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Technical and Economic Evaluation of Battery Storage Arbitrage in Turkey's Electricity Market: Integrating Battery Degradation and Circular Supply-Chain Constraints

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Abstract

The accelerating transition to electric mobility is generating a growing volume of retired EV batteries with considerable residual capacity. These batteries offer a strategic resource for more sustainable stationary BESS deployment through second-life valorization. However, extant techno-economic frameworks frequently rely on idealized assumptions, overlooking degradation trajectories and circular supply-chain constraints that are essential to a genuinely sustainable assessment. This study is an extension of a baseline model that demonstrates the feasibility of BESS for arbitrage in the Turkish electricity market, which is subject to fluctuations. The model is expanded to incorporate a more sustainability-conscious evaluation of the long-term viability of storage. This model captures pronounced seasonal price volatility to generate approximately $89,179 in augmented annual revenue. The study presents a comprehensive evaluation of new (first-life) and repurposed (second-life) EV battery systems. The incorporation of real-world degradation and supply-chain limits reveals that operational constraints significantly erode theoretical grid-connected profitability (reducing baseline Net Present Value (NPV) by up to 78%), particularly for the first-life system. Nevertheless, second-life BESS (SL-BESS) demonstrates superior financial performance. Despite exhibiting a lower round-trip efficiency (a constant 80%, versus the first-life system's initial 85%), requiring higher maintenance costs, and offering a shorter lifespan (7 years), the SL-BESS achieves an NPV of $81,219 and an Internal Rate of Return (IRR) of 22.8%, outperforming the first-life system (NPV: $66,490; IRR: 14.8%). This performance discrepancy is attributable to a 40% reduction in initial capital expenditure, which subsequently leads to an estimated 11.3% reduction in the Normalized Cost-to-Revenue Ratio (CRR, serving as a dimensionless financial proxy for LCOS). Sensitivity analysis highlights the significant influence of battery chemistry; substituting the baseline Lithium Iron Phosphate (LFP) cells with nickel-based chemistries accelerates capacity fade, consistent with well-documented chemistry-dependent degradation patterns (e.g., ~4000–5000 cycles for NMC versus 5000–8000 cycles for LFP before reaching 80% remaining capacity, with NCA assumed equivalent to NMC). This substitution reduces the project NPV by $11,000 to $19,000 in the model. Finally, the study highlights that widespread commercialization of SL-BESS requires overcoming information asymmetry through traceability mechanisms (e.g.,

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Battery Passports) and transitioning to service-oriented models (e.g., Battery-as-a-Service). These findings indicate that adopting circular business models is not only environmentally beneficial but also financially necessary for second-life storage to scale.

Keywords: battery energy storage systems; second-life EV batteries; second-life repurposing; electricity price arbitrage; battery degradation; circular economy; circular supply chain; techno-economic analysis; Turkish electricity market; sustainability

1. Introduction

Global efforts to decarbonize energy systems have driven a considerable increase in the use of variable renewable energy (VRE) sources, principally wind and solar photovoltaic (PV) generation [1,2]. Although essential for decarbonization, the inherent intermittency and non-dispatchability of VRE create significant challenges for power system stability and the effective functioning of energy markets, including increased price volatility, grid congestion, and difficulties in balancing supply and demand [3,4]. Energy storage systems (ESSs) address these challenges as a flexibility resource by decoupling energy production from consumption, thus enabling temporal arbitrage, frequency regulation, and capacity firming services [5,6].

Among storage technologies, lithium-ion BESS technology has seen significant cost reductions and performance improvements over the last decade, positioning it as the leading candidate for short- to medium-duration storage applications [7,8]. Technological advances have further supported their shift from niche applications to mainstream grid assets, particularly for energy time-shifting (arbitrage) [9,10]. The fundamental economic motivation behind merchant storage operations is the strategic exploitation of temporal variations in electricity prices, involving procuring (or self-generating) electricity during low-price periods and selling it during high-price periods. The financial viability of such strategies depends closely on the magnitude, frequency, and predictability of price spreads in wholesale electricity markets [11]. Yet BESS economic performance over its operational lifetime is far from static, shaped materially by battery degradation, state-of-health (SOH) evolution, and, for repurposed systems, the constraints of reverse logistics and circular supply-chain dynamics [12,13].

A substantial body of recent literature has examined the arbitrage value of BESS in liberalized markets. Studies of European and North American markets, including the German EPEX Spot and the Pennsylvania–New Jersey–Maryland (PJM) Interconnection, show that while pure energy arbitrage can be economically challenging under historically low price spreads, stacking multiple revenue streams—such as combining arbitrage with frequency response—can significantly improve project economics [14,15]. The impact of rising VRE shares is also multifaceted: it tends to depress average wholesale prices through the so-called merit order effect, while simultaneously increasing short-term price volatility and the frequency of extreme price events, which can open up more lucrative but riskier arbitrage opportunities [16,17].

The Turkish electricity market, administered by EPİAŞ, offers a particularly instructive case. Strong demand growth, a diversifying generation mix with growing VRE capacity, and heavy reliance on imported natural gas together contribute to significant price volatility [18,19]. Recent analyses by Peker and Sivrikaya [20] and Erdin and Ozkaya [21] point to the market's vulnerability to seasonal demand fluctuations (particularly high winter loads) and intra-day price spikes, suggesting a potentially favorable environment for storage arbitrage. Dedicated techno-economic assessments of BESSs for merchant arbitrage in Turkey nonetheless remain scarce: existing studies tend to focus on storage paired with

specific renewable energy sources [22] or on grid-scale storage for system services [23], overlooking storage as a value-adding asset for conventional or must-run generation within the current market structure. None of these studies has jointly examined how material degradation, second-life battery repurposing, and circular supply-chain constraints affect the long-term economic viability of such arbitrage strategies.

The round-trip efficiency of a battery system is defined as the percentage of the energy stored (charged) in the system that remains available for use once it has been retrieved (discharged). The index quantifies the proportion of energy input to the system that is recovered during the discharge process, with no energy loss. A plethora of studies have been conducted on the subject of round-trip efficiency. Whilst certain studies have assumed an efficiency value of 80% [24–26], other studies have assumed an efficiency value of 85% [27]. For the purposes of this study, round-trip efficiency has been set at 80% and 85%.

