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Article

Techno-Economic and Environmental Viability of Second-Life EV Batteries in Commercial Buildings: An Analysis Using Real-World Data

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Abstract

The rapid growth of electric vehicle markets is producing large volumes of retired lithium-ion batteries retaining 70–80% of their original capacity, suitable for stationary energy storage. This study assesses the techno-economic and environmental viability of second-life battery energy storage systems (SLBESS) in a California commercial building, using one year of operational data. SLBESS performance is compared with equivalent new battery systems under identical dispatch strategies, building load profiles, and time-of-use tariff structures. A dispatch-aware framework integrates multi-year battery simulations, degradation modeling, electricity cost analysis, and life cycle assessment based on marginal grid emissions. The economic analysis quantifies the net present value (NPV), internal rate of return (IRR), and operational levelized cost of storage ($LCOS_{op}$). Results show that SLBESS achieve 49.2% higher NPV, 41.9% higher IRR, and 13.8% lower $LCOS_{op}$ than new batteries, despite their lower round-trip efficiency. SLBESS reduce embodied emissions by 41% and achieve 8% lower carbon intensity than new batteries. Sensitivity analysis identifies that economic outcomes are driven primarily by financial parameters (incentives, acquisition cost) rather than technical factors (degradation, initial health), providing a clear rationale for policies that reduce upfront costs. Environmentally, grid emission factors are the dominant driver. Battery degradation rate and initial state of health have minimal impact, suggesting that technical concerns may be overstated. These findings provide actionable insights for deploying cost-effective, low-carbon storage in commercial buildings.

Keywords: second-life battery; techno-economic analysis; life cycle assessment; commercial buildings; demand charge management; battery energy storage

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1. Introduction

The rapid growth of the electric vehicle (EV) market has led to an unprecedented increase in the number of retired batteries. Although these batteries are unsuitable for high-performance automotive applications once their state of health (SOH) declines to 70–80%, they retain significant residual capacity and can deliver an additional 5–10 years of service in less demanding stationary energy storage applications [1–3]. Commercial buildings with on-site photovoltaic (PV) systems represent promising candidates for second-life battery (SLB) deployment. These buildings typically exhibit predictable load profiles, face significant demand charges, and increasingly seek to integrate renewable generation. When properly managed, SLB systems can lower electricity costs, improve PV self-consumption, and enhance grid flexibility, while extending the useful life of EV batteries and reducing their embodied carbon footprint [4].

However, the viability of SLBs in commercial contexts remains uncertain due to limited evidence regarding their technical performance, economic competitiveness, and environmental benefits. Declining new battery costs, logistics and testing requirements, limited data on degradation, and challenges in regulatory compliance further hinder large-scale adoption [5–7]. Extensive research has been conducted on the viability assessment of second-life batteries, employing both techno-economic analysis (TEA) and life cycle assessment (LCA) frameworks. Several studies have assessed the cost competitiveness and market potential of SLBs under varying assumptions of repurposing cost and electricity price. Rallo et al. analyzed real-world stationary storage systems in Spain and highlighted that aging dynamics significantly affect return on investment, emphasizing the need to account for degradation behavior in feasibility studies [8]. Steckel et al. used a Levelized Cost of Storage (LCOS) approach for utility-scale systems, emphasizing that SLB viability is highly sensitive to electricity market dynamics and processing cost [9]. Fallah et al. conducted a comparative techno-economic evaluation of used batteries across grid-based scenarios, finding that profitability can be maintained when the acquisition cost remains below approximately 25% of the new cell price, particularly for younger retired batteries with higher remaining capacity [10]. Lieskoski et al. examined the business potential of repurposing Tesla Model S/X batteries in Finland and found that pack- or module-level repurposing can be economically viable, while full disassembly to the cell level remains uneconomical due to labor costs [11]. Zhuang et al. developed a techno-economic decision support model showing that second-life battery value varies significantly by application ($23–273/kWh), with economic viability determined more by policy incentives and repurposing costs than by battery degradation characteristics [12]. Turan et al. demonstrated through dynamic degradation modeling and comprehensive cost analysis that second-life batteries achieve economic viability at 34–54% of new battery costs in off-grid applications, with sensitivity analysis identifying new battery purchase price as the dominant factor in SLB market pricing [13].

Environmental studies consistently demonstrate that SLBs yield substantial carbon and resource savings compared with new batteries. Cusenza et al. integrated load-match analysis and LCA to evaluate the reuse of EV batteries in nearly zero-energy buildings, showing that a 46 kWh second-life battery system enhanced both energy self-consumption and environmental performance [14]. Kamath et al. evaluated SLBs in residential and utility-level PV applications across the U.S. and found that SLBs reduced levelized electricity costs by 12–57% and life-cycle carbon emissions by 7–31% relative to new batteries [15]. Cheng et al. linked degradation, performance, and sustainability indicators, showing that higher initial SOH improves environmental outcomes [16]. Saez de Bikuña et al. found that automation and policy incentives such as tax credits and carbon pricing are crucial for maintaining SLB competitiveness [17].

Most prior studies, however, rely on static annual models that compute aggregate financial and environmental indicators using assumed average throughput, fixed performance parameters, and uniform operational patterns. Such approaches fail to capture the time-resolved dynamics of battery dispatch, including hourly variations in electricity prices, solar generation, building loads, and degradation trajectories. Moreover, few studies offer counterfactual comparisons between second-life and new battery systems operating under identical conditions, namely the same load profiles, tariff structures, control strategies, and operational constraints, making it difficult to isolate the true techno-economic and environmental trade-offs of battery reuse.

This study addresses these gaps through a comprehensive, dispatch-aware evaluation of a second-life battery energy storage system (SLBESS) deployed in a California commercial building. Using one year of high-resolution operational data, the study integrates TEA and LCA to evaluate both financial and environmental viability under real-world conditions.

