issue, no further work was done to decide where to truncate the sum:

$$f_{EV}(t) = 0.75 \sum_{i=1}^{14} r_i(t). \tag{5}$$

The factor 0.75 is to account for the average remaining capacity of a used EV battery being 75 % of its capacity when new. An increasing mean lifetime can be approximated by using a different μ in the term $Ra(t-\tau)$ in (4) for each generation. Illustrative examples are shown in Fig. 3. A longer mean lifetime results in lower rate of battery removal, simply because they last longer. For mean lifetime increasing linearly from $\mu = 8$ y in generation $i = 1$ to $\mu = 20$ y in generation $i = 14$, the battery removal rate declines slightly after an initial rise. The choice of 8 to 20 years is guided by past and current trends in battery development, and the fact that 20 years may be close to the average lifetime before scrappage of a vehicle in 2050 (in the USA, it has increased from 12.2 to 15.6 years in the period 1969 to 2014 [36]).

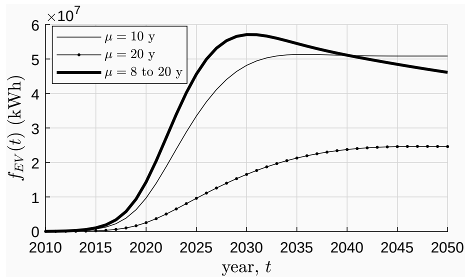

Figure 3: Rate of removal from EVs of used batteries under the Low uptake scenario and mean lifetimes 10 and 20 years, and increasing linearly from $\mu = 8$ y to $\mu = 20$ y.

There is a tendency for existing estimates of used EV battery supply [4, 5, 6, 18, 35] not to plateau like in this work, with the exception of Foster *et al.*'s 'pessimistic' scenario [18]. It may be that a plateau will occur later than the timeframes examined (most often up to 2030). It is also possible that these publications only extrapolate exponential growth, which clearly cannot continue indefinitely. Furthermore, the tendency is to predict what is probable, rather than what is necessary to tackle urban air pollution [3]. This might explain why the predictions in the literature tend to fall between the Low and Mediun scenarios in this work. The Medium and High scenarios are not outside the realm of possibility, and will be examined hypothetically. This is deemed useful because the aim of this work is not to make accurate predictions, but to explore the dynamics of the market, including in extreme and unlikely scenarios.

3.2. Constructing Price-Supply Curves

The price-supply curve $P_s(Q)$ at each year t is constrained thus:

- Price can never exceed $C_{batt}(t)$, the cost of a new stationary battery in year t, as there is no reason to buy a second-life battery for more than a new one,
- Quantity can never exceed $f_{EV}(t)$, the quantity of used EV batteries produced in year t,

- Price must always be above $(C_{recyc}(t) + C_{refurb}(t))$, as sale on to the second-life market is only done if the profit (price minus refurbishment cost) exceeds the income $C_{recyc}(t)$ possible from the competing alternative, immediate recycling.

These constraints are illustrated in Fig. 4 for an example year. The equation is (8) in Supplementary Section S2. As $C_{batt}(t)$, $C_{recyc}(t)$, $C_{refurb}(t)$, and $f_{EV}(t)$ all vary with time, the constraints shift from year to year. An example of this is shown in Fig. 6.

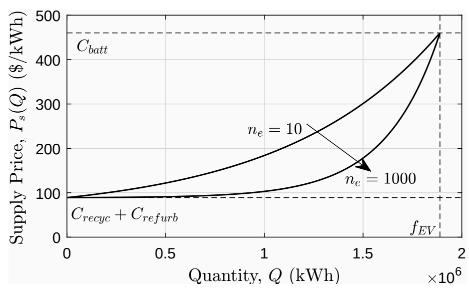

Figure 4: Two out of an infinite number of possible price-supply curves, both satisfying the constraints: $0 \leq Q \leq f_{EV}(t)$; $(C_{recyc} + C_{refurb}) \leq P_s(Q) \leq C_{batt}$ for all Q. Elasticity coefficient n_e is defined in the text.

The supply is expected to be more elastic at low sales quantities than high. More elastic means a more sensitive response to price changes, and so a shallower gradient to the price-supply curve [22]. The lack of data to constrain the price-supply curve for second-life batteries is addressed by approximating the curve as an exponential (see Supplementary Section S2) with an 'elasticity coefficient' n_e, which can be varied to make the curve more linear (n_e small) or less so (n_e large), while satisfying the above constraints.

The new stationary battery cost is taken to decrease exponentially from C_0 in 2010 (when $t = 0$) to a minimum of C_∞, at rate β: [17]

$$C_{batt}(t) = C_\infty + (C_0 - C_\infty)e^{-\beta t}, \tag{6}$$

To pinpoint C_0, C_∞ and β: due to the lack of analysis into price trends of stationary battery cells (that is, excluding inverter and installation costs), the cost of new EV battery cells is used as a proxy. Nykvist and Nilsson [1] surveyed the cost of EV batteries since 2006, finding 2010 costs to be around \$700/kWh on average, with a range \$200-\$1200/kWh. The cost decline was 14±6% overall. Berckmans *et al.* analyzed the factors contributing to the costs of lithium-ion batteries [37]. From these sources, a reasonable approximation to the trends they have found is obtained by setting $C_0 = \$700/\text{kWh}$, $C_\infty = \$50/\text{kWh}$ and $\beta = 0.14$. The cost of new stationary battery cells in 2016 was given by Reid and Julve as €500/kWh (\$568/kWh) [26], higher than the \$330/kWh of EV batteries that year. As there is such a spread in battery costs due to the different chemistries, one default and one high scenario for new stationary battery cost are tested in the Results section 4.3.