BESSs have moved from a niche balancing technology to a central pillar of modern power systems. According to the International Energy Agency, global battery storage capacity additions reached 108 GW in 2025 alone—roughly 40% more than in 2024 and eleven times the installed base of 2021—with LFP chemistries now accounting for about 90% of new deployments because of their tolerance for frequent cycling [28]. Around 80% of this new capacity was utility-scale, and the average contracted duration of new projects rose from roughly two hours in 2023 to three hours in 2025, signaling a structural shift from pure ancillary-service provision toward energy-shifting and arbitrage-oriented operation [29]. This scale-up, however, is occurring against a backdrop of tightening upstream conditions: global battery demand grew by more than 35% in 2025 to surpass 1.5 TWh, yet investment in critical minerals fell by 9%—the first substantial decline since 2020—with lithium-, nickel-, and cobalt-focused investment contracting sharply amid price weakness and policy uncertainty [30]. The juxtaposition of explosive deployment growth with a fragile and volatile upstream supply chain is precisely the tension that motivates an integrated technical–economic evaluation of storage arbitrage.

Energy arbitrage is a fundamental revenue stream for BESSs, yet recent studies demonstrate that its assessment is inextricably linked to the battery's health status. Thermal management plays a critical role in mitigating degradation and ensuring that batteries can be used for extended periods of time at high-performance levels, and recent comprehensive reviews have addressed advances in phase change materials, bio-inspired structures, and the growing role of artificial intelligence in thermal modeling, optimization, and intelligent control for battery thermal management [31]. As posited by Grimaldi et al., the failure to account for degradation in arbitrage models can result in an exaggerated estimation of profit [32]. Humiston et al. conducted a study in which they compared Linear-Calendar, Energy-Throughput, and Cycle-Based degradation models using ERCOT data [33]. Their findings demonstrated that the selection of a particular model had the potential to transform a profitable strategy into a 68.9% cumulative loss. This suggests that the efficacy of a degradation model, and not merely its incorporation, is a critical factor in determining valuation. In their seminal work, Holtorf and Shin pioneered a novel approach to address the timescale mismatch between market and aging dynamics [34]. Utilizing an approximate dynamic programming framework, they achieved remarkable gains, ranging from 10 to 25% over standard heuristics. Their findings underscore the critical role of physically grounded degradation models in ensuring accurate lifetime valuation.

A separate body of literature addresses battery-material circularity. Chacana-Olivares et al. identify disassembly as the primary impediment to effective recycling, a problem that is compounded by the diversification of chemical processes and the volatility of commodity prices [35]. Roslan et al. posit that reliable estimation of the State of Health is pivotal to the viability of second-life repurposing [36]. As stated in the World Economic Forum, value-

chain transparency gaps and uncertain recycling economics are cited as central barriers [37]. Furthermore, the IEA reports that storage now accounts for over 15% of lithium-ion demand amid falling critical-mineral investment [30].

These bodies of literature rarely intersect: arbitrage studies treat battery replacement as exogenous, while circularity studies overlook how operating strategy shapes the degradation trajectory that feeds end-of-life outcomes. Given the tight coupling of storage deployment and mineral-supply stress [28,30], and that degradation-model choice alone determines arbitrage profitability [33], this study integrates degradation-aware arbitrage optimization with circular supply-chain constraints (mineral price volatility, second-life value, recycling economics) to capture their combined effect on optimal storage operation.

This study addresses that gap by providing a transparent, preliminary assessment of the price-arbitrage potential of a BESS coupled with a constant-output power plant in Turkey. Using actual, recent hourly PTF data from 2024, the analysis applies a simplified, implementable daily arbitrage strategy to establish baseline economic viability. It first quantifies the additional annual revenue achievable through basic temporal arbitrage and then evaluates key financial indicators (NPV, IRR, PBP) under conservative assumptions. Beyond this idealized financial assessment, the study also examines, using parametric representations, how real-world material degradation and circular supply-chain constraints affect the long-term economic viability of BESS arbitrage. By conducting a comparative analysis of first-life and second-life systems, the study reveals that these operational constraints can substantially erode idealized project profitability. Yet, counterintuitively, it also demonstrates that repurposed second-life batteries can achieve superior financial performance compared to new systems. Finally, it discusses the sensitivity of the results to market dynamics and operational strategies. By linking idealized techno-economic modeling with this operational realism, the study establishes a foundational reference point for future, more complex optimization strategies, while contributing to the understanding of storage economics in emerging and volatile electricity markets such as Turkey's.

2. Materials and Method

This study presents a combined technical and economic assessment of battery-based electricity storage within the Turkish electricity market. This initiative marks the inaugural phase of a comprehensive research endeavor focused on optimizing energy storage systems amid electricity price volatility. The primary objective of this study is to evaluate the potential of short-term electricity storage to enhance the revenue stream of a power generation facility by exploiting temporal price arbitrage. In the context of real-world implementation of the model utilized in the present study, it is imperative to make predictions regarding future electricity prices and the amount of electricity generated from renewable energy sources. The following schematic diagram is provided for illustrative purposes (Figure 1).

The analysis was conducted for a hypothetical power plant with a constant generation capacity of 1 MWh per hour, corresponding to an installed capacity of 1 MW, and operating continuously. The proposed strategy differs from the traditional approach of feeding all generated electricity directly into the grid. Instead, this strategy uses a BESS to store electricity during low-price periods and sell it back to the grid during high-price periods. The most important assumption for this study is that sufficient battery storage capacity is always available (i.e., the system is operated under an idealized 100% availability assumption; this premise is critically revisited against real-world constraints in Section 4). The constant-power assumption is intended to eliminate the effects of fluctuations in renewable energy sources. The aim here is to demonstrate, using real-world data, how crucial it is to store electricity at the right time and sell it at the right time. We calculated each hour separately. In this particular context, it was hypothesized that each hour was characterized by either

a process of charging or discharging. The effectiveness of this strategy is evaluated by comparing system performance and economic outcomes under two scenarios:

- The sale of electricity is conducted without the utilization of storage facilities.
- The sale of electricity is supported by battery storage.