A time-series battery simulation model is developed to operate at one-minute resolution over a 10-year period, using measured data on building load profiles, rooftop PV generation, time-of-use (TOU) tariffs, and empirically validated battery degradation models. This approach captures the temporal dynamics of battery dispatch, including demand charge management and energy arbitrage, and quantifies their cumulative effects on economic returns and system performance. The framework quantifies net present value (NPV), internal rate of return (IRR), and operational levelized cost of storage ($LCOS_{op}$) while accounting for degradation effects and system availability. Second-life and new battery systems are evaluated under identical operational conditions, including the same building, PV system, load profile, tariff structure, control algorithm, and evaluation period, allowing rigorous isolation of the economic and environmental implications of battery reuse. The environmental assessment employs a cradle-to-grave LCA boundary incorporating marginal grid emission factors to quantify avoided emissions from battery discharge, as well as embodied impacts from repurposing, transportation, balance-of-system components, and end-of-life recycling credits. While the case study is site-specific, the methodological framework developed here is designed to be generalizable and can be adapted to other geographies by incorporating local load profiles, tariff structures, and grid emission factors.

Comprehensive sensitivity analyses across technical, economic, and policy parameters identify the key drivers of SLBESS viability and quantify associated uncertainty, revealing that policy incentives and acquisition costs dominate economic outcomes, whereas grid emission factors largely determine environmental performance. This study delivers actionable insights for building owners, policymakers, and technology providers aiming to evaluate and accelerate SLB deployment in commercial applications.

2. System Description and Data

2.1. Case Study Site

This study investigates a commercial building in San Diego, California, equipped with on-site PV generation and subject to a TOU tariff structure that includes both energy and demand charges. The site is representative of commercial buildings with high demand charges, predictable load profiles, and significant on-site solar generation, which are the conditions conducive to battery storage deployment.

Figure 1 illustrates the system architecture and power flow paths at the study site. The battery energy storage system consists of repurposed EV packs assembled into racks and connected to the building's distribution panel through a three-phase power conversion system (PCS). An energy management system (EMS) coordinates all components and executes various dispatch strategies, including rule-based heuristics and model predictive control (MPC). Energy flows include: (i) bidirectional power exchange between the building and the utility grid; (ii) bidirectional charging and discharging of the SLBESS; and (iii) unidirectional PV generation to the building, grid, or battery storage. This architecture enables flexible management of peak demand reduction, energy arbitrage, and PV integration.

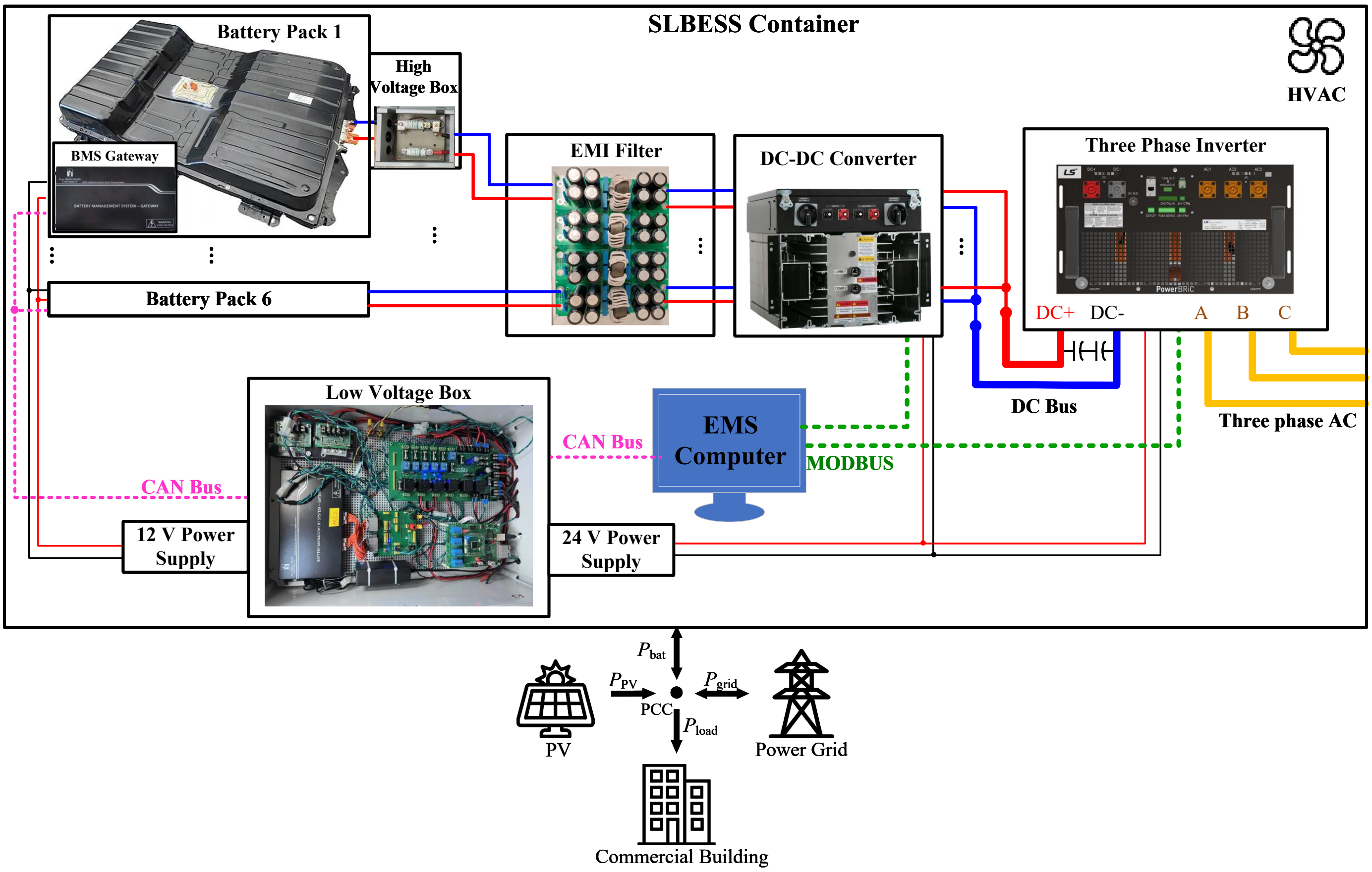


Figure 1. System schematic showing SLBESS architecture with repurposed EV battery packs, PCS, BMS gateway, EMS, and bidirectional AC/DC power flows between the building, grid, PV system, and battery storage at the point of common coupling (PCC).