For C_{refurb}: Casals *et al.* [14] calculated the refurbishment cost of EV batteries to be €87-360/kWh (\$104-409/kWh). Neubauer and Pesaran [17] quoted values of \$250-1000 per pack, meaning \$10-40/kWh, assuming capacity 25 kWh, as was common at the time [31]. This is quite a disparity. We take a central estimate of the refurbishment cost starting from \$400/kWh in 2010, a minimum eventual cost of \$20/kWh and a 14 % rate of decline, the same as for battery costs themselves. It is reasonable to suppose that the economies of scale and organizational efficiencies that are reducing battery costs may also be applicable to refurbishment processing. The present-day refurbishment cost is widely cited to be around €50/kWh (\$57/kWh) [26].

As for C_{recyc}, the Commission for Environmental Cooperation [12] reported that many battery recycling plants charge for their service (that is, $C_{recyc}(t) < 0$), but return a credit according to the value of the material recovered. Businesses were reluctant to reveal their exact charges and credits. Toyota offered bounties of \$100-500 for the return of used batteries, suggesting $C_{recyc}(t)$ in the region \$3-50/kWh, assuming batteries of capacity 10-30 kWh. The net credit from recycling may rise with increasing efficiency of recycling processes and scarcity of raw materials, or indeed *decrease* over time if new battery chemistries are invented using lower-cost materials [12]. In the absence of more information, we explore scenarios centred around a linearly increasing recycling net credit, from -\$5/kWh in 2010 (i.e. a net charge) to \$25/kWh in 2050.

The price-supply curve must be monotonically increasing. This is not possible if the new battery cost falls below the sum of refurbishment cost and recycling net credit ($C_{batt} < C_{recyc} + C_{refurb}$). In such a case, immediate recycling would always be a more attractive option to a potential seller of a second-life battery, and the buyer would have to buy a new battery for their stationary application. There would then be no second-life sales in that year ($Q_{eqm}(t) = 0$) and the second-life price for that year will be over-written with the cost of a new battery ($P_{eqm}(t) = C_{batt}(t)$). This way, a designer of a stationary application will have information on the battery cost they need to factor in, whether the battery is second-life or new. Example price-supply curves are shown in Fig. 6.

3.3. Constructing Price-Demand Curves

We propose a division into a lucrative but limited niche applications market, and a larger but cheaper mass market. The niche market includes: [16]

- Area regulation (battery net present value \$1050-2650/kWh for potential USA market size of 700 MWh),
- Power quality and reliability (\$700-1800/kWh for 10 GWh in USA),
- Transmission and distribution upgrade deferral (\$400-500/kWh for 6 GWh in USA),

as analysed by Eyer and Corey [16] and used by Neubauer and Pesaran to constitute their fixed market for second-life applications [17].

The mass market would likely consist mainly of home batteries. While home batteries today are still a luxury product, a drastic decrease in their price, as may be achieved by using second-life batteries, could change that. Madlener *et al.* calculated €73/kWh (\$87/kWh) to be a conservative estimate of the price at which a home battery recoups its own costs by increasing onsite consumption of rooftop PV energy, thus making savings on a German homeowner's electricity bills, for 10 years [10]. The retail cost of electricity is relatively high in Germany, so the breakeven price may be lower in other parts of the world [38].

In the absence of a global survey of all possible stationary applications and their corresponding net present values and market sizes, from which to form price-demand curves, the curve for each year is approximated as two linear segments. The linear coefficients are set to follow these constraints:

- $P_d(Q,t)$ can never exceed $C_{batt}(t)$, as there is no reason to buy a second-life battery for more than a new one,
- $P_{d(mass)}(N_{batt}(t),t) = 0$, that is, the highest possible annual demand $N_{batt}(t)$ (in kWh) can only be reached when price goes to zero,
- $P_{d(niche)}(Q,t)$ and $P_{d(mass)}(Q,t)$ join at the point (Q^*, P_d^*):

The two linear segments are joined by a quadratic polynomial to smooth the joint (more details in Supplementary Section S3).

The point (Q^*, P_d^*) is set by the size of the niche market and the maximum price that would be paid in the mass market. The mass-market segment decreases linearly from this point until $(Q, P_d) = (N_{batt}, 0)$, to account for diversity in mass-market uses and household incomes around the world. Even if a home battery recoups its own costs over its lifetime, the initial investment may still be too much for lower-income households, even if paying by instalments. Home battery suppliers could not then sell their product to these households, and would not buy so many second-life batteries to keep in stock. Note that the suppliers are potential second-life buyers, not homeowners, as the latter would likely buy a value-added product including power electronics and installation service.

The function $N_{batt}(t)$ may be expected to follow a similar form as $f_{EV}(t)$, since second-life batteries in a stationary application are durable goods with finite lifetime, like EV batteries in their first lifetime. The function is approximated by the same form as the solution $F(t)$ of (1):

$$N_{batt}(t) = A_N \left(\frac{1 - e^{-(p_N + q_N)t}}{1 + \frac{q_N}{p_N} e^{-(p_N + q_N)t}} \right) \tag{7}$$

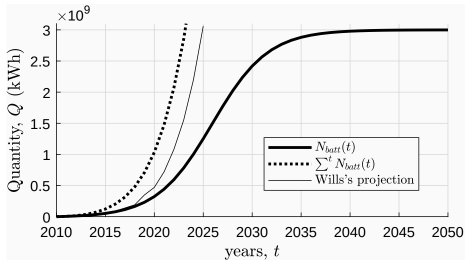

Figure 5: Maximum possible demand $N_{batt}(t)$ (kWh worldwide, annually), shown with its cumulative sum, and Wills's projection [35] for global battery fleet.

where $A_N = 3 \times 10^9$ kWh, $p_N = 0.0013$ y^{-1}, $q_N = 0.35$ y^{-1}. Though this form is usually used for the cumulative sales of a product, here it is being used to approximate the annual demand including replacements - see Fig. 5. The parameters were chosen to make $N_{batt}(t)$ plateau at a plausible maximum level for all the home batteries in the world, $A_N = 3$ TWh being equivalent to 2 billion households replacing a 15 kWh battery every 10 years. Another consideration was to make the cumulative sum of $N_{batt}(t)$ roughly follow Wills's projection for global battery fleet up to 2025 [35] (Fig. 5). Logically $\sum^t N_{batt}(t)$ should exceed these values, as demand must always exceed actual sales, since not all demand can be satisfied.

