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A digital solution framework for enabling electric vehicle battery circularity based on an ecosystem value optimization approach

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A circular economy for batteries is crucial for building a sustainable battery value chain, as end-of-life electric vehicle batteries can be given a second life or valuable raw materials can be harvested to make new batteries. However, significant challenges remain in forecasting availability, predicting remaining value, minimizing reverse logistics costs, and maximizing value recovery from end-of-life batteries. Here we devise an ecosystem value optimization approach powered by a digital solution framework, consisting of innovative analytical models and a trusted data platform, to optimize five key value drivers for battery circularity—safety, regulatory compliance, carbon footprint reduction, quality, and financials. The envisioned solution can help reduce average transportation costs of end-of-life batteries by 11% to 44% compared to current shipping practices, estimate battery health with error rates less than 1%, and improve value recovery by 52% to 60% by routing batteries with good health to second-life application providers.

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INTRODUCTION

A circular, responsible, and just battery value chain is pivotal for achieving the Paris Agreement target to stay below the 2 °C scenario by enabling 30% of emission reductions in power and transport sectors[1]. In 2021, global spending on electric vehicles (EV) hovered around USD 280 billion, and the total number of EVs on the world's roads reached roughly 16.5 million[2]. Under current policy plans reflected in the IEA Stated Policies Scenario (STEPS), the global EV market can expand to 200 million vehicles in 2030[2]. While experts broadly agree that EVs are much better in terms of the impact on climate in comparison with internal combustion vehicles, EV batteries production and unsafe disposal can adversely impact the environment and society. Millions of end-of-life (EOL) batteries are forecasted to retire by 2040—triggering serious waste management challenges. For example, EVs sold in 2019 alone would cause 500,000 tons of unprocessed battery pack waste[3]. Moreover, current supply chains for battery cathode are energy-intensive as materials move 50,000+ miles before they reach a Lithium-ion batteries (LIBs) cell factory[4]. Moreover, lithium and cobalt extraction are associated with high environmental and social risks—cobalt mining in the Democratic Republic of the Congo has been linked to human rights violations, and lithium extraction requires large quantities of energy and water in regions with scarce water resources[5].

On the other hand, a typical EV battery can retain 70% to 80% of its original capacity at the end of its usable first life. These EOL EV batteries can be repurposed for second-life applications such as stationary energy storage that require less frequent battery cycling[6]. Moreover, with advancements in recycling methods, raw materials can be recovered sustainably at scale. Researchers at the Recell Center have compared the environmental impacts to produce 1 kg of NMC111 from primary raw materials and recycled pyro-metallurgically, hydro-metallurgically, and by direct recycling. Direct recycling is shown to have the lowest environmental impact—consumes 27% of energy, uses 31% of water, and causes 32% of GHG emissions compared to the production from primary raw materials[7]. As per a financial viability study, recycling can be economically viable, with a net value ranging from a loss of \$21.43 per kWh to a profit of \$21.91 per kWh which strongly depends on transport distances, wages, pack design, and recycling method[8].

Even though it is now technologically and economically feasible to give EOL LIBs a second life or harvest valuable materials for making new batteries, significant challenges (Fig. 1) remain in forecasting and tracking EOL batteries, optimizing reverse logistics costs, and maximizing value recovery from EOL batteries. Since EOL Li-ion batteries are classified as hazardous materials, environmental regulations and policies mandate proper handling, transportation, and disposal of EOL LIBs. Although estimates for transportation costs vary widely among various studies—representing, on average, 41% of the total cost of recycling[9], high transportation costs can make battery circularity cost prohibitive for low-cobalt cathode-chemistry types. Hence, EOL battery remaining value estimation and reverse logistics costs optimization are important considerations for this industry.

EV battery circular economy is hindered by information silos, as different companies generate or record new data at various stages of the battery life cycle. Trusted information sharing among relevant stakeholders can be a win-win model for all stakeholders. For example, if an automotive dismantler acquires the used EV, the dismantler will benefit from the EV manufacturer sharing safe battery removal training videos and arranging for EOL battery transportation. On the other hand, OEMs will benefit by knowing the availability and health condition of LIBs to effectively estimate remaining value and ship to the right repurposing or recycling partner for value recovery maximization. Moreover, second-life providers would need to know how the battery has been used in its first life, dismantled, stored, and transported to its facility—information will enable them to efficiently repurpose the EOL batteries and effectively promote the repurposed product by providing transparency in its product quality. EV makers and battery manufacturers can use battery repurposing or recycling

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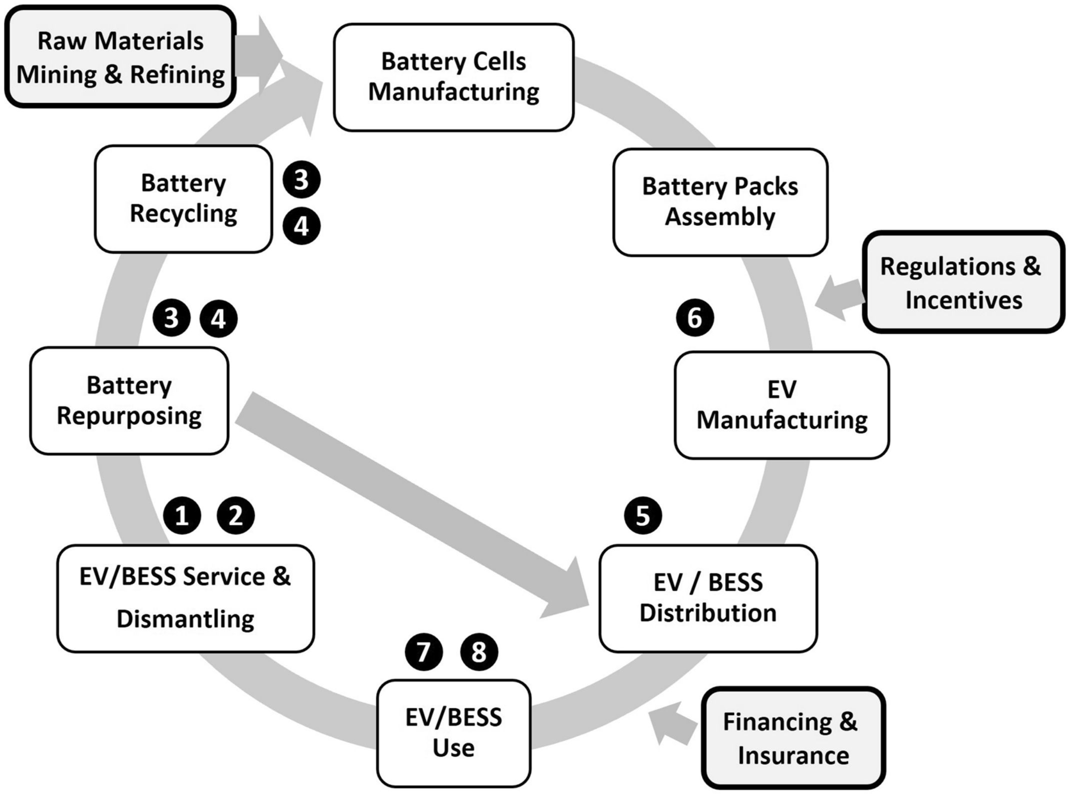

EV: Electric Vehicle; BESS: Battery Energy Storage System; Re*: Repurpose, Refurbish, Recycle

Supply-side Challenges

1. Estimate the remaining value of spent batteries
2. Minimize transportation costs of spent batteries to Re* plants

Re* Challenges

3. Handle non-uniform design, packaging, and condition of spent batteries
4. Ensure the quality of the repurposed battery pack and recycled materials

Demand-side Challenges

5. Offer optimal pricing and promotion of Re* products
6. Share relevant information with value chain partners in a trusted manner

New and Re* Product Use Challenges

7. Track condition and usage of products
8. Provide timely and quality service

Fig. 1 Challenges in battery circularity. Battery circularity challenges include remaining value estimation, transportation costs optimization, non-uniform design, quality assurance and pricing of repurposed and recycled products, and lifecycle management.

completion information in tracking carbon reduction due to reuse or material recovery from their products. An effective multi-party business collaboration is needed to increase the efficiencies of an entire battery value chain and enable a circular economy for LIBs.

To date, state-of-the-art solutions for enabling EV battery circular economy revolve around the concept of the Battery Passport originally proposed by the Global Battery Alliance (GBA). GBA Battery Passport program provides a global reporting framework and a digital platform to collect, exchange, collate, and report battery provenance, manufacturing history, and environmental, social, and governance (ESG) performance data among all authorized lifecycle stakeholders[10]. Germany's Federal Ministry for Economic Affairs and Climate Action (BMWK) recently announced its "Battery Pass" project, a government-funded R&D global project, and its 11 consortium members including automakers, renewable energy providers, and digital companies[11]. Battery passport systems may also help in certifying the provenance of the batteries to satisfy the United States' Inflation Reduction Act (IRA) criteria for tax credits[12]. Although battery passport systems have the potential to become valuable data sources in pursuing circular economy initiatives, they have inadequate provisions to support end-to-end management of EOL batteries.