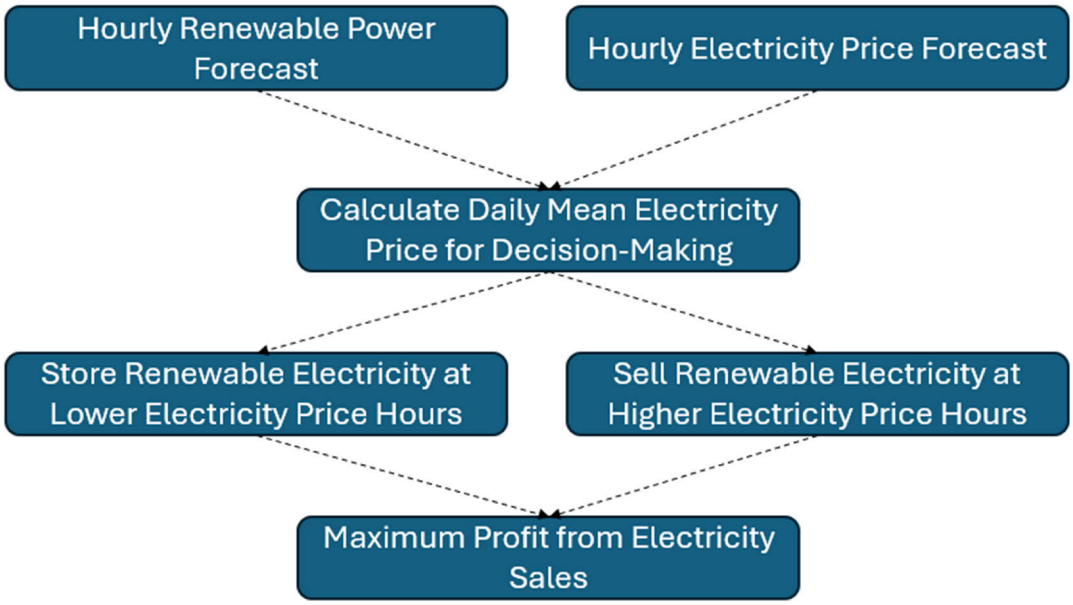


Figure 1. Schematic of storage and direct sale decision framework for renewable power generation.

The hourly electricity price data, represented by the PTF, were obtained from EPİAŞ, the Turkish electricity market operator. PTF data are widely used in market-based energy studies because they are widely regarded as reflecting real-time supply-and-demand balances and market volatility.

To capture seasonal and intraday price variability whilst maintaining computational efficiency, one representative week from each of four months—January, April, July and October 2024—was selected. For each month, the week most closely resembling the period's mean was selected. Consequently, analyses used the weekly data that best represented that period. The months under consideration correspond to winter, spring, summer, and autumn, respectively, and are hypothesized to adequately represent annual price dynamics. Each selected week is considered representative of the corresponding three-month period.

The hourly PTF values demonstrate significant daily, weekly, and seasonal fluctuations, which form the basis for the storage arbitrage strategy. As illustrated in Figures 2 and 3, the hourly PTF profiles for the selected representative periods are presented.

In January (Figure 2a), PTF values generally remained at higher levels, exhibiting significant hourly fluctuations. This indicates that increased demand and supply constraints during the winter period have heightened price volatility. In April (Figure 2b), average PTF levels were lower, but sharp price drops at certain times were particularly noteworthy. This trend suggests that increased renewable energy production and reduced demand during the seasonal transition are putting downward pressure on prices.

The model developed as part of this study operates under the assumption that a renewable energy plant generates 1 MW of power per hour on a continuous basis, with this electricity being either fed directly into the grid for sale or stored in a battery. It is further assumed that the stored electricity is sold at a price corresponding to that day's maximum PTF value. The calculations were performed under the assumption that the battery capacity is sufficient. Decisions are arrived at through a process of comparison between hourly PTF data and the day's average PTF value. Within this framework, if the hourly PTF value is

below the daily average PTF value, the storage option is activated; if it is above, the direct sale to the grid option is activated.

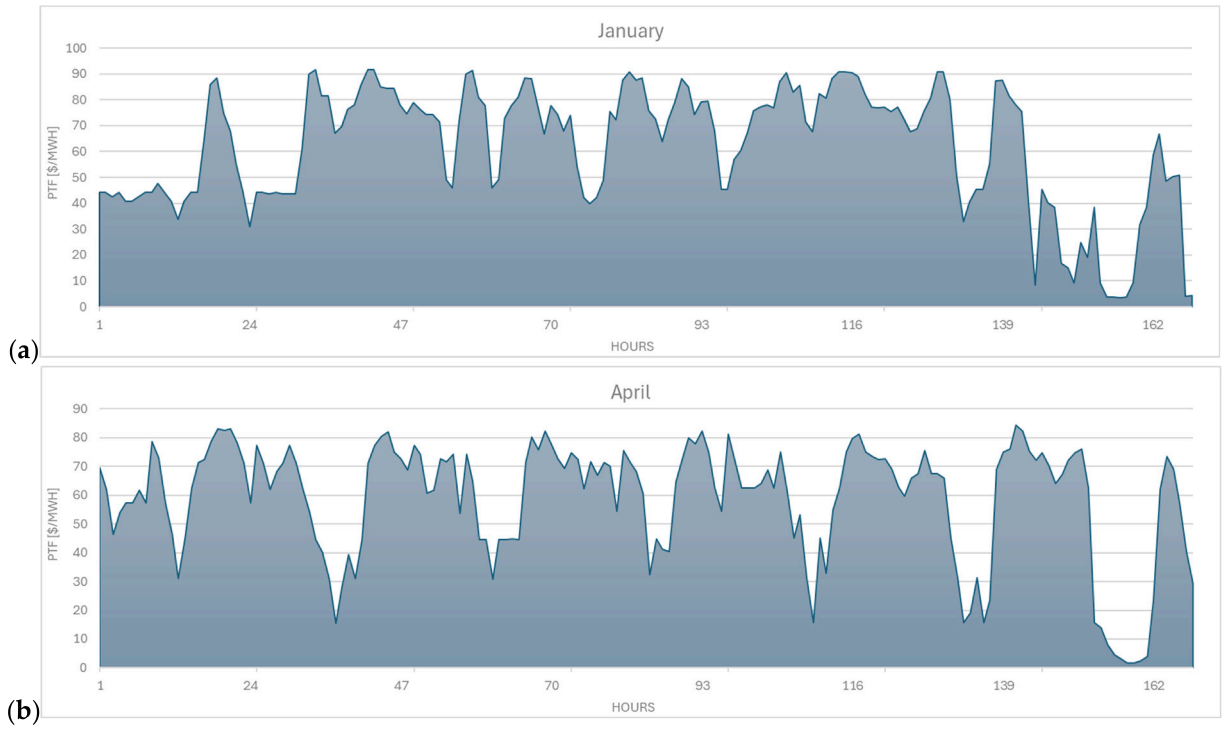


Figure 2. Hourly PTF values for January (**a**) and April (**b**).