It is possible that new mass-market uses for batteries will be developed in future, leading to even larger $N_{batt}(t)$. Furthermore, the point (Q^*, P_d^*) may not be static over time. For simplicity, we take them as static at $Q^* = 16.7$ GWh and $P_d^* = \$87$/kWh. Although Eyer and Corey calculated market size for stationary battery applications in the USA [16] rather than the world, suggesting 16.7 GWh is an under-estimate, it was for a potential total market rather than on an annual basis, so in fact 16.7 GWh would be a reasonable order-of-magnitude estimate. \$87/kWh was Madlener *et al.*'s estimate for the price at which a second-life home battery breaks even in Germany [10], and given the comparatively high retail cost of electricity there, it is a reasonable estimate for P_d^*. Some example price-demand curves are shown in Fig. 6.

4. Results

After defining a default scenario as a baseline for comparison, the effects of various driving factors on the average second-life price $P_{eqm}(t)$ and quantity sold $Q_{eqm}(t)$ are analyzed. The factors examined are:

- used EV battery supply rate
- cost of new batteries
- refurbishment cost
- recycling net credit
- elasticity of supply
- demand in both niche and mass markets

Through this, the strongest influences on the second-life price and quantity sold are inferred. The Matlab code used to generate the results is available to download as a research data file. Each run takes on the order of 2 s on a PC with 8 GB RAM running Matlab R2017b.

4.1. Default Scenario

Efforts were made to ensure the default scenario represents the most likely future outcome. Given the lack of available information, 'most likely' occupies a very wide parameter space. Although the predictions for average second-life price and quantity sold under the default scenario cannot be made with confidence, an understanding can still be gained of the impacts of the driving factors on these outcomes *relative* to the default scenario as defined in Table 2.

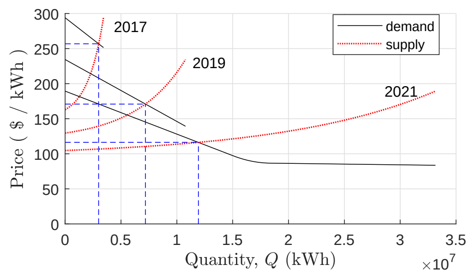

Figure 6: Price-supply and price-demand curves for 2017, 2019, 2021 under default scenario, showing how second-life price $P_{eqm}(t)$ and quantity sold $Q_{eqm}(t)$ are found from the curves' crossing points each year.

Parameter	Default Value(s)	Section
A, p, q	Medium uptake	3.1.2
$\mu(i)$	$(8 + \frac{12}{14}i)$ years	3.1.3
C_0	\$700/kWh	3.2
β	14 %	3.2
C_∞	\$50/kWh	3.2
$C_{recyc}(t)$	$(-5 + 0.75t)$ \$/kWh	3.2
$C_{refurb}(t)$	$(380e^{-0.05t} + 20)$ \$/kWh	3.2
n_e	10	3.2
(Q^*, P_d^*)	(16.7 GWh, \$87/kWh)	3.3
$N_{batt}(t)$	$A_N = 3$ TWh	3.3

Table 2: Parameter values for default scenario. Refer back to corresponding sections for more details.

Some example price-supply and price-demand curves under the default scenario are ahown in Fig. 6. The average second-life price $P_{eqm}(t)$ and quantity sold $Q_{eqm}(t)$ under the default scenario are shown in subsequent figures.

4.2. Effects of Used EV Battery Supply

The supply of used EV batteries, $f_{EV}(t)$ is determined by the EV uptake and the mean lifetime of EV batteries. Fig. 7 shows the evolution of second-life price for five EV uptake scenarios, for mean lifetime at the default of 8 to 20 y. The scenarios L1, L2, L3, M, H, correspond to eventual EV penetration rates of roughly 0.75 %, 5 %, 12.5 %, 45 % and 100 %, respectively. Parameters to generate $f_{EV}(t)$ for each scenario are given in Supplementary Section S4.

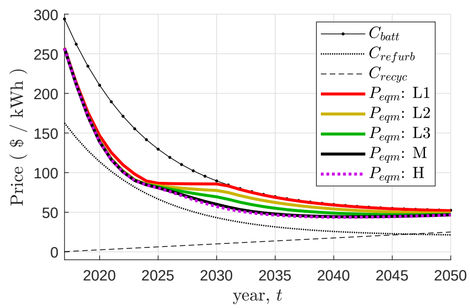

Figure 7: Average second-life price for different EV uptake scenarios, shown in comparison to the new battery cost, refurbishment cost and recycling net credit.

In all scenarios, the price falls rapidly until the supply of used EV batteries becomes significant, around 2025. Then there is a plateau in price until 2030 as the mass market for second-life batteries becomes significant. The plateau is more pronounced for lower EV uptake scenarios, where the supply does not increase quickly enough to offset the expanding pool of buyers bidding against each other and impeding the price decline.

Fig. 8 shows that while the absolute quantity sold is greater in higher uptake scenarios, the fraction of supply that gets sold is *less*. The quantity sold shows a decline towards the end of the time period, when immediate recycling becomes an increasingly attractive option (the dashed line in Fig. 7). This shows that the methodology here captures much richer market dynamics than previous work in the field.