2.2. Dataset

High-resolution operational data were recorded at one-minute intervals over a 12-month period. The dataset includes building load, PV generation, battery power, net load, system operating states, and environmental conditions (ambient and internal temperatures). Figure 2 shows the average daily profiles of building load and PV generation over the year. The building demonstrates consistent daily load patterns with pronounced peaks during business hours. PV generation leads to periods of negative net load at midday, indicating excess solar production available for battery charging or export to the grid. This combination of high demand charges and abundant midday PV makes the site ideal for demand charge management and PV self-consumption optimization. Table 1 summarizes key statistical characteristics of building load and PV generation.

Table 1. Summary statistics of building load and PV generation.

Statistical Indicator	Value	Unit
Average load	52.44	kW
Maximum load	158.51	kW
Minimum load	17.05	kW
Load factor	0.33	-
PV rated capacity	200	kW
Average PV generation power	48.99	kW
Maximum PV generation power	259.07	kW
PV capacity factor	0.19	-

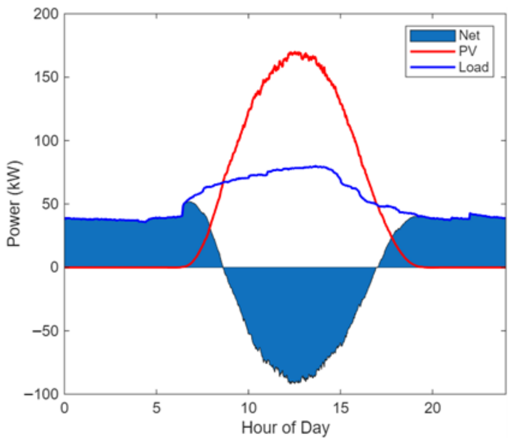


Figure 2. Average daily load and PV profile.

3. Methodology

This study introduces an integrated framework to evaluate the techno-economic and environmental viability of SLBESS in commercial buildings. The dispatch-aware framework uses one year of measured data on building load, PV generation, and battery operation from the study site. Figure 3 illustrates the overall research framework.

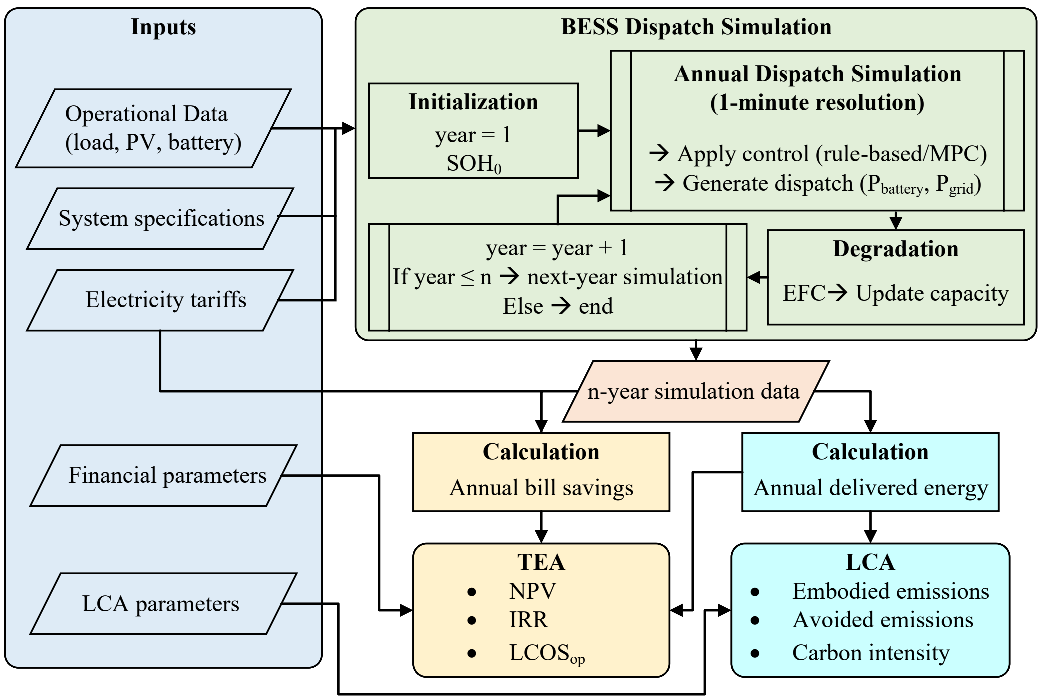


Figure 3. Integrated methodological framework showing battery dispatch simulation with annual degradation updates, followed by techno-economic assessment and life cycle assessment tracks.

The framework incorporates system specifications, high-resolution operational data, tariff structures, financial parameters, and life cycle inventories as primary inputs. The battery dispatch simulation employs dynamic modeling to track the state of charge (SOC), enforce power and energy constraints, and apply control strategies (rule-based or MPC) at one-minute resolution. For the details of system modeling and constraints, readers can refer to literature [18]. The simulation proceeds year by year, updating battery capacity based on equivalent full cycles (EFC) and applying degradation models (Section 4.1). The multi-year simulation generates time-series data on battery dispatch, grid power, and delivered energy, which serve as inputs to both techno-economic and environmental assessments.