To address gaps in the existing systems, we devise an ecosystem value optimization approach powered by a digital solution framework to manage five key value drivers for battery circularity—safety, regulatory compliance, carbon footprint reduction, quality, and financials. While many non-financial value drivers may not be fully quantified, we aim to use proxies for optimization purposes.

The overview of our ecosystem value optimization approach (Fig. 2a) is as follows:

1. Safe handling of lithium-ion batteries: During removal, storage, transport, repurposing, and recycling, EOL batteries must be handled with utmost care because they can cause injury to workers and people around them. The number of safety incidents that occurred anywhere in the reverse supply chain can act as a key performance indicator for this value driver. For proper handling of EOL batteries, the envisioned solution enables trusted data sharing of battery removal and handling instructions by automakers, tracking battery health conditions and diagnostics data reported by owners or service providers, and recording proof of safe handling during transport.
2. Regulatory and industry protocol compliance: EOL lithium-ion batteries are hazardous materials and hence subjected to hazardous materials regulations of the US Department of Transportation[13]. New regulatory proposals in Europe and California introduce mandatory requirements for end-of-life battery management putting the onus on automakers, dismantlers, and fleet owners. As per Underwriters' Laboratories (UL) standards, each EOL battery needs to be evaluated individually before repurposing because each battery may have been exposed to different charging and discharging conditions during its use in a vehicle. The envisioned solution enables end-to-end tracking and tracing of EOL LIBs by all authorized stakeholders—thus ensuring regulatory and industry protocols compliance.
3. Carbon footprint reduction: Several automakers have pledged to reduce the carbon footprint of their products. Repurposing and recycling EOL LIBs can help in their carbon reduction goals since the carbon footprint of the raw materials obtained by recycling electric car batteries can be 38% smaller than that of primary raw materials[14]. Moreover, the carbon footprint of LIBs recycled after their second life can be reduced by 8% to 17% compared to directly recycling LIBs after their electric vehicle use[15]. The envisioned solution approach uses estimated CO2 reduction for each EOL LIB as one of the factors in recommending optimal repurposing vs. recycling decisions. Also, through this solution, recyclers and repurposing companies can share actual recovery and yield information with respective automakers to record and track carbon footprint reduction.
4. Repurposed product or recycled material quality: A recent surge of electric bike fires in New York City has increased scrutiny of repurposed LIBs[16]. Moreover, battery manufacturers and automakers have concerns about the quality of recycled materials, potentially leading to the suboptimal performance of batteries. After analyzing stakeholder biases, effective intervention strategies can be designed to increase collection rates of EOL batteries and promote repurposed products. Consumer biases and misperceptions regarding the quality and desired attributes of refurbished and repurposed battery products can encumber the growth of second-life applications. In the envisioned solution framework, we also leverage our past work on behavioral economics to promote energy storage products made of repurposed EV battery cells[17].
5. Financials—revenue and costs: For an effective circular economy of EV LIBs, repurposing and recycling must be profitable, even for low-cobalt battery chemistry types. High reverse logistics costs, insufficient LIB volumes, and non-uniform battery designs are key challenges in scaling up repurposing and recycling operations. The envisioned solution approach can help simulate various reverse logistics network scenarios, aggregate EOL LIBs from service providers (dismantlers, independent repair shops, and dealers), and recommend which batteries should be shipped to which recycler or repurposing provider to maximize value recovery.

We designed a digital solution framework (Fig. 2b) for the battery ecosystem that will provide real-time visibility into the battery value chain operations, generate critical insights to optimize costs, and enable circular economy business models. Our design objectives are as follows:

1. Enable traceability and transparency in the battery value chain: Through a blockchain-based platform, connect and share business data amongst relevant stakeholders such as OEM, service partners, reverse logistics providers, and Re* partners. We use the term "Re*" as a short form for "Recycling, Repurposing, and Refurbishing". Blockchain technology, such as smart contracts and shared ledgers hold all components of a transaction accountable[18]. By recording each step of a transaction between different companies, the entire value chain gains the required transparency, and trust in the shared information. While battery passport systems are valuable data sources for tracking battery origin and usage, our solution approach extends these capabilities on collection, transport, repurposing, and recycling side of the ecosystem by tracking EOL battery availability, status in-transit, and repurposing/recycling completion. Moreover, business decisions such as EOL LIB acquisition and sales offers, repurposing or recycling decisions, and shipping requests can be automated via smart contracts.
2. Provide data-driven insights to increase operational efficiency in the ecosystem and promote circularity: Leveraging predictive and prescriptive analytics on the shared data combined with stakeholders' private data can help forecast EOL battery availability, enable data-driven decisions for Re* operation, plan collection routes, optimize transportation costs, maximize value recovery from EOL batteries, and track emissions savings. We leverage machine learning methods that are increasingly used for evidence-based decision-making across many walks of life[19]. Moreover, behavioral economics models have been designed to increase collection rates of EOL batteries and promote sales of repurposed or refurbished batteries.

Further details of our digital solution framework have been provided in the Methods section. A representative use case and analytical models to enable battery circularity has been described in the Results section.

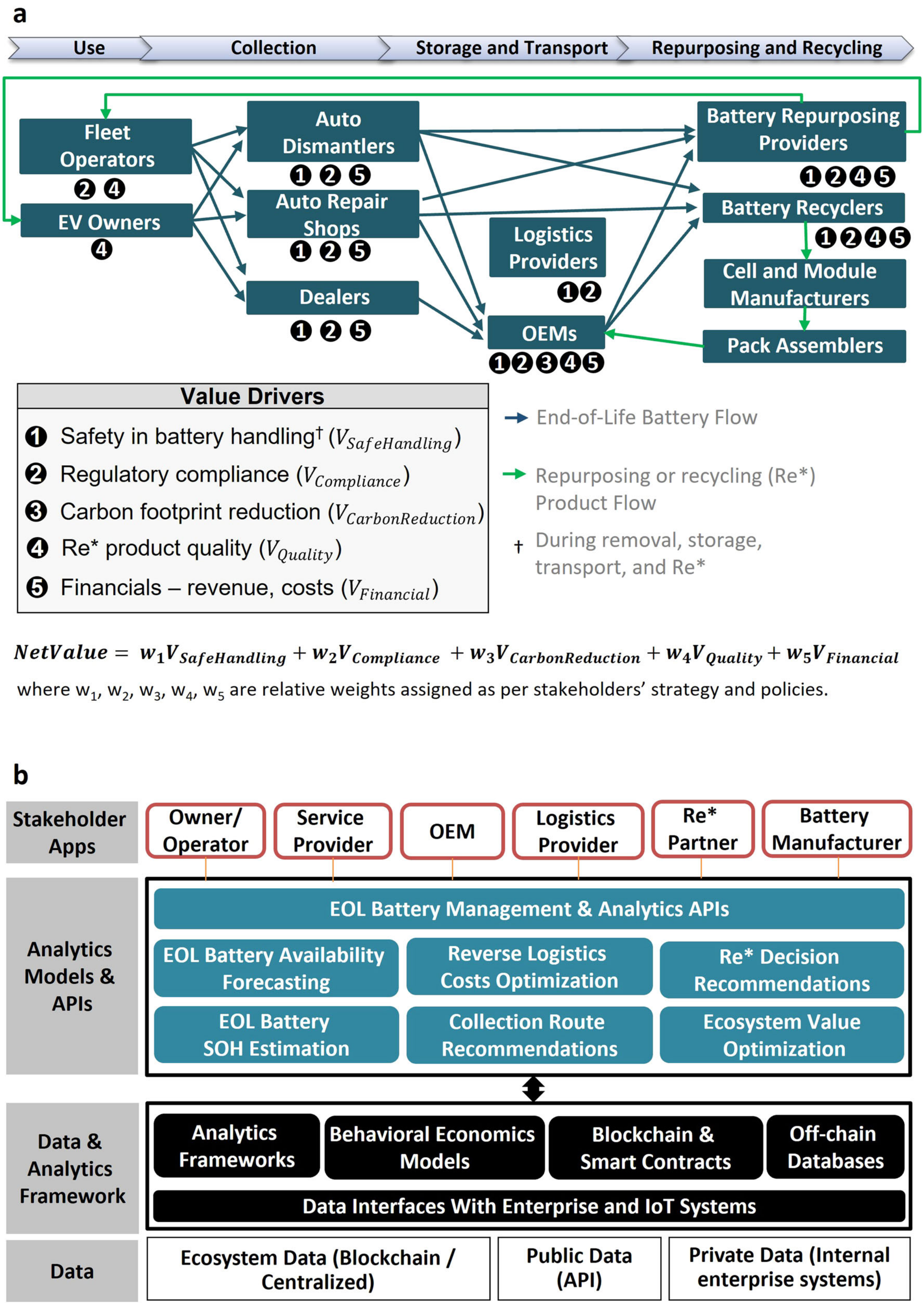

Fig. 2 Ecosystem value optimization approach powered by a digital solution framework. **a** Ecosystem value optimization approach. **b** Digital solution framework.