As seen in Fig. 8, even modest penetration of EVs could overwhelm the second-life market such that second-life usage does not postpone the need for

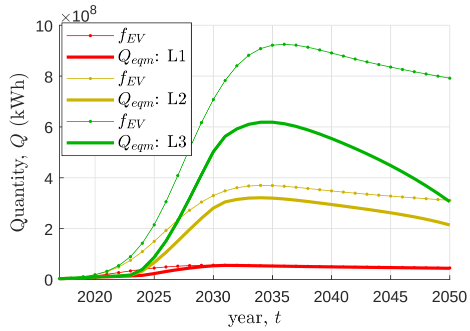

Figure 8: Quantity sold into second-life applications, shown in comparison to the total used EV batteries produced under different EV uptake scenarios.

recycling by much. To illustrate this, the cumulative amount of used EV batteries is plotted in Fig. 9 for the default (Medium) EV uptake scenario, without and with second-life usage.

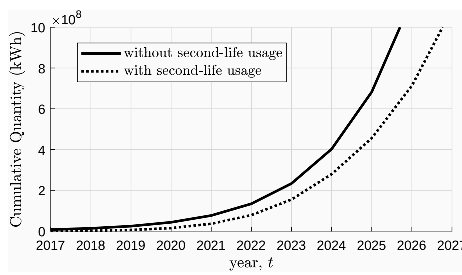

Figure 9: Cumulative amount of used EV batteries produced, and cumulative amount subtracting amount sold into second-life.

If EV battery recyling is not well-developed enough, then storing the batteries to a later date may be an option. But with a limit to storage space, this limit would be breached not much later with second-life usage compared to without. The delay varies depending on what the storage space limit is, but the delay is seen in Fig. 9 to be on the order of a year. Thus while second-life usage can delay the need to recycle an individual battery by 3-15 years [7], it delays recycling by not much more than one year when considered on the global fleet level.

4.3. Effects of New Battery Cost

It is found that around 2025, when EV usage becomes significant, the second-life price is subsequently almost unaffected by the cost of new batteries (see Fig. 10). In spite of the slightly higher second-life price when the new battery cost is higher, a greater quantity is sold (see Fig. 11). Logically, this is because buying second-life is more attractive than buying new when the price differential is greater.

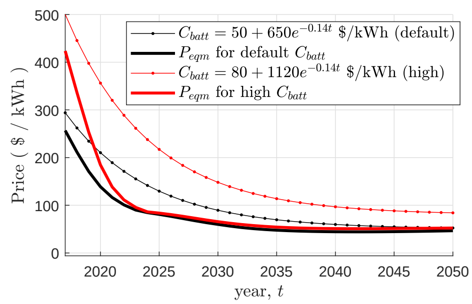

Figure 10: Average second-life price, shown in comparison to the new battery cost.

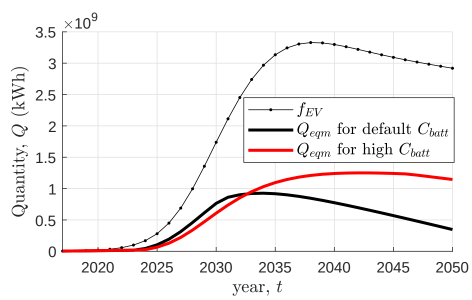

Figure 11: Quantity sold into second-life applications under different new battery cost evolution scenarios, shown in comparison to the total used EV batteries produced.

The lack of sensitivity of the second-life price to new battery cost nor to used EV battery supply (except when low) raises the question, what does influence the second-life price?

4.4. Effects of Refurbishment Cost and Recycling Net Credit

From observing Fig. 7 and 10, it is hypothesized that at Medium EV uptake or higher, the second-life price rapidly declines until around 2025 and subsequently closely follows the sum of refurbishment cost and recycling net credit. To test this hypothesis, some different scenarios for the evolution of recycling net credit were run. In Fig. 12, different $(C_{recyc}(t)+C_{refurb}(t))$ series are plotted with dashed lines (the values for $C_{recyc}(t)$ in \$/kWh are given in Fig. 13). The corresponding second-life prices lie slightly above these lines, supporting the hypothesis, but less well the lower $(C_{recyc}(t) + C_{refurb}(t))$ is. This is especially clear for the red line, $C_{recyc}(t) = -\$25/\text{kWh}$.

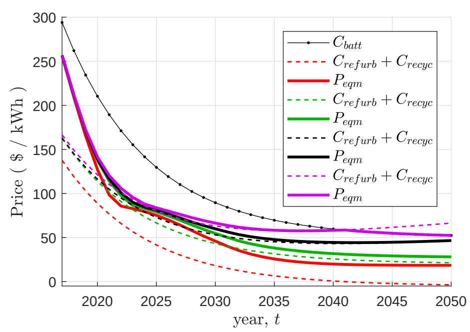

Figure 12: Average second-life price, shown in comparison to the new battery cost, and sum of refurbishment cost and recycling net credit, under different recycling net credit scenarios.

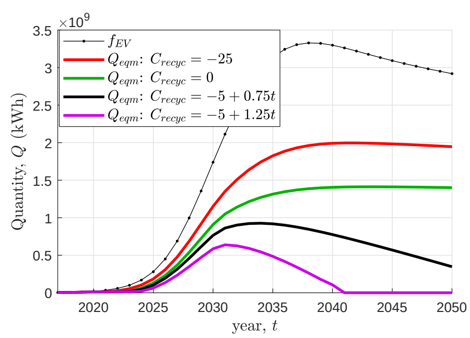

Figure 13: Quantity sold into second-life applications under different recycling net credit scenarios, shown in comparison to the total used EV batteries produced.