These simulation data are analyzed through two tracks:

- TEA quantifies bill savings under demand and TOU tariffs, calculates project-level NPV and IRR, and defines $LCOS_{op}$, which accounts for degradation and downtime impacts.
- LCA employs a cradle-to-grave boundary to capture the embodied impacts of repurposing, balance-of-system (BOS) components, transportation, charging electricity, avoided grid emissions, and end-of-life recycling credits.

Both analyses are extended through sensitivity analyses that vary technical, economic, and policy parameters to characterize uncertainty and identify key drivers of SLBESS viability. The results are synthesized into integrated insights to inform building owners, policymakers, and technology providers about the conditions under which SLBESS deployment becomes both financially and environmentally favorable.

3.1. System Boundary

The system boundary follows a cradle-to-grave perspective and includes:

- SLB collection, testing, and repurposing.
- Transportation to the installation site.
- BOS, PCS, and EMS production and installation.
- Use-phase operation, including availability, round-trip efficiency (RTE) and degradation.
- End-of-life dismantling and recycling, including material recovery credits.

3.2. Techno-Economic Assessment

The techno-economic assessment quantifies the financial viability of SLB systems over an n-year project lifetime. Three key metrics are considered: bill savings, NPV, and $LCOS_{op}$.

3.2.1. Electricity Bill Model

Electricity bills include energy charges and demand charges under the utility's TOU tariff. The energy charge is based on total electricity consumption and varies by time period:

$$C_E = \Delta t \sum_{t=0}^{T-1} \left[c_{\text{imp}}(t) \max(P_{\text{grid}}(t), 0) + c_{\text{exp}}(t) \min(P_{\text{grid}}(t), 0) \right] \tag{1}$$

where Δt is the time interval, T is the total number of time steps in each billing cycle, $P_{\text{grid}}(t)$ is net grid power (positive for import, negative for export), $c_{\text{imp}}(t)$ is the import electricity price (\$/kWh), and $c_{\text{exp}}(t)$ is the export price (\$/kWh). The formulation ensures that energy charges are calculated separately for import and export, accounting for different pricing structures.

The demand charge is based on the peak 15-min average power import during the entire billing cycle:

$$C_D = c_d(t^*) \cdot \max_{t \in \mathcal{T}} P_{\text{imp}}(t) \tag{2}$$

where $c_d(t^*)$ is the demand charge rate (\$/kW) corresponding to time t^* when peak grid import occurs, $\mathcal{T}$ represents all 15-min time windows within the billing period, and $P_{\text{imp}}(t) = \max(P_{\text{grid}}(t), 0)$ is the grid import power averaged over 15-min windows. This formulation captures the time-dependent nature of demand charges, which often vary between on-peak and off-peak periods.

The total electricity cost combines both components:

$$C_{\text{total}} = C_E + C_D \tag{3}$$

Bill savings S_{bill} are computed as the difference between baseline (no storage) and storage cases.

3.2.2. Net Present Value

The project NPV accounts for upfront capital expenditure (CAPEX), operations and maintenance (O&M) costs, bill savings, residual value, and financial incentives:

$$\text{NPV} = -(1-s)C_{\text{capex}} - \sum_{t=0}^{n} \frac{C_{O\&M}(t)}{(1+r)^t} + \sum_{t=1}^{n} \frac{S_{\text{bill}}(t)}{(1+r)^t} + \frac{C_{\text{res}}}{(1+r)^n}, \tag{4}$$

where C_{capex} is capital expenditure, $C_{O\&M}$ is operating cost, S_{bill} is annual bill savings, C_{res} is residual value, r is the discount rate, and s is the incentive fraction applied to CAPEX.

The internal rate of return (IRR) is defined as the discount rate r that results in a zero NPV.

3.2.3. Operational LCOS_{op}

LCOS_{op} quantifies the effective cost per kilowatt-hour of energy delivered to the building under real operational conditions:

$$\text{LCOS}_{\text{op}} = \frac{(1-s)C_{\text{capex}} + \sum_{t=0}^{n} \frac{C_{O\&M}(t)}{(1+r)^t} - \frac{C_{\text{res}}}{(1+r)^n}}{\sum_{t=1}^{n} \frac{E_{\text{del}}(t)}{(1+r)^t}}. \tag{5}$$

This metric inherently accounts for round-trip efficiency, system availability, and capacity degradation through the denominator $E_{\text{del}}(t)$, which represents actual energy throughput rather than nameplate capacity.

3.3. Environmental Assessment

The LCA quantifies net life-cycle greenhouse gas (GHG) emissions associated with the battery energy storage. The total impact is calculated as:

$$I_{\text{net}} = I_{\text{embodied}} + I_{\text{transport}} + I_{\text{charge}} - I_{\text{avoided}} - I_{\text{recycling}} \tag{6}$$

where I_{embodied} denotes emissions from repurposing activities (e.g., testing and refurbishment) and the manufacturing of BOS, PCS, and EMS components. $I_{\text{transport}}$ represents emissions associated with transportation and site delivery. I_{charge} represents grid-related emissions incurred during battery charging from the grid. I_{avoided} represents avoided grid emissions resulting from battery discharging. $I_{\text{recycling}}$ represents credits for material recovery at the end of life.

Battery charging emissions and avoided emissions are computed using a marginal emission factor μ, which represents the carbon intensity of displaced grid generation:

$$I_{\text{charge}}(t) - I_{\text{avoided}}(t) = \mu\,[P_{\text{dis}}(t) - P_{\text{ch,grid}}(t)]\,\Delta t \tag{7}$$

where $P_{\text{dis}}(t)$ is the battery discharging power, and $P_{\text{ch,grid}}(t)$ is charging power sourced from the grid (charging from PV is considered carbon-neutral within the system boundary), and μ is the marginal emission factor $\text{kgCO}_2\text{e/kWh}$ for the California grid.