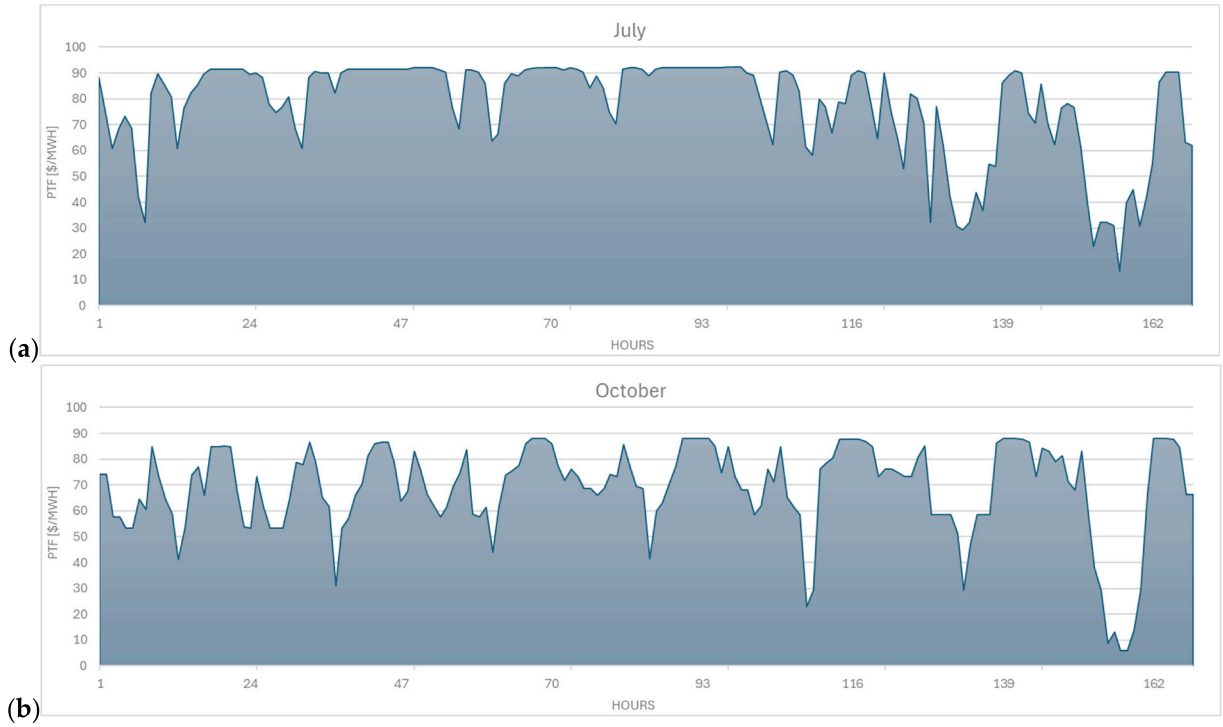


Figure 3. Hourly PTF values for July (**a**) and October (**b**).

The hourly operating decision (S_t) is made by comparing PTF_t at time t with the daily average PTF_{ave}:

$$S_t = \begin{Bmatrix} 0,\ if\ PTF_t < PTF_{ave}\ (Storage\ Mode) \\ 1,\ if\ PTF_t < PTF_{ave}\ (Direct\ to\ Utility\ Sales\ Mode) \end{Bmatrix} \quad (1)$$

The hourly revenue generated (R_{gen}) based on the storage and grid-sale modes, the amount of renewable electricity (P_{el}), and the battery storage round-trip efficiency (η_{bat}) are calculated using the following formula.

$$R_{gen} = \begin{Bmatrix} S_t = 0,\ (1 - S_t) \times P_{el} \times PTF_{max} \times \eta_{bat}\ (Storage\ Mode) \\ S_t = 1,\ S_t \times P_{el} \times PTF_t\ (Direct\ to\ Utility\ Sales\ Mode) \end{Bmatrix} \quad (2)$$

In July (Figure 3a), PTF values generally remained high and stable within a narrow range. Increased summer cooling demand kept prices high for most of the day, while a few sharp declines indicated short-term supply–demand imbalances. In October (Figure 3b), prices were more volatile, with significant declines during certain hours. Seasonal declines in demand and variability in renewable production increased PTF volatility.

The operational rules are defined as follows:

- The process of electricity storage occurs during periods in which PTF falls below the daily average price.
- The stored electricity is then discharged and sold to the grid during hours when the PTF exceeds the daily average price.

This approach constitutes a simplified yet robust arbitrage strategy that does not require predictive forecasting, rendering it suitable for practical implementation and preliminary feasibility assessment.

It is hypothesized that the battery system operates at an average round-trip efficiency of 85%, accounting for losses during both charging and discharging. Storage and discharge decisions are evaluated daily, and system operation is assumed to be unconstrained by grid access or regulatory limitations.

The economic performance of the energy storage system is evaluated by comparing the additional revenue from price arbitrage with the battery system's investment and operational costs. All calculations are conducted on a USD basis to ensure consistency and comparability.

The following standard financial indicators are utilized:

- NPV;
- IRR;
- Discounted Payback Period (DPP).

These indicators facilitate a comprehensive assessment of profitability, investment attractiveness, and capital recovery time. Discounted cash flow analysis is applied over the project lifetime.

To facilitate a systematic evaluation, several simplifying assumptions are adopted:

- It is imperative to note that all financial calculations are conducted in US dollars.
- The discount rate (interest rate) is assumed to be 7.75%.
- The preliminary financial outlay required for the acquisition of the battery energy storage system is $250,000.
- The economic lifetime of the storage system is assumed to be 10 years.
- The estimated annual operation and maintenance (O&M) costs are $10,000, with an annual escalation rate of 0.5%.