As expected, the less lucrative the option of immediate recycling is compared to refurbishment followed by second-life sale, the lower the price at which sellers are willing to conduct the transaction, and the more such transactions are made (see Fig. 13). In fact, the magenta line represents $C_{recyc}(t)$ increasing to \$45/kWh in 2050, against which second-life sale cannot compete, when refurbishment costs around \$20/kWh and the refurbished battery must be sold for less than the new battery cost of \$50/kWh in that year. The result is no second-life sales are made after 2041 under this scenario. The same is true whether it is refurbishment cost $C_{refurb}(t)$ or recycling net credit $C_{recyc}(t)$ that is high.

4.5. Effects of Supply Elasticity

Under the default scenario, the sum $(C_{recyc}(t) + C_{refurb}(t))$ comes so close to the new battery cost $C_{batt(t)}$ that the second-life price is very insensitive to supply elasticity, as varied via the elasticity coefficient n_e. (See Fig. 4 for an illustration of lower and higher n_e.) To see more clearly the effect of varying n_e, we set $C_{recyc}(t) = -\$25/\text{kWh}$.

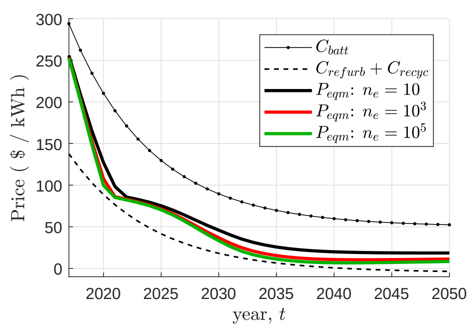

Figure 14: Average second-life price, shown in comparison to the new battery cost, and sum of refurbishment cost and recycling net credit, for different elasticity coefficients.

Even so, the difference n_e makes to the second-life price is small, bringing it closer to $(C_{recyc}(t) + C_{refurb}(t))$ when n_e is higher, as shown in Fig. 14. The effect on quantity sold is more noticeable: larger n_e corresponding to more elastic supply at low quantities (and more inelastic at high quantities) means

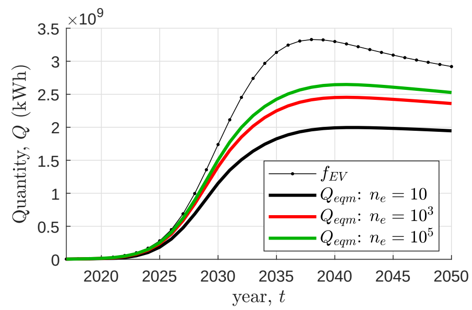

Figure 15: Quantity sold into second-life applications, shown in comparison to the total used EV batteries produced, for different elasticity coefficients.

more willingness to sell even at modestly higher price, and therefore more sales at higher n_e, as shown in Fig. 15.

4.6. Effects of Demand Size

The parameter A_N in (7), which signifies the eventual maximum annual global demand for second-life batteries, is varied from 1 TWh to 30 TWh. The figure of 30 TWh would imply 2 billion households replacing a 15 kWh home battery every year, which seems an unrealistically frequent disruption, or some as yet unthought-of mass-market use being developed. Nonetheless, extreme values are run to show their effect. Again we set $C_{recyc}(t) = -\$25/\text{kWh}$ to show the effect more clearly in Fig. 16.

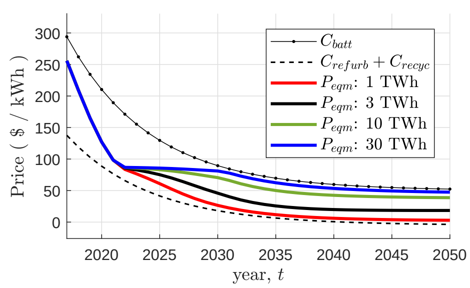

Figure 16: Average second-life price, shown in comparison to the new battery cost, and sum of refurbishment cost and recycling net credit, for different eventual annual global demand sizes.

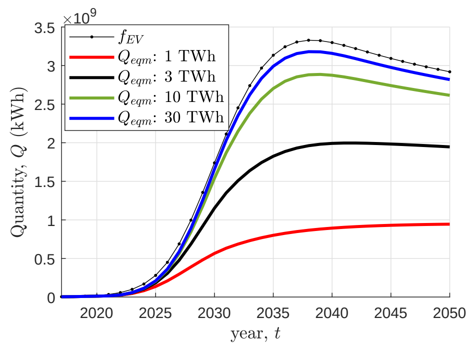

Figure 17: Quantity sold into second-life applications, shown in comparison to the total used EV batteries produced, for different eventual annual global demand sizes.

The higher the eventual demand, the higher the second-life price, much like the effect of lower EV uptake. A higher demand results in a greater proportion of the used battery supply being sold, even at Medium EV uptake (Fig. 17). The effects of a different niche market size Q^* and maximum mass market price P_d^* were also investigated, with results shown in Supplementary Section S5.

5. Discussion

From the results one can infer the driving factors that most strongly influence the price of second-life batteries and the quantities sold. The strongest influence appears to be the refurbishment cost and recycling net credit, for if the second-life price were to drop below their sum, immediate recycling would become the more attractive option. But the lower the sum $(C_{recyc}(t) + C_{refurb}(t))$, the more influence is exerted by other driving factors. Next is the supply of used EV batteries relative to demand: a low supply or high demand forces the second-life price upwards. The elasticity of supply, and the cost of new batteries, exert much smaller influence on the second-life price. The exception is for the years up to 2025, a higher new battery cost results in a much higher second-life price, whereas subsequently the much increased supply brings the size of this effect down to almost nothing.

In spite of all these different driving factors, the second-life price always follows a similar pattern: a rapid decrease until around 2025, followed by a few years of almost unchanging price, followed by a close adherence to $(C_{recyc}(t) + C_{refurb}(t))$. The stability of the second-life price from 2025 onwards can be understood by considering the price-supply curve. It is constrained between $(C_{recyc}(t)+C_{refurb}(t))$ from below and $C_{batt}(t)$ from above, and these two points are separated by \$50/kWh or less after 2025 in the default scenario. Thus there is little room for variation in the price, regardless of other influences.