The final carbon intensity (CI) of delivered energy is:

$$CI = \frac{I_{\text{net}}}{\sum_t E_{\text{del}}(t)} \quad [\text{kgCO}_2\text{e/kWh}]. \tag{8}$$

4. Results and Discussion

4.1. Simulation Parameters and Setup

Table 2 summarizes the simulation parameters. The sensitivity range column specifies the bounds used in the uncertainty analysis (Section 4.3). The simulation parameters used in this study were compiled from a combination of existing literature and publicly available industrial data [9,15,19,20].

Table 2. Simulation parameters.

Parameter	Second-Life Battery	Sensitivity Analysis Range	New Battery
Initial SOH (%)	80	(70, 90)	100
Initial energy (kWh)	362	(100, 600)	362
Round-trip efficiency (%)	86	(80, 93)	92
SoC range (%)	10–90	-	10–90
Degradation rate (%/1000 EFC)	6.3	(4, 8)	-
System Availability (%)	98	(96, 100)	98
Core cost ($/kWh)	100	(50, 200)	200
O&M cost (% of C_{capex})	2.5	(1, 4)	2.0
Discount rate (%)	8	(5, 10)	8
Incentive rate (%)	25	(0, 50)	25
Inflation rate (%)	2.5	-	2.5
Residual value rate (%)	5	(0, 10)	20
Marginal emission factor ($kgCO_2e/kWh$)	0.291	(0.10, 0.49)	0.291
Battery embodied emissions ($kgCO_2e/kWh$)	70	-	120
Battery transport emissions ($kgCO_2e/kWh$)	5	-	5
BOS embodied emissions ($kgCO_2e/kWh$)	32	-	32
PCS embodied emissions ($kgCO_2e/kWh$)	28	-	28
Expected Lifetime (years)	10	-	10

The system's maximum power is set to one-fourth of its energy capacity, consistent with standard 4-h energy storage configurations. Although second-life and new batteries begin with the same initial capacity (362 kWh), they differ in their initial states of health. Second-life batteries start at 80% SOH while new batteries start at 100% SOH. Accordingly, all SOH and EFC calculations are referenced to the rated full capacity. For SLB systems with 362 kWh at 80% SOH, the rated full capacity is calculated as 362/0.8 = 452.5 kWh. For new systems at 100% SOH, the rated full capacity remains 362 kWh. All subsequent degradation metrics and EFC counts are normalized to these rated full capacities.

The round-trip efficiency of second-life batteries (86%) is lower than new batteries (92%) due to increased internal resistance from previous cycling. The SOH degradation model for new batteries is given by:

$$\mathrm{SOH} = 100 - a(1 - e^{-b \times \mathrm{EFC}}) - c \times \mathrm{EFC} \tag{9}$$

where coefficients $a = 5.6038, b = 0.01, c = 0.0063$ are fitted from laboratory cycling test data [21]. This semi-empirical model captures the two-phase degradation behavior typical of lithium-ion batteries, combining an exponential term for rapid initial degradation with a linear term for the slower, long-term capacity fade.

For second-life batteries, a linear degradation model is used, based on field and laboratory data, assuming a capacity fade of 6.3% per 1000 EFCs. The linear degradation assumption for second-life batteries represents the empirically observed post-knee aging phase reported in [21], where capacity fade proceeds approximately linearly below 75% SOH. While other studies identify nonlinear degradation behaviors across chemistries [22], this work employs a constant rate to simplify comparison between systems. The sensitivity range of 4–8% per 1000 EFC encompasses this variability, ensuring robustness of the techno-economic and environmental trends despite model simplification.

The EFC is calculated as the cumulative energy throughput divided by the rated full capacity:

$$\mathrm{EFC} = \frac{\sum_t E_{\mathrm{throughput}}(t)}{E_{\mathrm{rated,full}}} \tag{10}$$

where $E_{\mathrm{throughput}}(t)$ is the energy charged or discharged at time step t.

System availability accounts for unplanned outages and maintenance windows. In the simulation, downtime periods are randomly distributed throughout the year. During these intervals, the battery is excluded from dispatch, and the building operates without storage support.

The core cost of SLBs includes collection, testing, and refurbishment, while the cost of new batteries reflects pack manufacturing prices. A lump-sum core cost is used to avoid unnecessary parameter expansion and focuses the analysis on dominant techno-economic factors. O&M costs are expressed as annual percentages of CAPEX: 2.5% for SLBs and 2.0% for new batteries, reflecting the added complexity of managing heterogeneous second-life packs. The incentive rate represents a generic upfront capital cost reduction used for analytical purposes and is not linked to any specific policy. Residual value reflects end-of-life salvage potential: 20% for new batteries, assuming second-life repurposing, and 5% for SLBs, limited to material recovery.

A marginal emission factor of 0.291 $\mathrm{kgCO_2e/kWh}$ represents the average marginal emission intensity of the California grid. The embodied emissions of SLBs account only for testing and refurbishment, and are significantly lower than those of new batteries, which include the full manufacturing burden. Transport emissions, as well as embodied emissions from BOS and PCS components, are assumed to be identical for both systems.

Sensitivity analysis explores the parameter ranges shown in the table to quantify uncertainty bounds and identify key drivers of system viability.

4.2. SLB vs. New Battery Counterfactual Analysis

Figure 4 presents the comparative operational performance of both systems over the 10-year project lifetime under identical dispatch conditions. Figure 4a,b illustrate the capacity and SOH trajectories. The second-life battery capacity declines from 362 kWh to approximately 303 kWh by year 10, corresponding to 67% SOH relative to its rated full capacity. The new battery capacity declines from 362 kWh to approximately 285 kWh, maintaining 79% SOH. Although both systems begin with identical usable capacity, the new battery experiences greater absolute capacity loss due to the rapid initial fade followed by linear degradation, as captured in Equation (9). In contrast, the second-life battery follows a steadier linear decline, having already undergone the early-life accelerated degradation phase during its first-life automotive application.

Figure 4c shows that annual delivered energy decreases as capacity degrades. The second-life battery delivers more annual energy than the new battery during years 2–10, due to its higher remaining capacity. In year 1, when both systems have identical capacity, the new battery delivers slightly more energy due to its higher round-trip efficiency.