- The annual escalation rate of electricity prices is estimated to be 0.5%.
- It is hypothesized that each selected representative week is representative of the average behavior of the corresponding three-month period.

These assumptions are consistent with commonly reported values in the literature and are intended to provide a conservative yet realistic basis for economic evaluation.

Within the specified framework, calculations are conducted for both storage-enabled and non-storage scenarios. The discrepancy in annual electricity sales revenue between these cases signifies the gross benefit of energy storage. In contrast, the net economic benefit is determined by accounting for capital and operational expenditures.

This methodological approach facilitates a transparent assessment of the technical feasibility and economic viability of battery energy storage systems operating under Turkey's current electricity market conditions. However, this baseline framework assumes idealized operating conditions and does not account for battery degradation or supply-chain limitations that may affect long-term performance. To address this gap, Section 4 introduces a complementary methodological framework for assessing battery degradation and circular supply-chain constraints, thereby extending the feasibility analysis over the storage system's operational lifetime.

3. Baseline Results and Discussion

In accordance with the methodological framework and assumptions delineated in the preceding section, the impact of electricity storage on power plant revenues was analyzed for a generation facility characterized by a constant output of 1 MWh per hour. The analysis was conducted for scenarios with and without battery energy storage using representative weekly price data from January, April, July, and October.

A daily arbitrage strategy was implemented, whereby electricity generated during hours with PTF values below the estimated daily average was stored and subsequently discharged during peak-price hours. As shown in Figures 4 and 5, the hourly electricity revenues resulting from the operational scenarios under investigation are illustrated for selected representative periods.

Figure 4 compares the hourly electricity revenues with and without energy storage for January and April. In both periods, the battery energy storage system (BESS)-supported scenario shifts a portion of the generated electricity from low-price hours to high-price hours, thereby increasing revenue from the same amount of electricity generated. This result directly reflects the BESS's temporal arbitrage function, which exploits intraday variability in electricity prices.

Figure 5 compares hourly electricity revenues with and without storage in July (Figure 5a) and October (Figure 5b). When storage is not used in July (Figure 5a), revenues are distributed over a wider range, with significant drops observed during certain hours. In contrast, integrating storage concentrates revenues at higher levels, reducing volatility and providing a more stable revenue profile throughout the day. This shows that storage is an effective arbitrage tool under market conditions with exploitable intraday price spreads. In October (Figure 5b), revenues remained at moderate levels without storage but declined sharply at times. Using storage largely eliminated these low-revenue periods, consolidating revenue within a narrower range and providing protection against price volatility.

The findings clearly indicate that incorporating energy storage has a substantial impact on the revenue profile. In the absence of storage, revenue is directly proportional to the hourly PTF pattern, resulting in limited income during off-peak hours and exposing the producer to market volatility. Conversely, during periods of ample storage capacity, revenue accrues disproportionately to periods of high demand, effectively decoupling generation from real-time market prices.

This outcome underscores the pivotal economic role of energy storage as a temporal value-shifting mechanism, rather than a conventional energy-generation asset. It is evident that even with a simplified operational strategy, substantial revenue gains are achieved, thereby confirming the sensitivity of electricity market revenues to intraday price spreads.

A comparison of scenarios with and without storage indicates a marked increase in daily and annual revenues when storage is deployed. The representative daily analyses demonstrate that the strategic storage of electricity during low-price hours and its subsequent sale during peak periods consistently generate higher income across all selected seasons.

As illustrated by Figure 6, there is a clear monthly variation in the additional income obtained from electricity storage over the course of a year. A clear seasonal pattern is evident. The period of maximum storage-related additional income is observed to occur during the winter months, with a peak in January (approximately \$9800) and a sustained high level of income through February to April. This behavior is consistent with increased electricity demand during periods of lower temperatures, driven primarily by heating needs and higher overall system load, which in turn elevate market-clearing prices.

As of May, a marked decline in income became evident, with revenues reaching a nadir of approximately \$5000 in July. This mid-year minimum is indicative of reduced demand and comparatively flatter intraday price spreads during the summer months, which, in turn, limit opportunities for high-value electricity sales. Despite a modest recovery from August to October, income levels remain significantly below winter levels.