Unlike the second-life price, the quantity sold is sensitive to all factors considered. The supply of used EV batteries has the greatest influence on absolute quantity sold, though the sales as a fraction of supply decreases the greater the supply. The refurbishment cost and recycling net credit strongly influence second-life sales according to how lucrative immediate recycling is compared to second-life sale. The size of the mass market strongly influences what proportion of the supply can be sold into second-life applications, whereas the niche market size has no such amplifying effect, only an additive one. The high-end mass-market price P_d^* only influences how quickly the second-life sales increase, and not the long-term shape of $Q_{eqm}(t)$. A higher new battery cost induces more sales, and to a lesser extent, so too does elasticity of supply.

The fact that second-life price is insensitive to most influences is fortunate for potential buyers of second-life batteries. This helps buyers and designers of systems using second-life batteries to calculate expected replacement costs, and to decide when to begin investing. Around 2025 would appear to be the best time, in order to reduce costs, but this depends on the system objectives and its other components. For potential sellers, the sensitivity of expected second-life sales quantity to nearly everything is problematic, as their target market is then difficult to estimate. For the same reason it is difficult for governments to know how much to budget for if deciding to subsidize second-life battery purchases.

As well as developing more accurate estimates of refurbishment cost, recycling net credit, shape of price-supply and price-demand curves, and other driving factors, it would be useful for future work on this topic to address the assumption of frictionless global free trade. This may be done by drawing the boundary around a single country, or dividing the world into economic areas each with their own second-life battery price. In either case, the option of importing batteries (new or second-life) would compete with the options of buying new or second-life batteries internally, and the option of exporting used EV batteries would be an alternative to refurbishing and selling into the internal second-life market or recycling immediately. The solution of such a system must find the flows of used battery imports and exports, as well as internal second-life price and quantity sold within each economic area.

The impacts of government subsidies to buyers and/or sellers of second-life batteries and/or for recycling can be investigated by suitable modifications of the price-demand and price-supply curves [22]. But for the results of such analysis to be reliable, the different driving factors must be pinpointed more accurately than here. The shape of the price-supply and price-demand curves (specifically their elasticity) require special attention, as by definition they determine the response of sales quantities to small changes in price brought about, for example, by government subsidies.

Future work should also address the option of stockpiling used batteries, for example if their recycling value is increasing faster than warehousing costs. Another important feature that has been neglected throughout this work is the variation in battery chemistries and degradation states. Given the constraints on second-life battery price, it may be insufficient simply to adjust the average second-life price by some factor to account for degradation significantly different from average. Such adjustment may take the price below $(C_{recyc}(t)+C_{refurb}(t))$ or above $C_{batt}(t)$, in which cases the transaction will not happen. The modelling framework developed here may need to be applied separately to sub-markets for different battery chemistries and/or second-life applications. Possible interactions between the sub-markets would complicate matters.

While the methodology developed here can be adapted to address some of the assumptions described in Section 2.2, others are less straightforward to address. These include the assumption of rational actors in perfect competition, and the absence of feedbacks with other sectors of the economy. There is no accounting for improbable disruptive events, such as the widespread adoption of hydrogen vehicles.

6. Conclusions

A methodology has been presented for calculating the evolution of second-life EV battery price. Unlike previous work on this topic, our methodology uses concepts from microeconomics to incorporate the effects of supply and demand, and how they are affected by the competing options of immediate recycling (rather than selling into second-life) and buying new (rather than buying second-life).

Though there is too much disagreement over the input data to make predictions with any accuracy, a methodological framework has been elucidated, which can be populated with data and revised over time. In the meantime, some analyses have been conducted to investigate the sensitivity of the price to various driving factors. The price is insensitive to most factors except the battery refurbishment cost and recycling net credit. On the other hand, the quantities sold are very sensitive to nearly everything. The direction of response of price and quantity to each driving factor can be logically explained, which should give some confidence to using the methodological framework.

Even without sufficient data to accurately parameterize the model, some interesting qualitative observations may be made:

- The second-life price does not generally vary in proportion to the new battery price, as Neubauer and Pesaran assumed [17].
- Though the second-life market can expand in response to low second-life price, its ability to do so diminishes with greater supply, somewhat vindicating their approximation of a fixed second-life market [17].
- The need for recycling is not much diminished by second-life usage, firstly because the supply of used batteries will likely be too large to all be sold

into second-life, and secondly because second-life batteries still need to be recycled at the end of their second life.

- The viability of the second-life market is questionable: if the price is too close to that of a new battery, that price will not be paid for a less efficient product that must be replaced sooner; the price can be lowered the more supply exceeds demand, but this is undesirable from a resource use point of view; or the price can be lowered if recycling is a comparatively unattractive option, but it must still be attractive enough to be done at least at the end of second lifetime.

If promoting the second-life battery industry is such a fine balancing act, one might ask, why not focus research efforts purely on recycling instead? To answer this definitively, more information is needed on the cradle-to-cradle environmental impact of second-life batteries compared to new batteries in stationary applications. Sathre *et al.* [6] find a net positive impact, but they compared second-life batteries to a scenario with no batteries. Would the greater conversion losses of a less efficient second-life battery outweigh the embodied emissions of manufacturing a new one?

Whether recycling or refurbishing, electrifying transport or pedestrianizing, one certainty remains: it should not be an option to allow petrol and diesel vehicles to continue polluting our towns and contributing to climate change.

Acknowledgements

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Supplementary Information

S1. Capacities of BEVs and PHEVs

Sales data for the most common makes/models of BEV and PHEV from the EV Volumes website [31, 32, 33] and nominal battery capacity for each make/model from the websites of the EV manufacturers are tabulated in the spreadsheet BEV_PHEV_salesdata.xls. They are used along with unit sales data from the International Energy Agency [30] to calculate total annual (kWh) first-time EV sales. These are summarized in Table S3 below. As 2010 was the first year with complete unit sales data [30], it was taken as $t = 0$.