Figure 4d illustrates annual bill savings, showing that new systems generate approximately \$21,213–\$19,515 per year over the 10-year period, while SLB systems yield \$20,599–\$19,424 annually. Although operating with higher usable capacity in years 2–10, SLB generate slightly lower annual savings than new batteries throughout the project due to lower round-trip efficiency, which diminishes both energy arbitrage value and demand charge reduction potential. Table 3 summarizes the comparative economic performance. A lower upfront investment allows SLB systems to achieve superior project-level economics, despite lower operational revenue. With a 23.3% lower initial investment, SLB systems deliver an NPV of $45,358 compared to $30,401 for new systems, representing a 49.2% improvement. The IRR reaches 14.4% for SLB systems versus 10.2% for new batteries, corresponding to a 41.2% relative increase. The operational levelized cost is $183/MWh for SLB systems, compared to $212/MWh for new systems, representing a 13.7% reduction. These results demonstrate that the capital cost advantage of repurposed batteries outweighs the operational revenue penalty associated with lower efficiency.

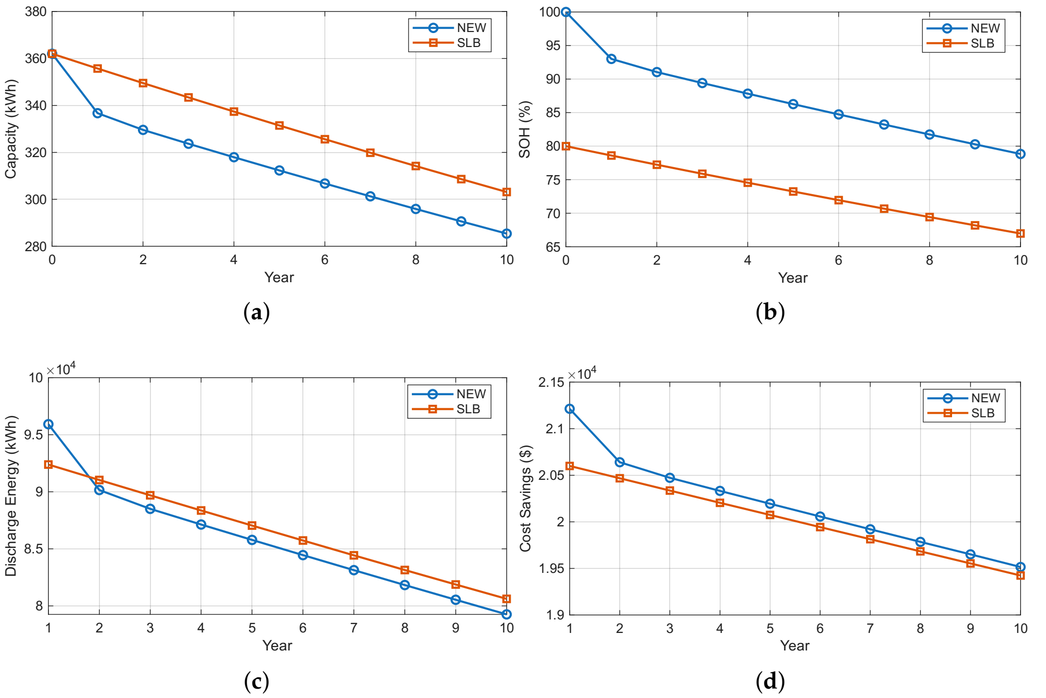


Figure 4. Annual operational performance: (**a**) Capacity trajectory. (**b**) SOH trajectory. (**c**) Delivered energy. (**d**) Cost savings (Revenue).

Table 3. Economic performance comparison between new and SLB systems under rule-based dispatch over 10-year project lifetime.

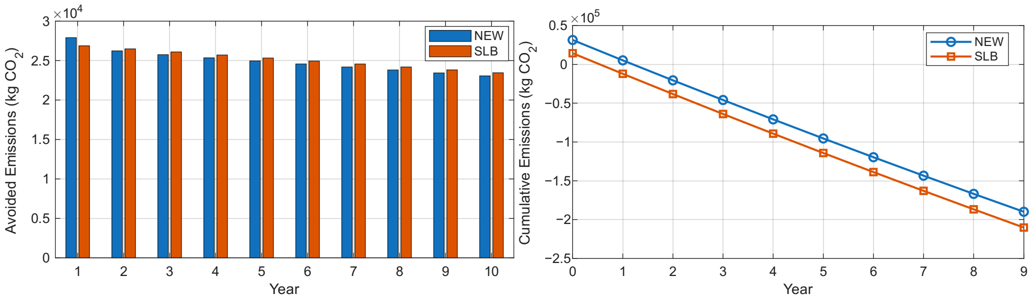
Metric	New Battery	Second-Life Battery	Advantage
Initial Investment ($)	116,745	89,595	−23.3%
NPV @ 10 years ($)	30,401	45,358	+49.2%
IRR (%)	10.2	14.4	+41.9%
$LCOS_{op}$ ($/MWh)	212	183	−13.8%

Table 4 presents the comparative environmental performance of both systems. Embodied emissions for SLB systems are 41.2% lower than those of new systems, as repurposing avoids the manufacturing burden associated with new cell production. The carbon intensity of delivered energy is −0.25 $kgCO_2e$/kWh for SLB and −0.23 $kgCO_2e$/kWh for new systems. The more negative value for SLB systems indicates that, despite lower efficiency, substantially reduced embodied emissions enable an 8.7% improvement in carbon intensity per kilowatt-hour delivered.