RESULTS

Representative use case

Our work is driven by a real use case (Fig. 3), where EV OEMs collect their EOL batteries from service partners (dealers, independent repair shops, and dismantlers), transport these EOL LIBs to OEM warehouses, and then ship the EOL LIBs to their Re* partners for repurposing, refurbishing, recycling based on battery chemistries and conditions. The current practice of bringing LIBs from service partners to OEM warehouses and shipping to Re* partners from OEM warehouses lead to very high shipping and handling costs. Although the current annual volume of EOL batteries ranges from 2000 to 10,000 at these OEMs, EOL battery availability is expected to increase by multiple orders of magnitude in the next five to ten years. Tracking and collecting EOL batteries from the long tail of independent repair shops and dismantlers can be a daunting task. Our solution framework enables trusted information flow among relevant stakeholders and helps simulate various shipping scenarios and recommends optimal shipping policies, replacing current practices of double handling and transport.

To demonstrate the potential benefits of our solution approach, we have simulated data for a major automaker that aims to ramp up global sales of existing and new EV models. For privacy reasons, we cannot give the exact name of the company, so we will simply refer to it as "the OEM" throughout this paper.

Forecasting EOL batteries availability

Based on the EV registration data from external sources such as California open data portal[20] and the OEM's EV sales data, EOL battery availability can be forecasted for the next 5 years as per the following steps:

Step 1: For each EV (make and model), we determine the probability distribution of EOL battery return at different ages. The number of battery-returns in the year y is modeled as a discrete random variable that follows the binomial distribution:

$$D_i(k) = \Pr(k; n_{y-i}, p_i) \tag{1}$$

where p_i is the probability a EOL battery is returned at age i; n_{y-i} is the number of new EVs sold at year $y-i$; and $k = 0, 1, \ldots, n_{y-i}$.

This age distribution can be learned from historical data collected with actual EOL battery-returns. Otherwise, we can assume a normal distribution centered around the warranty period of these batteries.

Step 2: To estimate the distribution of the total number of batteries returned at year y, we merge all these distributions D_i. For any two independent count variables X and Y with discrete probabilities $\Pr_X(x)$ and $\Pr_Y(y)$, the distribution for their sum $Z =$

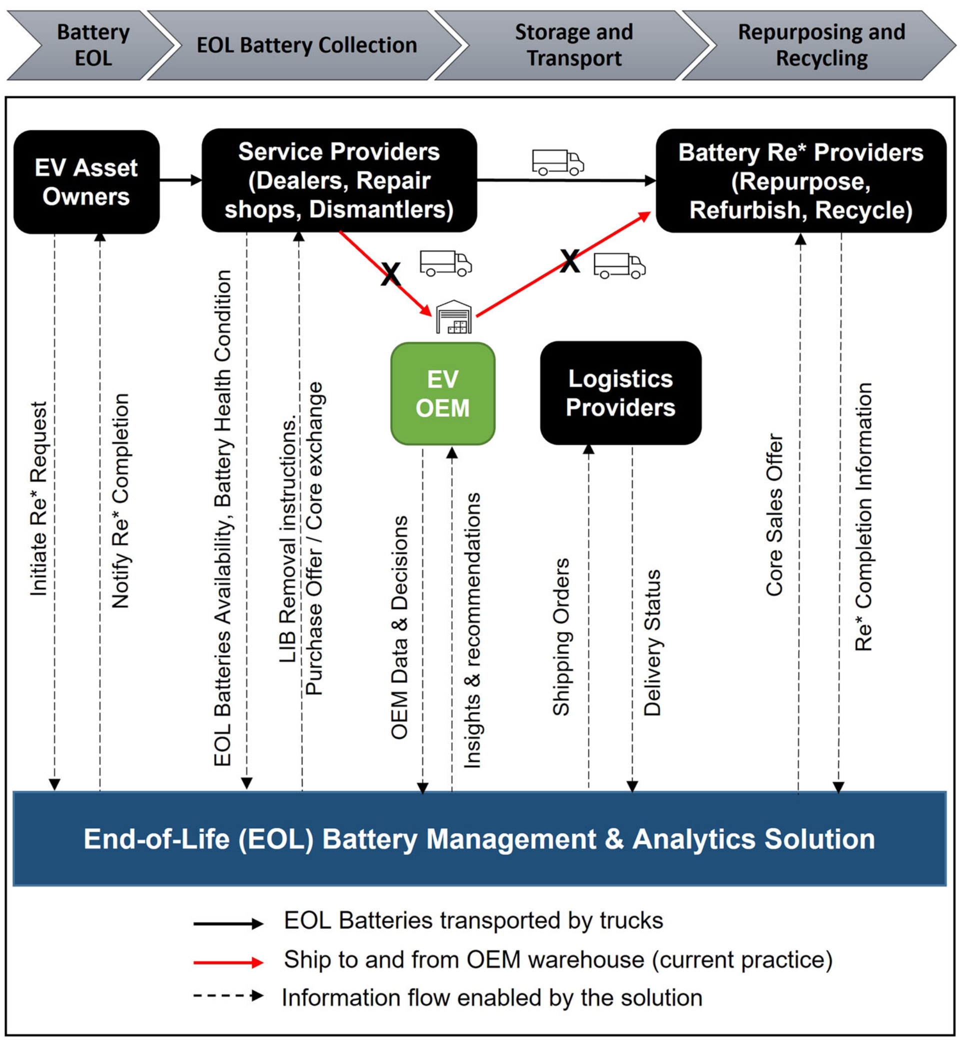

Fig. 3 A representative use case for battery circularity. EV OEMs assign their logistics providers to collect their EOL batteries from service partners (dealers, independent repair shops, and dismantlers), transport these EOL LIBs to OEM warehouses, and then ship the EOL LIBs to their Re* partners for repurposing, refurbishing, recycling based on battery chemistries and conditions.

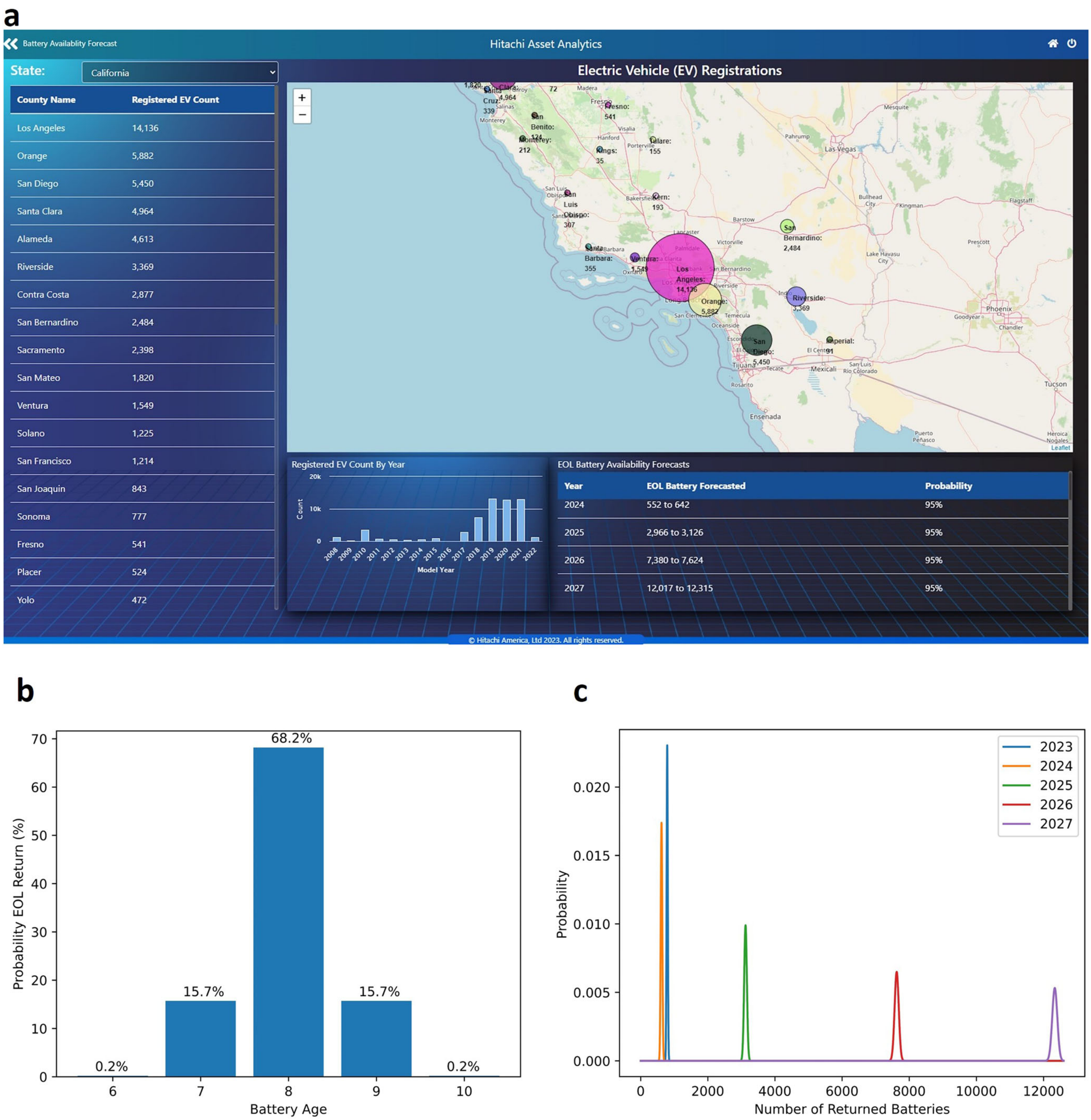

Fig. 4 End-of-life battery availability forecasting. **a** EOL battery availability forecasts. **b** EOL returns probability as function of age (Yearly registrations: $n = 14$). **c** EOL battery returns probability distribution (Forecast years: 2023 to 2027). Copyright 2023 by Hitachi America, Ltd. Image used with permission from Hitachi America, Ltd.