Year	BEV sales (cumul.)	BEV sales (annual)	BEV average capacity (kWh)	PHEV sales (cumul.)	PHEV sales (annual)	PHEV average capacity (kWh)	Total annual sales (GWh)
2010	16 420	16 420	(26.0)	390	390	(9.0)	0.430
2011	55 160	38 470	(27.0)	9 420	9 030	(9.5)	1.132
2012	112 940	57 780	(28.0)	69 700	60 280	(10.0)	2.221
2013	226 780	113 840	30.8	161 290	91 590	10.5	4.468
2014	420 330	193 550	29.1	295 060	133 770	10.6	7.050
2015	745 610	325 280	31.7	517 000	221 940	12.0	12.97
2016	1 208 900	463 290	40.4	805 320	288 320	12.5	22.32

Table S3: Deriving total EV battery capacity annual sales from cumulative BEV and PHEV fleets [30] and average battery capacities [33], values in 2010-2012 (in parentheses) extrapolated back from 2013-2016.

S2. Mathematical Formulation of Price-Supply Curve

The price-supply curve for second-life batteries is approximated as an exponential:

$$P_s(Q) = (C_{recyc} + C_{refurb}) + A_s(e^{(\alpha_s Q)} - 1) \tag{8}$$

where the price P_s (\$/kWh) is a function of quantity Q (kWh), and the dependence on t is only implied above;
$A_s(t) = \frac{1}{n_e}(C_{batt}(t) - (C_{recyc}(t) + C_{refurb}(t)))$,
$\alpha_s(t) = \frac{\ln(1+n_e)}{f_{EV}(t)}$,
the new battery cost is taken to decrease exponentially from C_0 in 2010 (when $t = 0$) to a minimum of C_∞, at rate β: [17]

$$C_{batt}(t) = C_\infty + (C_0 - C_\infty)e^{(-\beta t)}, \tag{9}$$

and $f_{EV}(t)$ is the production rate of used EV batteries as found in Section 3.1.3. Inserting these expressions into (8), one finds
$P_s(0,t) = C_{recyc}(t) + C_{refurb}(t)$, as required to have $P_s(Q,t) > (C_{recyc}(t) + C_{refurb}(t))$ for all Q (as otherwise recycling would be preferable to second-life sale), and
$P_s(f_{EV}(t), t) = C_{batt}(t)$, as required to have $P_s(Q,t) < C_{batt}(t)$ for all Q, and $Q \leq f_{EV}(t)$, that is, the quantity sold cannot exceed the supply of used EV batteries in year t.

S3. Mathematical Formulation of Price-Demand Curve

The niche-market and mass-market segments of the price-demand curve, (10) and (11) respectively, are joined by a quadratic function to smooth the joint.

$$P_{d(niche)}(Q) = a_{d1}Q + b_{d1} \qquad 0 \leq Q < Q^* \tag{10}$$

$$P_{d(mass)}(Q) = a_{d2}Q + b_{d2} \qquad Q^* < Q \leq N_{batt}. \tag{11}$$

The constraint that $P_d(Q,t)$ can never exceed $C_{batt}(t)$, leads to: $b_{d1}(t) = C_{batt}(t)$.

The other constraints are that $P_{d(mass)}(N_{batt}(t),t) = 0$, that is, the total possible demand $N_{batt}(t)$ that year can only be reached when price goes to zero, and $P_{d(niche)}(Q)$ and $P_{d(mass)}(Q)$ join at the point (Q^*, P_d^*). This leads to:

$$a_{d1} = \begin{cases} -\left(\frac{C_{batt}(t)-P_d^*(t)}{Q^*(t)}\right) & C_{batt}(t) > P_d^*(t) \\ 0 & C_{batt}(t) \leq P_d^*(t) \end{cases},$$

$$a_{d2} = \begin{cases} -\left(\frac{P_d^*(t)}{N_{batt}(t)-Q^*(t)}\right) & C_{batt}(t) > P_d^*(t) \\ -\left(\frac{C_{batt}(t)}{N_{batt}(t)-Q^*(t)}\right) & C_{batt}(t) \leq P_d^*(t) \end{cases},$$

$$b_{d2} = \begin{cases} \left(\frac{N_{batt}(t)P_d^*(t)}{N_{batt}(t)-Q^*(t)}\right) & C_{batt}(t) > P_d^*(t) \\ \left(\frac{N_{batt}(t)C_{batt}(t)}{N_{batt}(t)-Q^*(t)}\right) & C_{batt}(t) \leq P_d^*(t) \end{cases}.$$

The quadratic function smoothing the joint around (Q^*, P_d^*), spans the domain $Q \in [Q_a, Q_b]$, where:

$$Q_a = \begin{cases} Q^* - \frac{15}{100} f_{EV} & Q^* > \frac{15}{100} f_{EV} \\ 0 & Q^* \leq \frac{15}{100} f_{EV} \end{cases},$$

$$Q_a = \begin{cases} Q^* + \frac{15}{100} f_{EV} & Q^* + \frac{15}{100} f_{EV} < f_{EV} \\ f_{EV} & Q^* + \frac{15}{100} f_{EV} \geq f_{EV} \end{cases}.$$

The factor $\frac{15}{100}$ is chosen to ensure a joint that is smooth but the two linear segments are still distinct. To determine the coefficients a, b, c of the quadratic polynomial

$$P_{joint}(Q) = aQ^2 + bQ + c \qquad Q_a \leq Q \leq Q_b,$$

the following conditions are imposed:

- $P_{joint}(Q_a) = P_{d(niche)}(Q_a)$
- $P_{joint}(Q_b) = P_{d(mass)}(Q_b)$
- $\frac{dP_{joint}}{dQ}|_{Q_b} = a_{d2}$

In other words, the quadratic section joins continuously to each linear segment, at Q_a and Q_b, and the gradient is continuous at Q_b. There are not enough degrees of freedom (only three coefficients determine a quadratic polynomial) to ensure continuous gradient at Q_a as well. We rejected the option of a cubic function to smooth the joint because this can lead to inflection points, when the price-demand curve should be monotonically decreasing.