Figure 5a shows that annual avoided emissions range from approximately 27,000 $kgCO_2e$ in year 1 to 23,000 $kgCO_2e$ in year 10 for both systems. SLB systems achieve slightly higher avoided emissions than new systems in years 2–10 due to greater energy throughput, except in year 1, when the higher efficiency of new systems compensates for equal initial capacity. Cumulative net emissions in Figure 5b indicate carbon payback within the first year for both systems, with SLB systems exhibiting slightly better cumulative performance due to lower embodied emissions.

Table 4. Environmental performance comparison between new and SLB systems under rule-based dispatch over 10-year project lifetime.

Metric	New Battery	Second-Life Battery	Advantage
Battery embodied emissions ($kgCO_2e$)	43,440	25,340	−41.2%
Transport emissions ($kgCO_2e$)	1810	1810	-
BOS embodied emissions ($kgCO_2e$)	11,584	11,584	-
PCS embodied emissions ($kgCO_2e$)	2534	2534	-
Carbon intensity ($kgCO_2e/kWh$)	−0.23	−0.25	−8.0%



(**a**) (**b**)

Figure 5. Annual GHG emissions: (**a**) Avoided emissions. (**b**) Cumulative emissions.

This comparison highlights that the lower acquisition cost and reduced embodied emissions of SLBESS outweigh its technical performance limitations, resulting in superior economic returns and competitive environmental outcomes for commercial building applications.

4.3. Sensitivity Analysis

4.3.1. Impact of Control Strategy

Advanced control strategies can enhance SLBESS economic performance by optimizing dispatch relative to TOU tariff structures and PV generation patterns. Table 5 compares the performance of rule-based and MPC strategies for SLBESS over the 10-year project lifetime. Under MPC, SLBESS achieves an NPV of $56,914, compared to $45,358 under rule-based control, representing a 25.5% improvement. The IRR increases from 14.4% to 16.6%, while $LCOS_{op}$ decreases from $183/MWh to $173/MWh. The carbon intensity becomes less negative (from −0.25 to −0.23 $kgCO_2e/kWh$), indicating slightly lower net carbon reduction per kWh delivered, as MPC's increased throughput generates proportionally more charging emissions. These results demonstrate that advanced control strategies can extract additional value from SLBESS through improved forecasting and dispatch optimization.

Table 5. Performance comparison with different control strategies.

Metric	Rule-Based	MPC	Advantage
NPV @ 10 years ($)	45,358	56,914	+25.5%
IRR (%)	14.4	16.5	+14.6%
$LCOS_{op}$ ($/MWh)	183	173	−5.5%
Carbon intensity ($kgCO_2e/kWh$)	−0.25	−0.23	+8.0%

4.3.2. Key Parameter Sensitivities

Figure 6 presents tornado diagrams quantifying the sensitivity of key performance metrics, including NPV, $LCOS_{op}$, and carbon intensity, to variations in technical, economic, and environmental parameters for SLBESS. Each parameter is varied across the range defined in Table 2, while all other variables are held at baseline values.

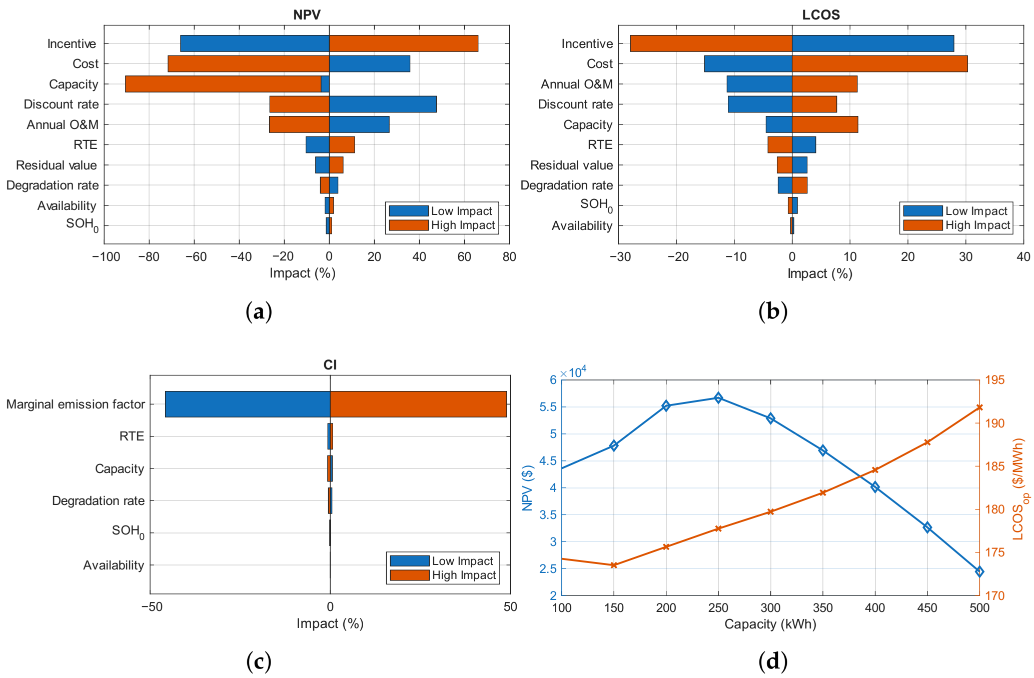


Figure 6. Sensitivity analysis: (**a**) tornado diagram of NPV. (**b**) tornado diagram of $LCOS_{op}$. (**c**) tornado diagram of carbon intensity. (**d**) economic metrics with different capacities.

NPV sensitivity: The incentive rate is the dominant factor, producing NPV variations from −66% to +66% across the 0–50% range, followed by the core cost ($50–$200/kWh), which results in an NPV variation from 36% to −71%. Capacity exhibits a nonlinear impact, as illustrated in Figure 6d: NPV peaks at intermediate capacities (250 kWh), where system size balances revenue potential against capital expenditures. Undersized systems fail to capture available PV and demand charge reduction opportunities, while oversized systems incur excessive capital expenditures without proportional revenue gains, due to limited building load and solar generation. This finding underscores the importance of sizing storage to the local PV-to-load ratio. Discount rate, O&M, and round-trip efficiency exhibit moderate influence. Degradation rate, initial SOH, residual value, and availability demonstrate minimal sensitivity ($<\pm10\%$), suggesting that moderate variations in battery condition do not substantially affect project viability.