$X + Y$ can be simply written as:

$$\Pr_Z(z) = \sum_{x+y=z} \Pr_X(x) \times \Pr_Y(y) \tag{2}$$

Using the distribution obtained this way for the total count, we can derive its means and standard deviation. For each year in the 5-year forecast horizon, we use this approach to estimate the number of EOL batteries returned that year with a 95% prediction interval.

Our forecast (Fig. 4) shows that more than 22,500 EV battery packs of this OEM will be reaching the end of life by 2027 just in California.

The method we propose to forecast EOL batteries availability is based on current publicly available EV registration data and does not rely on historical time series of returned EOL batteries which may not be available. Alternatively, if these time series data are available in sufficient volumes, we may consider traditional time series forecasting methods leveraging for example ARIMA or LSTM models (see[21] for ARIMA and LSTM model comparison). Long short-term memory (LSTM)[22] is a deep learning network architecture that excels at processing sequences of data points to predict outcomes that can be single data points or sequences themselves. What makes LSTM networks so powerful at processing sequence data is their ability to learn when to remember and when to forget pertinent information, especially in long sequences. Since meaningful benchmarking of our proposed method is not available, our forecast method as described above is our best option as it is based on actual EV cars currently in circulation. Going forward, we need to collect data on returned EOL batteries and use it to test accuracy of our forecasting method.

Reverse logistics network simulation and planning for EOL batteries transportation

We have designed a multi-product dynamic model for the reverse logistics–value recovery network interlinking collection points, storage facilities, and value recovery plants with geographically distributed supply and recovery locations.

In designing a reverse logistics network, many structural and operational entities need to be considered, including:

- Supply of EOL batteries: arrival process (e.g., Poisson or other non-parametric models), mixture of chemistries and batteries with different health conditions.
- Physical location of dealerships, warehouses, and Re* partners: these locations are needed to optimize transportation costs which are a function of moving distance.
- Transportation costs and various trucking policies of logistics partners: full-truck load vs. on-demand policies, weight-based and distance-based costing methods.
- Batteries collection routing methods: clustering of battery collection points.
- Warehousing costs: storage cost difference between dealerships and warehouses affects optimal trucking policies.
- Battery chemistries and recovery value offered by Re* partners: used to match batteries of specific chemistries with specific Re* partners. The best match depends not only on the values offered by these partners but also the costs to ship batteries to their location.

The complexity of these models precludes using purely analytical methods based on statistical analysis and queuing networks to estimate business metrics to optimize such as net profit. Our choice of using a stochastic-simulation-based approach to solve the estimation problem is driven by its flexibility and simplicity, the availability of easy-to-use software modeling and simulation frameworks such as MESA[23] and AnyLogic[24], and the fact that current crop of computing resources is powerful enough to run large-scale simulations.

The financial value driver, *NetProfit* for reverse logistics of EOL batteries is formulated as follows:

$$NetProfit = \max \sum_{i=1}^{n} \left(Revenue_{i,k} - Cost_{i,j,k,l}\right) \tag{3}$$

where $Revenue_{i,k}$ is revenue from recycling or repurposing of battery i at value recovery point (recycler or repurposing provider) k;

$Cost_{i,j,k,l}$ is sum of EOL battery acquisition cost $(a_{i,j})$, storage costs at collection point j and transportation cost of battery i from collection point j to value recovery point k under truckload condition l.

The above formula can be expanded as follows:

$$NetProfit = \max \sum_{i=1}^{n} \left(p_{i,k}y_{i,k} - d(j,k)c_{i,l} - t_j s_{i,j} - a_{i,j}\right) \tag{4}$$

where the revenue term, $p_{i,k}y_{i,k}$ can be represented as unit price of repurposed product or recycled material times yield from battery i at value recovery point k;

the transportation cost term, $d(j,k)c_{i,l}$ can be represented as distance, $d(j,k)$ between collection point j and value recovery point k times cost per unit distance, $c_{i,l}$ for battery i given the truckload condition l;

the storage cost term, $t_j s_{i,j}$ can be represented as number of days, t_j in storage times storage cost per day, $s_{i,j}$.

For the operational optimization of reverse logistics decisions, we have leveraged an EOL battery availability forecast model to train a reinforcement learning model[25] to maximize business outcomes over a given time horizon.

Based on the reverse logistics simulation (Fig. 5a) for the OEM's EOL battery management use case, there is potential to reduce transportation costs of EOL batteries by 11% to 44% compared to the baseline shipping scenario and improve value recovery by 52% to 60% by routing high-value EOL batteries to second-life application providers. In this simulation, we have used 126 dealers from 5 states and calculated costs and revenues for three different annual counts of EOL battery returns (2000 in a year; 10,000 in a year; 20,000 in a year).

EOL battery health estimation

An EOL battery's remaining economic value critically depends on the battery state of health (SOH), a measurement that indicates the level of degradation and remaining capacity of the battery. To estimate SOH at the pack level, we use voltage time series measured during the relaxation phase of a charge-discharge cycle. These measurements are easy-to-collect because they can be made using generic battery testers. Using these voltage time series as input and the measured remaining capacities as output can take a long time to complete. Inspired by the use of Long short-term memory (LSTM) architectures in different application areas such as image processing, manufacturing, or autonomous systems[26], we trained a bidirectional LSTM[27] regression model for predicting remaining capacities:

Bidirectional LSTM Regression: Relaxation Voltage Time Series → Remaining Capacity. It turns out the shape of this battery relaxation voltage time series is highly predictive of the remaining capacity of the battery, and we can achieve prediction error rates as low as 1%.

We have also considered an alternative machine learning method to estimate a battery SOH using relaxation voltage time series as input. In this method, we use the first 3 statistical moments (maximum, variance, and skewness) of the input voltages as features to predict battery SOH using SVR (Support Vector Regression[28]) with a Gaussian kernel:

SV Regression: Relaxation Voltages Max, Variance, Skewness→ Remaining Capacity. This SVR method is simpler to implement than the LSTM method that we recommend, but by using statistical moments as predictors, we completely ignore sequence information inherent in a time series. As a result, we expect the LSTM method to be more accurate than the SVR method in predicting SOH. Indeed, our empirical results show that we can achieve prediction error rates around 0.93% under LSTM vs. 1.27% under SVR (Fig. 5b, c). While both methods are extremely accurate, the LSTM method is 36% better than the SVR method.

For the second-life applications, a repurposing provider may be interested in estimating the number of good modules (for example, module SOH ≥ 80%) based on pack SOH before they decide to procure the EOL battery. Similarly, a refurbishing provider would like to estimate the number of good cells beforehand. We frame this problem as estimating a conditional expected value for the number of good modules and the number of good cells given the SOH of the pack. Formally, given a battery pack Z and its SOH z, we would like to estimate:

$$E(N_Z|Z = z) \tag{5}$$

where N_Z is a random variable that represents the number of good cells or modules in the pack, and $E(.)$ denotes expected