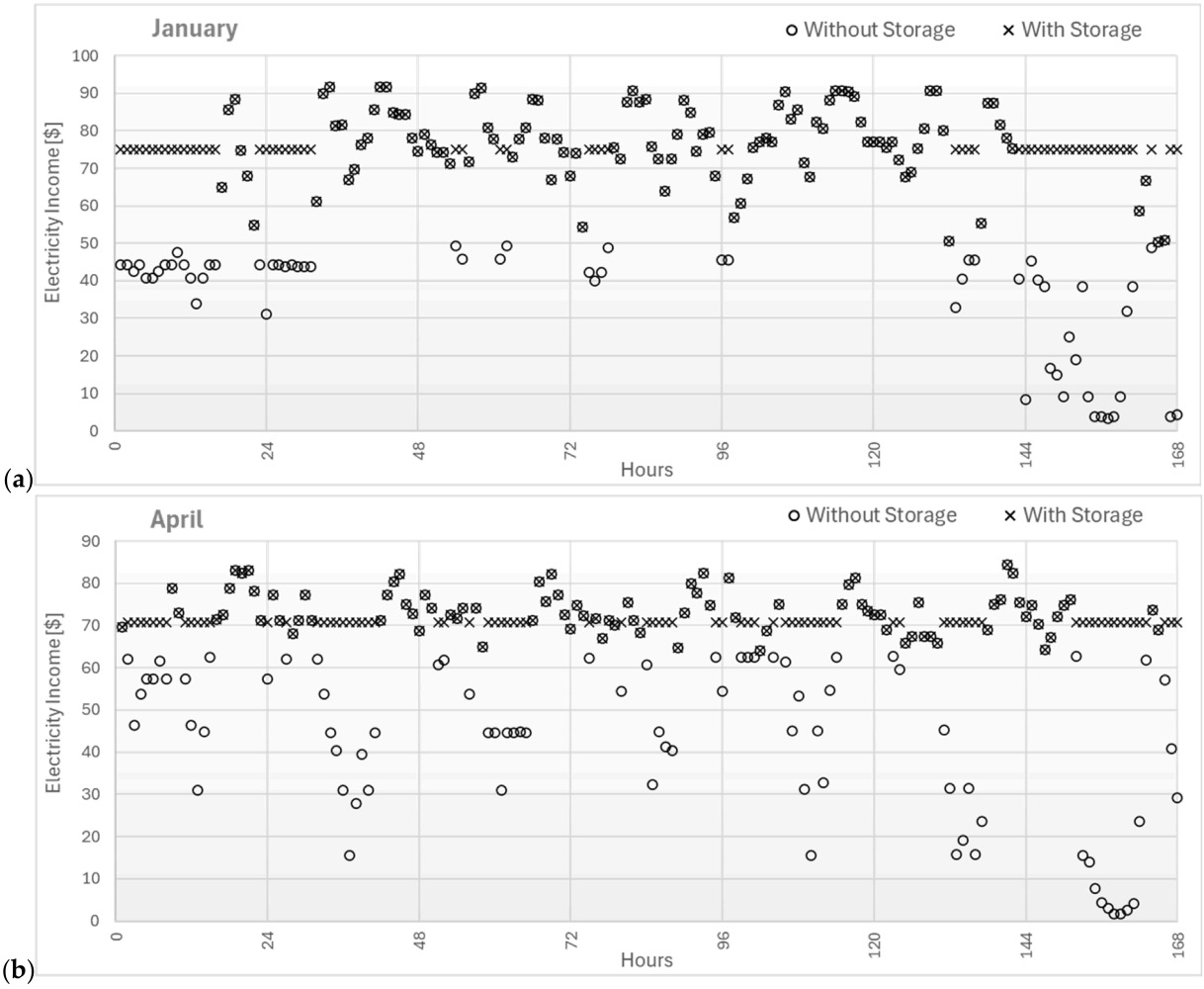


Figure 4. Hourly electricity income for January (**a**) and April (**b**).

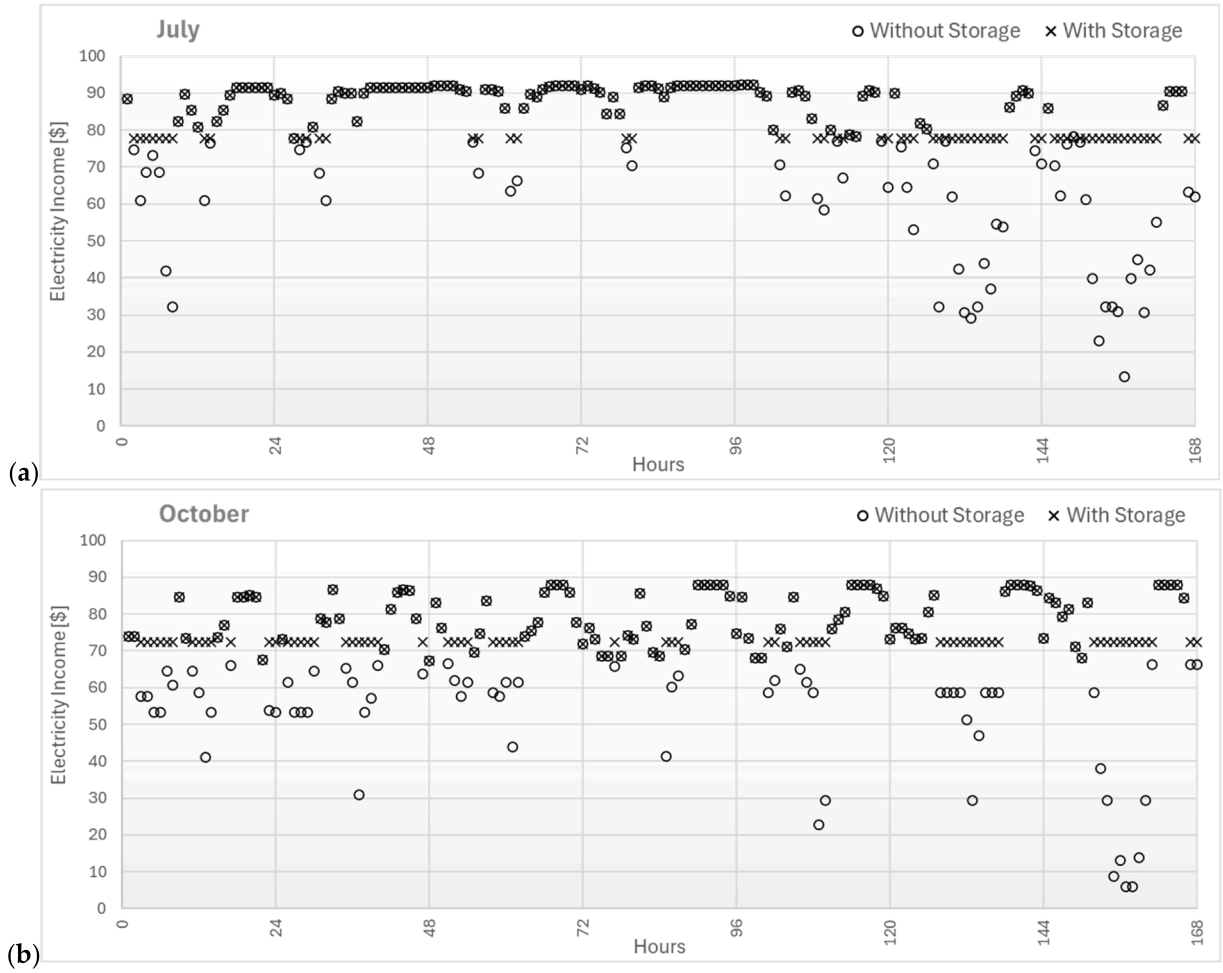


Figure 5. Hourly electricity income for July (**a**) and October (**b**).