To evaluate the coefficients a, b, c, a matrix equation is formed from the constraints, and solved:

$$\begin{bmatrix} y_a \\ y_b \\ a_{d2} \end{bmatrix} = \begin{bmatrix} Q_a^2 & Q_a & 1 \\ Q_b^2 & Q_b & 1 \\ 2Q_b & 1 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

where $y_a = P_{d(niche)}(Q_a)$, $y_b = P_{d(mass)}(Q_b)$, to find:

$$a = \left(\frac{y_a - y_b}{Q_a^2 - 2*Q_a*Q_b + Q_b^2}\right) - \left(\frac{a_{d2}}{Q_a - Q_b}\right)$$
$$b = \left(\frac{2Q_b(y_b - y_a)}{Q_a^2 - 2*Q_a*Q_b + Q_b^2}\right) + a_{d2}\left(\frac{Q_a + Q_b}{Q_a - Q_b}\right)$$
$$c = \left(\frac{Q_b^2 y_a + Q_a y_b (Q_a - 2Q_b)}{Q_a^2 - 2*Q_a*Q_b + Q_b^2}\right) - a_{d2}\left(\frac{Q_a Q_b}{Q_a - Q_b}\right).$$

S4. EV Uptake Scenario Parameters

Tabulated below in Table S4 are parameters to generate $f_{EV}(t)$ under scenarios L1, L2, L3, M, H, as used in Section 4.2. L1, M and H are Low, Medium, High. L2 and L3 are additional scenarios in between Low and Medium, to show the trend more clearly in the Results. The EV penetration percentages are rough values derived from summing all the first-time sales $\sum g_{EV}(t)$ and assuming average battery capacity 40 kWh and vehicle fleet of 2 billion.

	A (kWh)	p	q	EV penetration
L1	6.05×10^8	0.0112	0.6039	0.75 %
L2	4.00×10^9	1.87×10^{-4}	0.5696	5 %
L3	1.00×10^{10}	7.56×10^{-5}	0.5661	12.5 %
M	3.60×10^{10}	2.11×10^{-5}	0.5645	45 %
H	8.00×10^{10}	9.50×10^{-6}	0.5641	100 %

Table S4: Bass model parameters for various EV uptake scenarios, and corresponding eventual penetration of EVs into the vehicle fleet.

S5. Additional Results

See the discussion in Section 4.6. Changing the niche market size to the larger value of $Q^* = 167$ GWh (again, static) only causes the second-life price to be higher until around 2030, as by that time the new battery cost has declined enough that there ceases to be a distinction between niche market and mass market (see Fig. S18). That is, when $C_{batt} \to P_d^*$, the two line segments constituting the price-demand curve converge on the same gradient, and thereafter the curve switches from concave to convex. The resultant quantity sold is larger by roughly 100 GWh, suggesting that an increase in the niche market size translates to the same order of magnitude increase in second-life sales (see Fig. S19).

A run was conducted with maximum mass market price P_d^* at the lower values of \$70/kWh and \$60/kWh (each static), as may happen if home battery suppliers incur more overheads in addition to the batteries themselves. These made almost imperceptible difference to the second-life price, and only slowed down the increasing part of $Q_{eqm}(t)$ before it converged to $Q_{eqm}(t)$ for the default scenario (see Fig. S19).

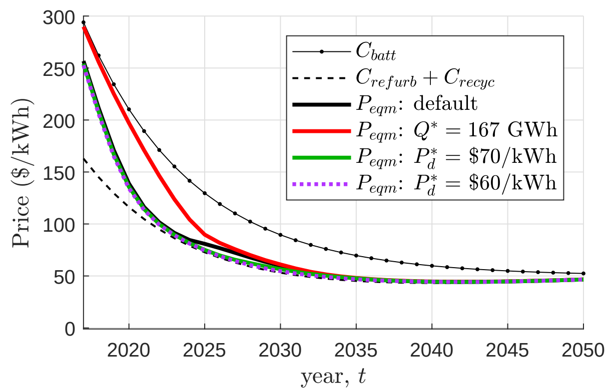

Figure S18: Average second-life price, shown in comparison to the new battery cost, and sum of refurbishment cost and recycling net credit, for different niche-market sizes Q^* and mass-market maximum prices P_d^*. Default, $P_d^* = \$60$/kWh, and $P_d^* = \$70$/kWh, are almost indistinguishable from each other.

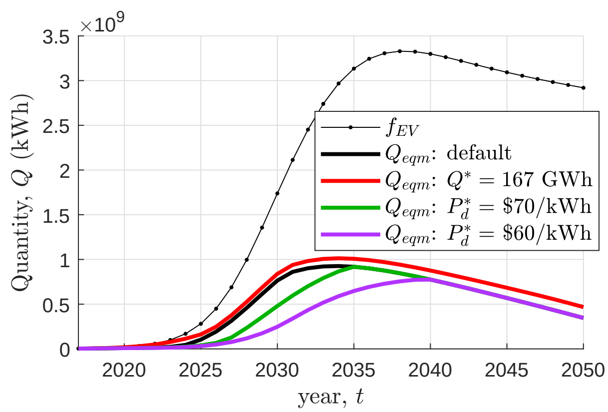

Figure S19: Quantity sold into second-life applications, shown in comparison to the total used EV batteries produced, for different niche-market sizes Q^* and mass-market maximum prices P_d^*.