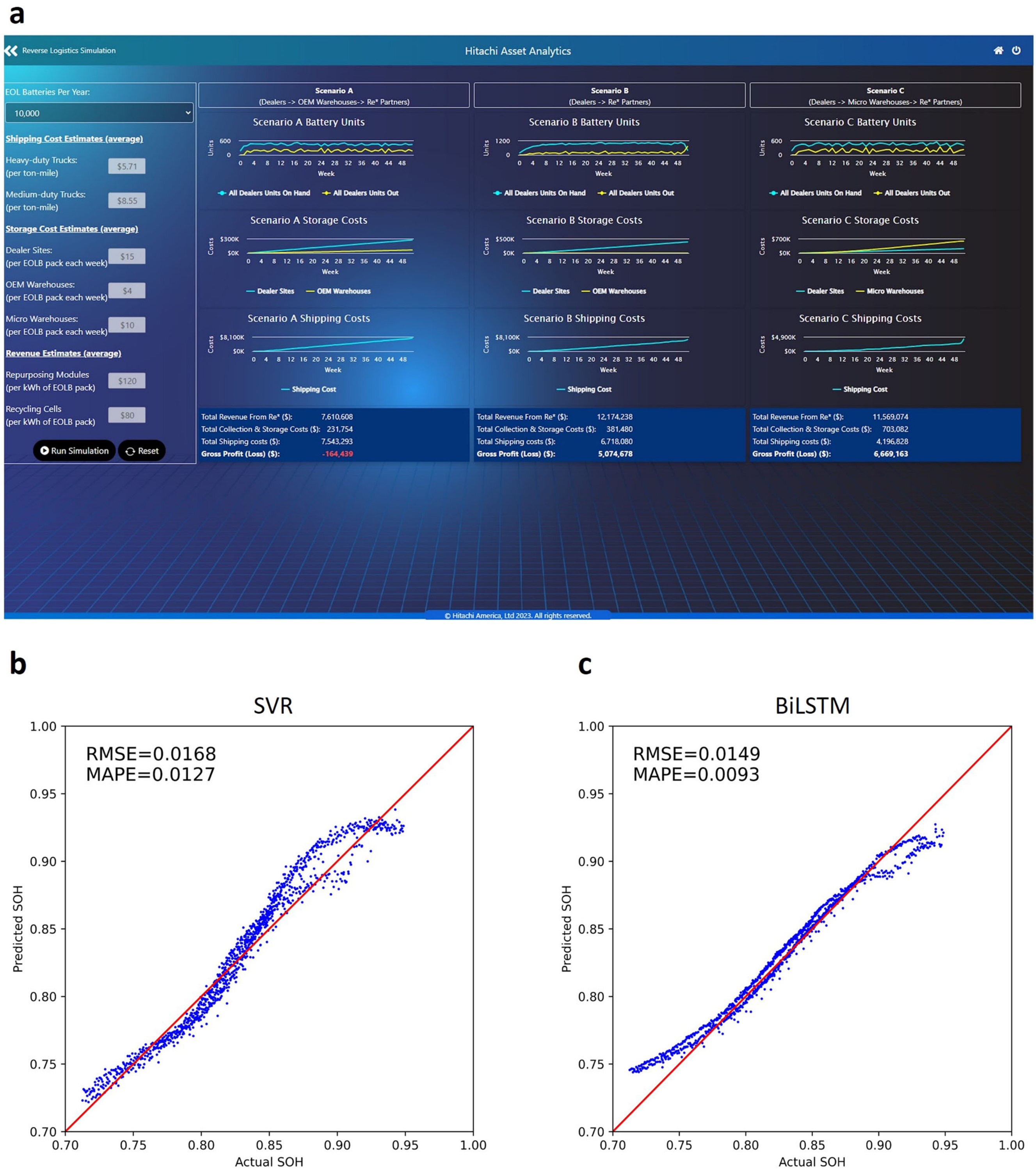

Fig. 5 Reverse logistics simulation and State of Health (SOH) estimation. **a** Reverse logistics simulation. **b** SOH estimation using SVR. **c** SOH estimation using BiLSTM. Copyright 2023 by Hitachi America, Ltd. Image used with permission from Hitachi America, Ltd.

value. We developed an efficient solution for this conditional expectation problem. Also, for calculating prediction uncertainties, we need to estimate statistical variance which can be written as:

$$E({N_Z}^2|Z = z) - (E(N_Z|Z = z))^2 \tag{6}$$

for which we also developed an efficient solution.

Having an accurate SOH estimation at not only the pack level but also the module and cell levels allows us to precisely match battery conditions with Re* providers' specific requirements, thereby maximizing the recovery value for the EOL battery.

Remaining value and offer price recommendation for EOL battery purchase

A battery's remaining value will be a function of the Re* providers that satisfy the match and the recommended offer is based on not

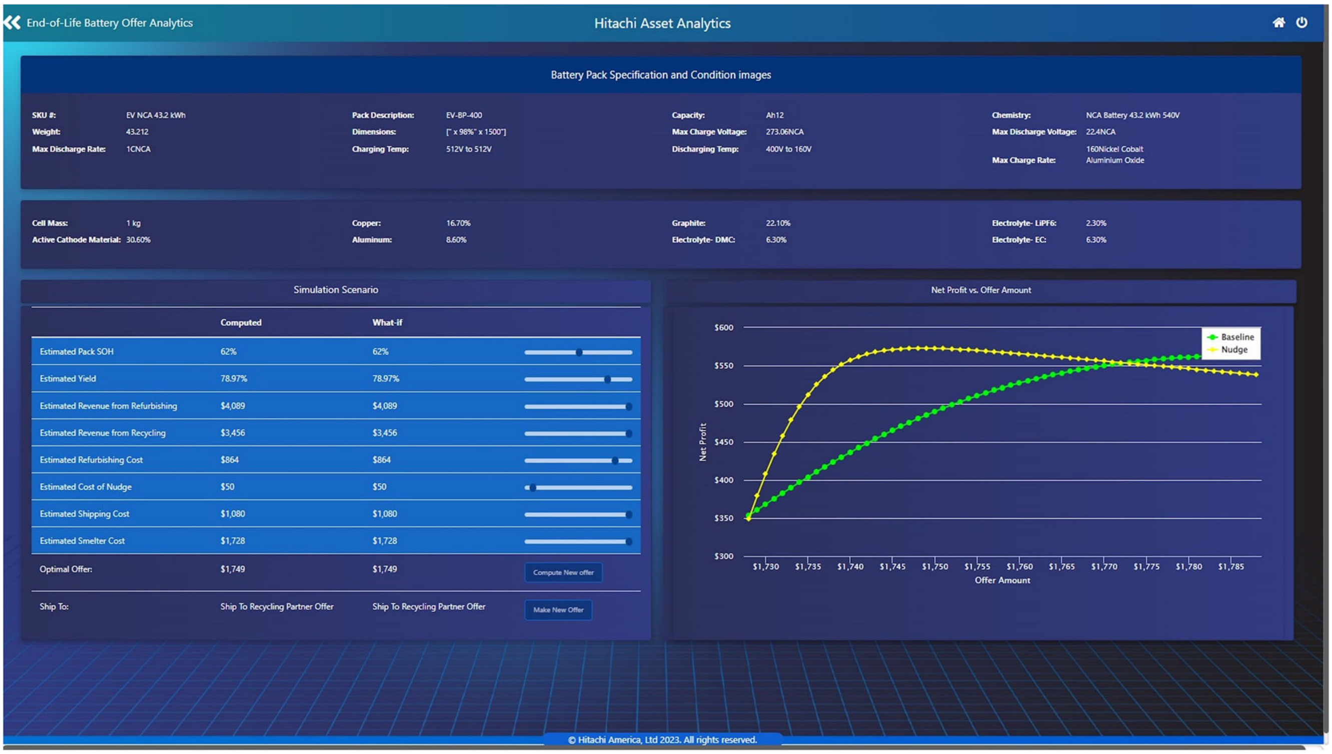

Fig. 6 Remaining value estimation of the end-of-life battery and optimal offer price recommendation. Our work shows that the OEM can potentially make a gross profit of $507 to $667 per EOL battery of small EVs (20kWh to 30kWh size) by optimizing offer costs and routing EOL batteries to the appropriate Re* provider. Today, many OEMs get zero or negative returns from their EOL batteries' collection and recycling. Copyright 2023 by Hitachi America, Ltd. Image used with permission from Hitachi America, Ltd.

only the remaining economic value but also the cost to transport the battery to the Re* provider's location. Using historical transaction or survey data collected under different pricing levels and behavioral intervention strategies such as nudging, we build a behavioral-economics-based pricing model that predicts the likelihood of offer acceptance. Since different interventions have associated costs, we recommend an optimal nudging strategy and pricing level that minimize EOL battery acquisition costs.

When dealing with third parties outside a dealership network that hold EOL EV batteries, an OEM creates an offer to purchase these batteries from these third parties, we call battery owners. There are two ways to incentivize an owner to sell a EOL battery to the OEM: price and nudges[29] which for example appeal to the owner's reputation to support sustainable energy solutions. While the net battery acquisition cost is a function of both EOL battery price and price of nudging, what really needs to be minimized is the *expected* net acquisition cost which also depends on the probabilities of offer acceptance:

$$\mathit{Net\ Acquisition\ Cost} * \Pr(\mathit{Offer\ Acceptance}) \tag{7}$$

To predict offer acceptance, we built a logistic regression model that uses price, nudge, and their interaction term as predictors to estimate the probabilities of offer acceptance:

$$\Pr(\mathit{Offer\ Acceptance}) = \mathit{Sigmoid}(\mathit{Linear\ combination\ of\ Price, Nudge\ and\ Price} * \mathit{Nudge}) \tag{8}$$

This model can be trained using historical transaction data between OEMs and battery owners. Then the best price and nudge recommendation would minimize the expected net acquisition cost that accounts for price of nudging:

$$\mathit{argmin}_{\mathit{price,nudge}}\ \mathit{Net\ Acquisition\ Cost} * \Pr(\mathit{Offer\ Acceptance}) \tag{9}$$

Our work (Fig. 6) shows that the OEM can potentially make a gross profit of $507 to $667 per EOL battery of small EVs (20kWh to 30kWh size) by optimizing offer costs and routing EOL batteries to the appropriate Re* provider. Today, many OEMs get zero or negative returns from their EOL batteries' collection and recycling.