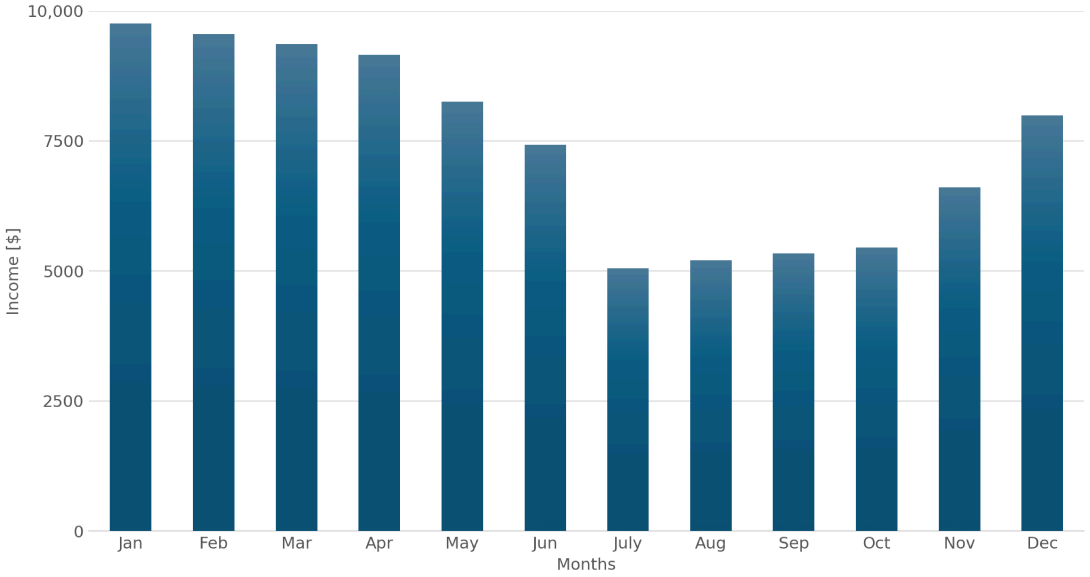


Figure 6. Monthly additional income obtained from electricity storage.

A marked rebound occurs in November and December, indicating the re-emergence of higher price volatility and demand as the system transitions back into winter. December income has increased to approximately $8000, underscoring robust end-of-year market conditions. The figure under consideration highlights pronounced intra-annual variability

in storage-related arbitrage income, thereby emphasizing the strong season dependence of electricity market income. This variability reinforces the economic rationale for electricity storage systems, as storage can be strategically used to capitalize on higher-value periods and mitigate revenue losses during low-income months, particularly when arbitrage opportunities are limited.

The aggregation of these results over a year demonstrates that electricity storage generates an additional annual revenue of approximately $89,179. This observed gain can be attributed primarily to the significant intraday price volatility in the Turkish electricity market, during winter and transition periods, when price spreads create more favorable conditions for temporal arbitrage.

It is important to note that these gains have been achieved without increasing generation capacity. This underscores that value creation is entirely attributable to operational optimization rather than to additional energy production. This finding is consistent with broader market observations, in which energy storage profitability is closely associated with price volatility rather than average price levels.

The financial feasibility of the storage system was assessed by considering an economic lifetime of 10 years. The cumulative discounted cash flows associated with this storage investment are shown in Figure 7.

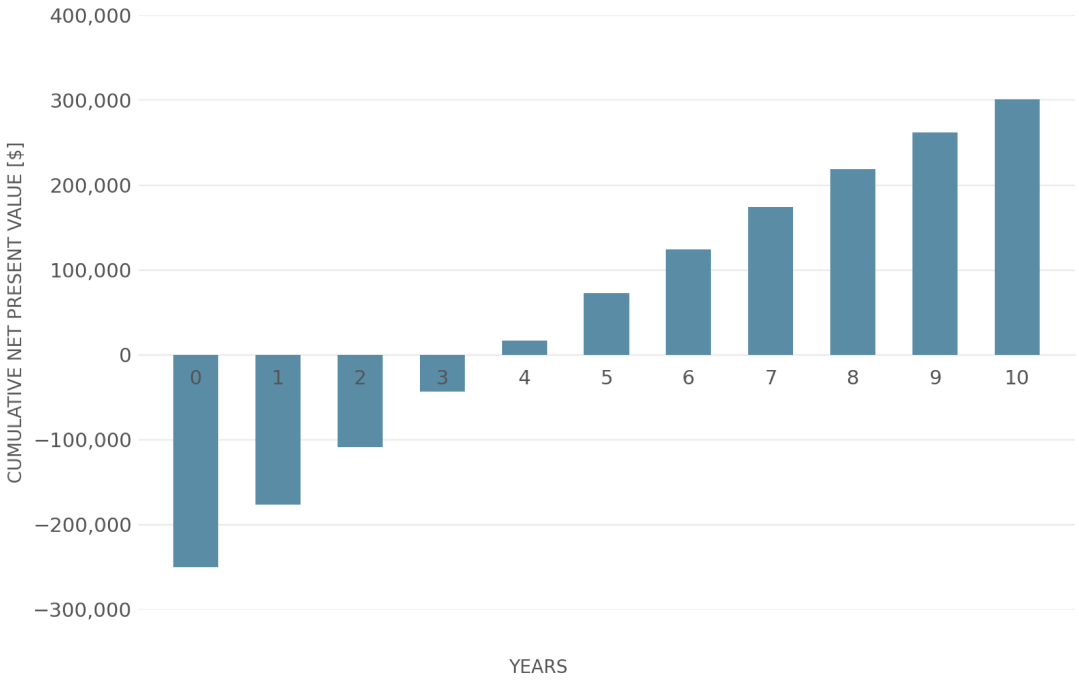


Figure 7. Cumulative Net Present Values for the electricity storage investment.

The economic evaluation yielded an NPV of $297,972, indicating a robust profitability margin under the assumed market and cost conditions. The IRR is 30%, significantly higher than the assumed discount rate of 7.75%. This strongly supports the investment's financial attractiveness.

The DPP determined from the cumulative present value of net profits is estimated to be 3 years and 9 months. This relatively brief payback period indicates that battery energy storage systems can expeditiously recoup their initial capital expenditures, even when conservative assumptions regarding price escalation and operational efficiency are employed.

Whilst the results clearly indicate that electricity storage is economically viable under the adopted assumptions, several factors merit further discussion. Firstly, the profitability of storage is inherently dependent on the magnitude and persistence of price fluctuations. A

reduction in intraday price spreads, potentially due to market saturation, increased storage deployment, or regulatory interventions could result in a decline in arbitrage revenues.