$LCOS_{op}$ sensitivity: Incentive rate and core cost remain the most influential factors, while round-trip efficiency and O&M costs gain relative importance due to their direct effect on energy delivered.

Carbon intensity: The marginal emission factor overwhelmingly dominates, with a range of 0.10–0.49 $kgCO_2e/kWh$ yielding carbon intensity values from −0.38 to −0.15 $kgCO_2e/kWh$, representing a 95% swing. This highlights that the climate value of SLBESS is highly dependent on grid carbon intensity, with greater benefits achieved in fossil-fuel-dominant grids. Round-trip efficiency ranks second, while capacity and degradation rates exhibit minimal influence, as both embodied and avoided emissions scale proportionally with throughput.

The sensitivity analysis reveals distinct parameter hierarchies across economic and environmental performance dimensions. Economic viability is primarily driven by financial parameters, including incentives, capital cost, and discount rate, while environmental outcomes are dominated by grid emission factors and round-trip efficiency. Technical parameters frequently cited as barriers to second-life adoption, such as degradation rate, SOH, and availability, exhibit low sensitivity across all metrics, suggesting that concerns about battery condition may be overstated relative to economic and policy factors. The critical influence of the incentive rate on both NPV and $LCOS_{op}$ highlights the enabling role of policy support, while the dominance of the marginal emission factor underscores the importance of region-specific environmental assessments.

4.4. Discussion

This dispatch-aware assessment, based on one year of high-resolution operational data, demonstrates that SLBESS can deliver superior economic and environmental performance in commercial buildings, despite reduced technical specifications. Counterfactual analysis reveals that acquisition cost and policy incentives are the primary drivers of system viability. Sensitivity results show that commonly cited barriers to second-life adoption, including degradation rate, SOH, and availability, exhibit minimal impact within realistic ranges. Specifically, the low sensitivity of $LCOS_{op}$ and NPV to the degradation rate suggests that the economic impact of potential non-linear degradation is likely minimal over the project's 10-year horizon, as financial returns are dominated by early-year performance. System sizing, grid carbon intensity, and control strategy emerge as more critical to performance than battery condition. These findings suggest that SLBESS deployment in commercial buildings is economically and environmentally viable under supportive policy and market conditions. Acquisition cost, incentive availability, and grid carbon intensity are the critical enablers. Although the study on a single commercial building in San Diego gives location-specific results of NPV, IRR and carbon intensity, the comparative advantage of SLBBESS over new batteries and the sensitivity analysis trends are expected to hold in regions with similar conditions. In addition, the proposed framework is portable and can be applied to other sites by substituting location-specific inputs.

Several limitations should be acknowledged: (1) This study is based on a single commercial building in San Diego, which may not represent the diversity of climates, building types, or tariff structures. (2) Battery degradation was modeled using empirical cycling data rather than physics-based electrochemical models or advanced machine learning approaches, introducing uncertainty in long-term performance projections, particularly when extrapolating across diverse operational conditions and heterogeneous battery populations. (3) LCA results depend on region-specific emission factors and assumptions regarding second-life burden allocation. (4) The economic analysis assumes stable tariffs and incentive programs, both of which are subject to policy changes. (5) One year of operational data is repeated across the project lifetime, not accounting for year-to-year variations in load profiles or tariff structures.

Future work should extend this study in several directions: (1) Multi-site validation across diverse climates, building types, and utility rate structures to improve generalizability; (2) Integration of physics-based and data-driven degradation models to improve lifetime prediction accuracy. Recent AI-enabled frameworks address data scarcity, heterogeneity, and cross-condition prediction challenges for battery reuse and recycling [23]. Integrating such advanced models could further improve long-term performance projections in future work. (3) Prospective analyses that incorporate dynamic electricity prices, evolving grid emission factors, and projected technology cost trajectories; (4) Assessment of hybrid revenue models that combine bill savings with grid services such as frequency regulation, demand response, and capacity markets; (5) Evaluation of regulatory pathways, safety certification, and standardization frameworks to accelerate commercial-scale deployment.

5. Conclusions

This study evaluated the techno-economic and environmental viability of second-life battery energy storage systems in commercial buildings, using one year of high-resolution operational data from a case study in San Diego, California. A comparative assessment against equivalent new battery systems under identical operating conditions provides field-validated insights into deployment viability.

SLBESS demonstrates superior economic performance despite lower technical specifications, achieving 49% higher NPV, 42% higher IRR, and 14% lower operational levelized cost of storage over a 10-year project lifetime. The lower acquisition cost of SLBESS outweighs efficiency penalties, demonstrating that the economic advantages of repurposing can offset performance limitations. Environmentally, SLBESS reduces embodied emissions by 41% and achieves 9% lower carbon intensity, with carbon payback occurring within the first year.

Sensitivity analysis shows that economic viability depends primarily on financial parameters, such as incentive rate and acquisition cost, while environmental outcomes are dominated by grid emission factors. Parameters frequently cited as barriers to second-life adoption, such as degradation rate, SOH, and availability, exhibit minimal sensitivity, suggesting that technical concerns may be overstated relative to economic and policy drivers. This hierarchy of parameters offers an actionable guide: policymakers should focus on financial incentives to accelerate deployment, while developers should target regions with carbon-intensive grids to maximize environmental benefits. The minimal sensitivity to battery degradation suggests that design standards can be relaxed, reducing repurposing costs.

These findings demonstrate that second-life batteries can provide cost-effective, low-carbon energy storage in commercial buildings, with acquisition cost and grid carbon intensity emerging as critical enablers under favorable policy conditions. The dispatch-aware framework developed here offers actionable insights for stakeholders considering second-life battery deployment.

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