Tracking EOL batteries through reverse logistics workflow

Using EOL battery tracking dashboard, OEMs (or their partner on their behalf) can track availability of EOL batteries at dealer, repair shops, and dismantler locations, make purchase and sales offers, track status of Re* operations. The OEM can maintain an online training library for safely removing EOL batteries from its EV models. Dealers and dismantlers can notify VIN number of the acquired EV to OEM through this system, and in return the OEM provides battery removal instructions, offers a market-competitive price to purchase EOL battery, and makes arrangements for reverse logistics. For demonstration purposes (Fig. 7), we have onboarded 2,100 EOL batteries in our solution, which can be scaled up to process data for tens of thousands of EOL batteries.

Collection route recommendation

To minimize transportation costs, it is important to consider truck payload mix and capacity utilization and travel route when hopping from location to location to collect batteries. So given the destination location of a given Re* provider and the locations where EOL batteries are available to be collected, we compute the shortest Hamiltonian path taken by a truck that minimizes transportation costs that are a function of both weight and distance traveled.

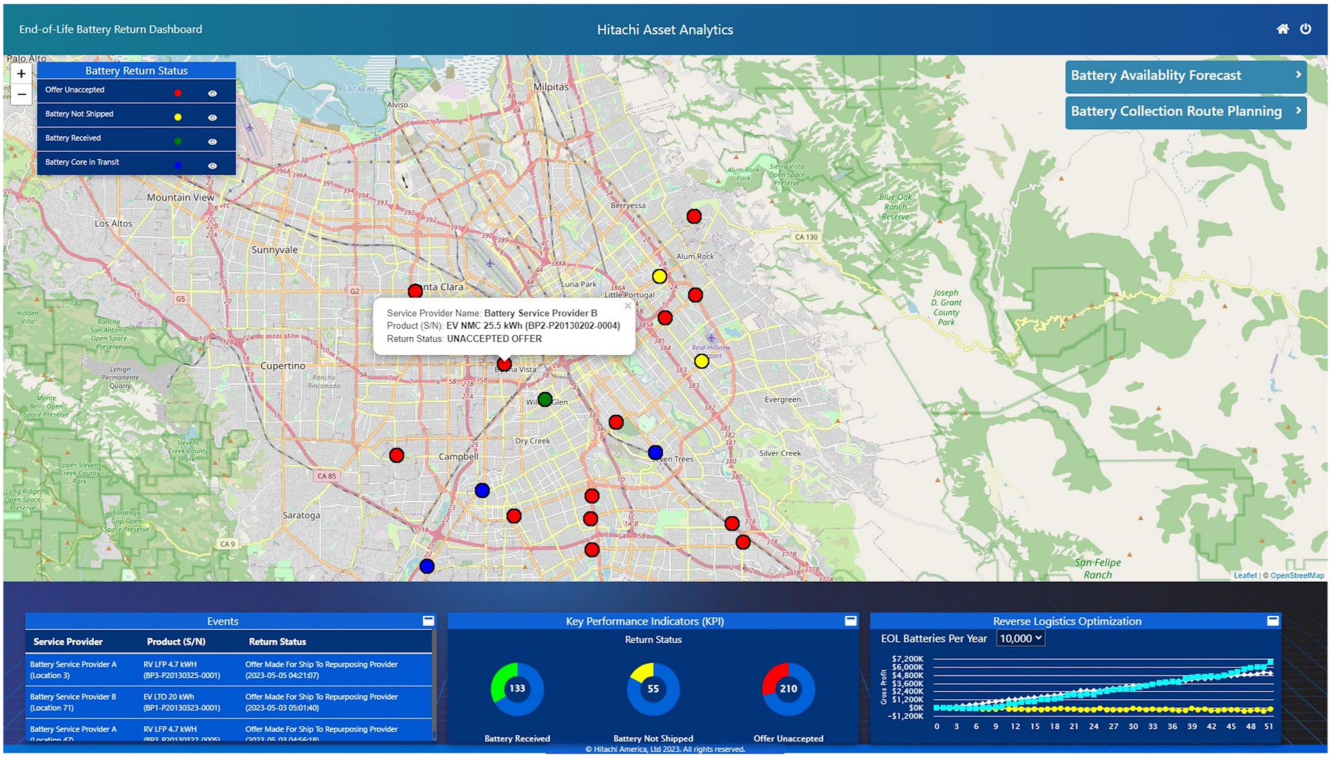

Fig. 7 **End-of-life battery tracking dashboard.** For demonstration purposes, we have onboarded 2,100 EOL batteries in our solution, which can be scaled up to process data for tens of thousands of EOL batteries. Copyright 2023 by Hitachi America, Ltd. Image used with permission from Hitachi America, Ltd.

The SHP (shortest Hamiltonian path) problem is a classic case of a NP-hard (computationally very hard) problem and so far, the state-of-the-art solution can be attributed to the Bellman-Held-Karp (BHK) dynamic programming algorithm[30,31] By contrast, our solution uses a radically different approach by framing SHP as heuristic search[32], a class of problem-solving methods pioneered in the field of AI in the late 60 s. By developing special heuristics tailored to the SHP problem, our solution turns out to outperform BHK by almost 2 orders of magnitude (at least for problem sizes up to 16) and thus allows larger route optimization problems to be solved exactly.

For demonstration purposes (Fig. 8), we have selected 11 service partner locations in Los Angeles County from where EOL LIBs need to be collected and our solution recommends a shortest collection route with a total distance of about 80 miles thus minimizing transport costs and emissions.

DISCUSSION

In this paper, we have described an important end-of-life EV batteries management use case. State of the art Battery Passport Systems have inadequate features to support and optimize end-to-end management of EOL batteries. We have devised an ecosystem value optimization approach powered by a digital solution framework to manage five key value drivers for battery circularity—safety, regulatory compliance, carbon footprint reduction, quality, and financial. Leveraging this solution framework, we have developed a comprehensive end-to-end management solution that helps capture relevant data from associated stakeholders through a trusted platform and leverage a set of analytical methods providing data-driven insights to increase operational efficiency in the ecosystem and promote circularity. This ecosystem solution enables strong business collaboration between all stakeholders in the OEM ecosystem and facilitates a win-win model for all stakeholders—OEMs and its Re* partners receive information about availability and health conditions of EOL batteries, whereas dealers and dismantlers benefit from EV model-specific training resources, market-competitive core purchase offers, and reverse logistics arrangements.

As batteries account for significant embedded greenhouse gas emissions in electric vehicle production, carbon footprint reduction should be a key consideration for battery circularity strategy. Extending battery life by reusing and repurposing in a second or third-life application followed by recycling using a low energy-intensive recycling technique can help automakers and fleet owners towards their carbon reduction goals. Our solution approach provides the ability to keep track of carbon footprint reduction from each EOL battery using an estimated CO2 reduction factor for a combination of battery pack types and recycling or repurposing techniques. Moreover, repurposing providers, recycling partners, and logistics providers can share energy consumption data during the reverse logistics and value recovery processes to help stakeholders obtain a better estimate of carbon footprint reduction.

We firmly believe our proposed solution has all the important features necessary to truly accelerate the circular economy for batteries. While we have developed the first set of analytical models to prove our idea, we understand that each organization's use case is different and a one-size-fits-all approach will not work. Hence, we have been developing a library of analytical models to adapt for different scenarios. Further validation of our analytical models has been planned with asset owners, OEMs, and recyclers.

METHODS

Ecosystem value optimization approach

To enable key value drivers for battery circularity, Ecosystem Value Optimization function can be represented as follows:

$$NetValue = f\left(V_{SafeHandling}, V_{Compliance}, V_{CarbonReduction}, V_{Quality}, V_{Financial}\right) \quad (10)$$

where $V_{SafeHandling}, V_{Compliance}, V_{CarbonReduction}, V_{Quality}, V_{Financial}$ are value drivers for safe handling, regulatory compliance, carbon

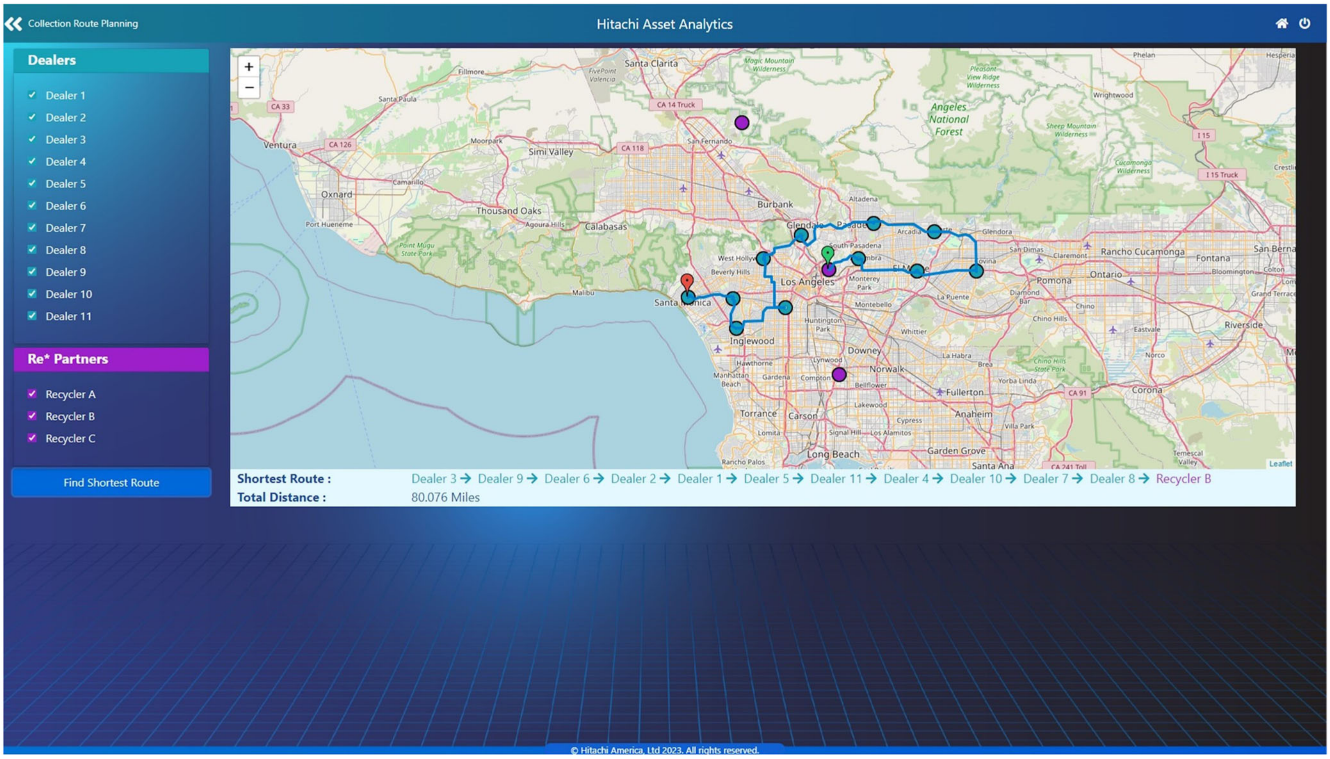

Fig. 8 End-of-life battery collection route optimization. For demonstration purposes, we have selected 11 service partner locations in Los Angeles County from where EOL LIBs need to be collected and our solution recommends a shortest collection route with a total distance of about 80 miles thus minimizing transport costs and emissions. Copyright 2023 by Hitachi America, Ltd. Image used with permission from Hitachi America, Ltd.

footprint reduction, quality of repurposed products and recycled materials, and financials respectively. The above equation can be further expressed as

$$\begin{aligned} NetValue = & w_1 V_{SafeHandling} + w_2 V_{Compliance} \\ & + w_3 V_{CarbonReduction} + w_4 V_{Quality} + w_5 V_{Financial} \end{aligned} \tag{11}$$

where w_1, w_2, w_3, w_4, w_5 are relative weight for each value driver as per stakeholder company policies. Moreover, $V_{Financial}$ can be expressed as:

$$V_{Financial} = RevenueRealization - CostIncurred \tag{12}$$

While it is difficult to quantify the non-financial value drivers, we have tried to use different proxies for quantification. For example, value of safe handling can be measured in economic value of life and property; value of compliance can be measured in terms of penalties, value of carbon reduction can be quantified as carbon price per ton, and value of quality can be estimated based on expected loss of sales and brand recognition. These values may be different for different stakeholders.

Forecasting spent batteries availability

Below is additional information about our method for forecasting spent batteries availability:

- Car registration data can be downloaded from CA EV registration website[20]
- Python SciPy open-source library, version 1.10.1 was used to compute the Binomial distribution.
- Custom code was used for adding independent random count variables.
- For 95% prediction intervals for a given distribution, *Mean* ± *Standard Deviation* was used as an approximation.

Reverse logistics network simulation and planning for EOL batteries transport

Below is additional information about our method for reverse logistics simulation:

- Simulation-based analysis of reverse logistics was performed using Mesa v1.2.1, an open-source agent-based modeling library in Python. To analyze and compare multiple reverse logistics scenarios using stochastic simulation, the same randomly drawn data sample was used as simulation input across all scenarios to ensure a fair comparison. EOL batteries' arrival process was modeled using a Poisson distribution. Proportions of EOL LIB battery chemistries and health conditions are randomly generated using multinomial distributions. These statistical distributions were computed using the Python SciPy library v1.10.1.
- Transport routing optimization uses distance estimates between various (long, lat) locations. These distances are computed using the PyPI geopy open-source library v2.3.0 which provides popular geocoding services.
- The total annual number of EOL EV batteries received by US dealers are distributed among the largest counties among the largest states based on the number of EV registrations by county.

EOL battery health estimation

Below is additional information about our method for EOL battery health estimation:

- Relaxation voltage data that we downloaded was reformatted to a usable form using custom code.
- The BiLSTM model was trained using Tensorflow Keras library v2.8.0 with input sequences of 14 relaxation voltage values.

Support Vector Machines regression model was trained using Python open-source library scikit-learn v1.2.2 with input of the first 3 statistical moments over the 14 voltage values namely, maximum, variance, and skewness. Training set consists of 21,117 voltage sequences and the test set has 1,113 sequences.

- Prior probability distributions of cells or modules are needed to compute conditional estimates of pack-level SOH, but specific distributions are not required in our methods. The most conservative choice is to use a uniform distribution.
- Estimation of good modules and good cells counts, conditioned on pack-level SOH, was computed using custom code.

Remaining value and offer price recommendation for EOL battery purchase

Below is additional information about our method for offer price recommendation:

- A prior survey response data was used as the proxy for introducing the effect of nudge in the EOL battery purchase offer acceptance model. This online survey was conducted through SurveyMonkey using two cohorts of 200 paid participants—the first cohort was given a questionnaire without nudge, and the second cohort was given the same questionnaire with nudge. Survey was designed to analyze participants' attitude towards repurposed batteries compared to new batteries and effect of nudge—environmental and economic benefits of battery repurposing was highlighted for nudge.
- For EOL battery purchase offer acceptance, we built a logistic regression model using offer price, nudge, and price*nudge interaction term as predictors, and offer acceptance as outcome. Model was implemented using custom code.

Collection route recommendation

Below is additional information about our method for collection route recommendation:

- Transport routing optimization uses distance estimates between various locations specified as longitude and latitude. These distances are computed using the PyPI geopy open-source library v2.3.0 which provides popular geocoding services. To find the best routes, exact shortest Hamiltonian paths were computed using custom code.
- Truck payloads mix that maximizes capacity utilization was computed using custom code.
- We used OEM Los Angeles County dealership location data to simulate where EOL EV batteries are returned and available to be collected.

Digital solution framework

Considering the complexity of end-of-life battery management, a digital solution framework (Fig. 2b) has been designed comprising the following components:

- Permissioned blockchain network: A permissioned blockchain network has been designed based on the Hyperledger Fabric platform—a modular and extensible open-source system[33] that supports pluggable consensus protocols and pluggable identity management protocols, and provisions channel architecture to enable privacy and confidentiality of business transactions. Permissioned blockchain comes with an extra layer of privilege to choose who can take part in the transactions within the network, with the identity of every member known to all members[34]. By utilizing the network infrastructure of Hyperledger, a large number of businesses including supply chain partners and downstream companies (often new and transient organizations such as repair shops) can be onboarded to the OEM's business network thus enabling effective and trusted information sharing.
- Off-chain databases and document repository: Non-transactional data and private date can be stored in off-chain database systems such as MySQL and CouchDB respectively. For document sharing such as training videos, storage services such as AWS S3 can be utilized.
- Data interfaces with IoT and Enterprise systems: Since there are diverse data sources - enterprise and IoT (e.g., sensor-based tracking of battery condition), a scalable and extensible data integration platform such as Apache airflow[35] is needed to programmatically author, schedule, and monitor data workflows. Hardware or software-based root of trust mechanisms such as a Trusted Platform Module (TPM) should be used to establish trust in IOT computing[36].
- Analytics services: To derive predictive and prescriptive insights, machine learning frameworks such as TensorFlow[37] and scalable reinforcement learning framework such as RLlib[25] have been used.
- Micro-apps: Our micro apps approach at the front-end layer allows the development of complex apps by assembling highly focused small apps rather than building a big application from scratch. A suite of micro-apps has been designed for each stakeholder in the ecosystem.

Blockchain network design for the representative use case

For this use case demonstration purposes, we consider 13 organizations—3 service partners (a dealer, an independent repair shop, and a dismantler) each serving an asset owner (EV owner or fleet company), 3 Re* partners (a repurposing, a refurbishing, and a recycling provider), 3 reverse logistics companies (transports EOL batteries from service partners to chosen Re* partners).

In the representative workflow for end-of-life battery management (Fig. 9), EV Fleet owners initiate EOL battery Re* request (typically when a battery is replaced by dealers or repair shops, or used EV is sold to dismantlers) and share battery purchase information, and battery health and usage anomalies (recorded in owner's IT system) with the respective service partner. The Service partner removes, inspects, and stores the EOL battery, notifies OEM regarding the EOL battery, and shares service diagnostics with OEM. For each EOL battery, OEM selects relevant Re* partner and Logistics provider. For the EOL battery, OEM makes a purchase offer to the Dealer (or it could be a core exchange process) and a sales offer to the chosen Re* partner. Upon acceptance of these offers, OEM submits a shipping request to a logistics provider which in turn provides a quote. The logistics provider transports EOL batteries from dealers to Re* partners (shipments can be batched to optimize transportation costs). Upon completion of Re* operation (repurpose, refurbish, or recycle), the Re* partner notifies OEM, and then OEM, Service partner, and Asset Owner records EOL battery Re* request completion for regulatory purposes.

For the representative use case involving an EV OEM, 3 service partners, 3 asset owners, 3 logistics providers, and 3 Re* partners, a blockchain network has been set up using Hyperledger Fabric v2.2 LTS. The partner organizations have two peers each and are onboarded into a private blockchain network for the EV ecosystem value chain. Peer nodes in the blockchain network are configured for RAFT Ordering Service. Hyperledger fabric framework offers channel concepts for conducting private and confidential transactions between two or more specific network members[38]. A channel design (Fig. 10) has been created as follows:

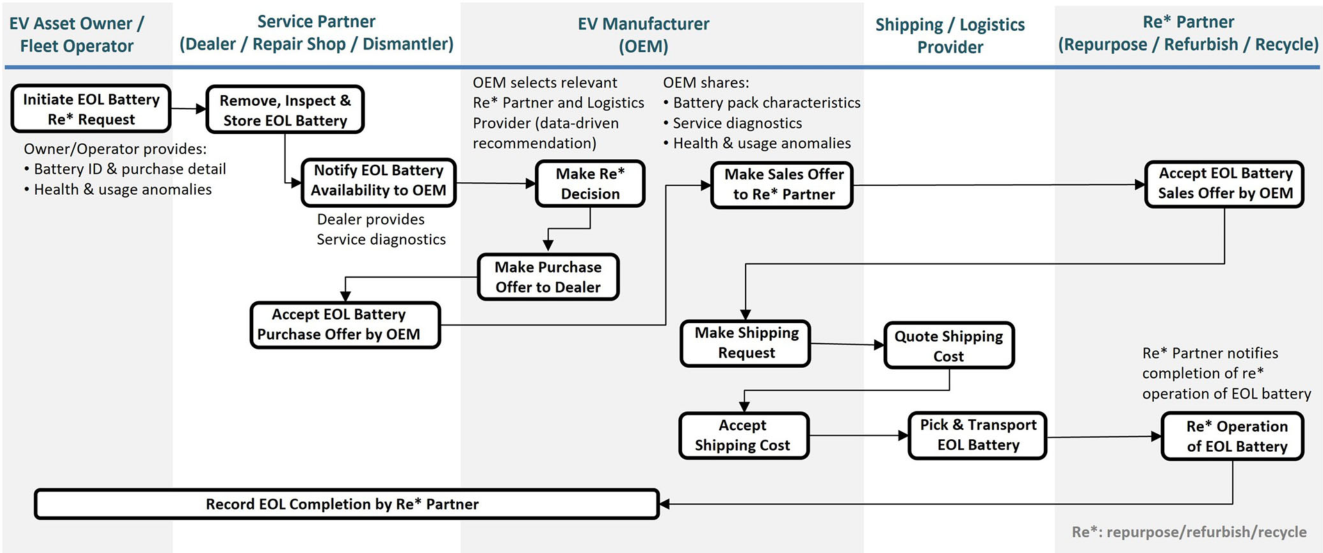

Fig. 9 Representative workflow for end-of-life battery management. A representative workflow for end-to-end management of end-of-life batteries involving all stakeholders including EV fleet owners, service providers (dealers/repair shops/dismantlers), OEM, logistics providers, and recycling/repurposing providers.

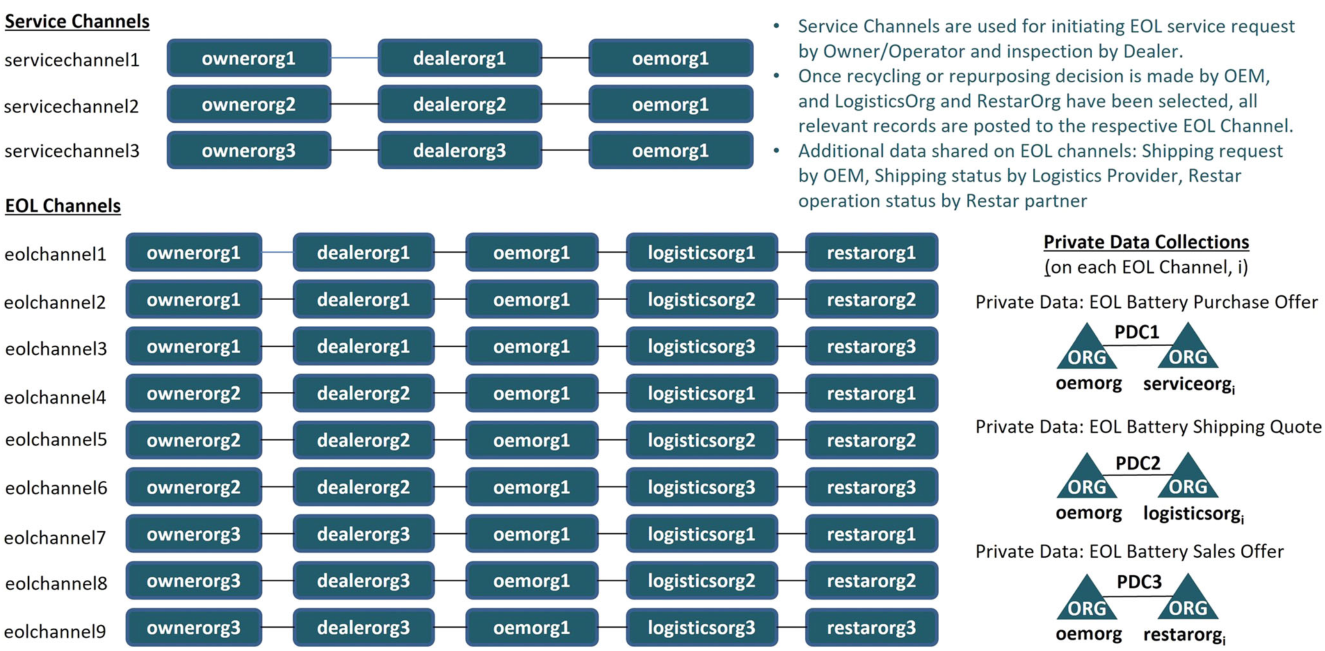

Fig. 10 Blockchain network design for the representative use case. For the representative use case involving an EV OEM, 3 service partners, 3 asset owners, 3 logistics providers, and 3 Re* partners, a blockchain network has been set up using Hyperledger Fabric v2.2 LTS.

- 3 Service Channels: Each service channel has been created between OEM, a service partner, and an asset owner. Service Channels are used for initiating EOL service requests by asset owners and inspection by service partners. Once a Re* decision is made by OEM, and the logistics organization and Re* partner have been selected, all relevant records are posted to the respective EOL channel.
- 9 EOL Channels: Each EOL channel has been created between the OEM, a service partner, an asset owner, a logistics provider, and a Re* partner. Additional data shared on EOL channels includes shipping request by OEM, shipping status by logistics provider, Re* completion status by Re* partner.

In the Hyperledger Fabric framework, Private Data Collections (PDC) are used to manage confidential data that two or more organizations on a single channel want to keep private from other organizations on that channel. For the OEM's EOL Battery management use case, relevant PDCs have been created in each EOL channel. For example, on each EOL channel joined by multiple network members (the OEM, a service partner, an asset owner, a logistics provider, and a Re* partner), EOL battery purchase offers can be privately shared between the OEM, and the service partner using PDC1, whereas shipping quotes can be shared privately between the OEM and the logistics provider using

PDC2. Similarly, EOL battery sales offers can be shared privately between OEM and its Re* partner using PDC3.

We confirm that this work is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere. Our study is not subject to dual use research of concern. Online survey participants gave their informed consent for inclusion before they participated in the survey.

Reporting summary

Further information on research design is available in the Nature Research Reporting Summary linked to this article.

DATA AVAILABILITY

Car registration data is accessible from the California open data portal[20], providing vehicle counts broken down by ZIP code, model year, fuel type, make and duty (light/heavy) of registered vehicles. OEM North America dealership location data can be purchased from commercial data services. State-level EV registration data can be downloaded from Atlas EV Hub[39]. SOH prediction models were trained and tested using relaxation voltage data downloaded from Zenodo[40]. The OEM related data are not publicly available due to them containing business sensitive information but are available from the corresponding author on reasonable request.

CODE AVAILABILITY

Code is copyrighted as per our company policies, however code snippets can be made available for editors and reviewers upon reasonable request.

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AUTHOR CONTRIBUTIONS

All authors contributed to the ecosystem value optimization approach, wrote, and reviewed the paper.

COMPETING INTERESTS

The authors declare no competing interests.

ADDITIONAL INFORMATION

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