Secondly, the present analysis employs a simplified daily-average-based charging and discharging strategy. While this approach is effective, it does not fully exploit all market opportunities. The implementation of more sophisticated strategies, including hourly price forecasting, state-of-charge optimization, and degradation-aware control algorithms, has the potential to enhance revenue further and extend battery life.

The storage system sizing was not optimized in the present study. The selected configuration is based on the assumptions of a fixed investment cost and an efficiency level. In practice, the optimization of battery capacity, power rating, and cycling frequency should be considered in unison to ensure a balanced approach that considers capital costs, operational flexibility, and degradation effects.

The results of the study indicate that even a basic storage strategy can transform a conventional power generation facility into a more flexible and profitable market participant. In the context of electricity production in volatile markets, such as that experienced by Turkey, the utilization of battery energy storage has been identified as a viable strategy to mitigate risk and stabilize revenue. From a broader perspective, these findings support the role of energy storage as a pivotal enabling technology for market-based power systems, especially during the transition towards greater proportions of variable renewable energy sources.

While the preceding analysis establishes the technical and economic feasibility of battery arbitrage under idealized operating assumptions, practical investment decisions require consideration of additional constraints arising from battery degradation and the circular supply chain. These factors influence system availability, usable operational capacity, maintenance requirements, project lifetime, and acquisition costs, thereby altering the financial performance of BESS investments. The following section systematically incorporates these real-world constraints into the techno-economic assessment using the parameterization framework introduced in Table 1.

Table 1. Cause-and-effect framework illustrating how real-world material and circular supply-chain constraints are operationalized within the techno-economic model.

Idealized Baseline Assumption	Circular Supply-Chain & Material Constraint	Operational Consequence & Model Parameter	Financial Outcome
Constant 85% Efficiency	Cell-to-cell heterogeneity & capacity fade	Time-varying efficiency & DoD decline	2.5% to 3.9% annual revenue erosion
100% Uptime	Reverse-logistics fragmentation & testing delays	Reduced system uptime (Availability = 93%) [a]	Lower annual gross revenue
Standard Maintenance	Thermal complexity & continuous monitoring	Advanced balancing needs (O&M premium: +$2000–4000/year) [b]	Lower net revenue & increased OPEX
10-Year Lifetime	Accelerated degradation & end-of-life threshold	Operational lifetime reduced to 7–8 years [c]	Fewer total revenue-generating years and lower project NPV

[a] **Availability Parameter Formulation:** For the second-life system (Scenario B), this 5–10% reduction reflects the generalized empirical downtime range associated with reverse logistics, safety protocols, and testing. To strictly quantify this constraint within our techno-economic assessment, a deterministic penalty of 7% was adopted as a representative conservative baseline (i.e., conservative relative to the 10% upper-bound penalty) within this empirical range. To ensure a mathematically equitable comparison, the same 93% system availability factor is applied to Scenario A to account for standard first-life downtime factors (e.g., scheduled maintenance, grid-code compliance testing, and unplanned outages typical of utility-scale BESS operations). [b] **O&M Premium Formulation:** The $2000–$4000 premium reflects the anticipated increase in operational complexities: a $2000 premium was adopted for Scenario A to account for the realistic advanced thermal balancing required for degrading first-life cells, while the upper-bound $4000 premium was applied to Scenario B to additionally encompass the reverse logistics, safety protocols, and testing complexities inherent to second-life systems. [c] **Lifetime Constraint Formulation:** The adopted 7-year operational lifespan for SL-BESS is consistent with the 5 to 11-year range reported for grid-oriented applications [38] and parallels the consensus in recent techno-economic assessments [12]. Although our linear degradation model deliberately excludes the knee-point's non-linear acceleration for computational tractability, the empirically observed 7-year lifetime reflects the point at which real-world second-life batteries typically reach this critical degradation threshold (~60% SOH). Thus, our model's linear approximation is conservatively calibrated to terminate just before this accelerated aging regime is reached.

4. Extended Analysis: Material Degradation and Circular Supply-Chain Constraints on BESS Arbitrage Feasibility

Bridging the idealized financial framework from Section 3 with a realistic operational assessment requires the introduction of 'Usable Depth of Discharge (DoD)' as a dynamic proxy for battery State of Health (SOH), capturing the revenue erosion caused by progressive capacity fade in both first- and second-life applications.

In reality, BESS integration into wholesale markets is limited by material-level cell heterogeneity, capacity fade, and complex reverse-logistics dynamics [12,13]. This section re-evaluates the prior idealized assumptions against these real-world constraints to determine their actual economic impact. Four key assumption–constraint–impact pathways are outlined in Table 1 and detailed in the subsequent subsections.

Table 1 illustrates the causal pathway through which real-world material degradation and circular supply-chain constraints are operationalized as explicit techno-economic model parameters. Rather than modeling reverse logistics as an independent optimization problem, the present framework translates these real-world constraints into measurable parameters governing system availability, usable capacity, maintenance requirements, and capital expenditure, which subsequently determine the financial performance of the BESS investment. These constraints are not independent; they interact through compounding mechanistic pathways that erode theoretical arbitrage revenues significantly: Section 4.1 translates these limitations into a direct initial operational penalty, driven primarily by sub-unity initial DoD and availability derating, followed by an annual revenue erosion attributable to capacity and efficiency degradation, depending on the battery source (new vs. second-life) and operational context. This annual revenue erosion compounds over the operational lifetime, contributing to the overall Net Present Value (NPV) reduction discussed in Section 4.3.

The underlying drivers of these parameters, namely cell heterogeneity, usable capacity derating, and O&M premium escalation (Section 4.2), alongside their compounding impacts on overall financial viability and project lifetime (Section 4.3), are examined sequentially in the following subsections, each grounded in the mechanistic and empirical literature on second-life battery performance. This erosion stems from specific technical and structural barriers. On the technical side, second-life battery packs exhibit pronounced cell-to-cell variation inherited from divergent first-life operational and environmental histories. This heterogeneity does not remain static; minor manufacturing deviations among cells are progressively amplified during long-term cycling, compounding the divergence in performance across a repurposed pack [39]. The scarcity of first-life operational data limits the accuracy of degradation knee-point forecasting, undermining assumptions of stable long-term availability. This scarcity is largely attributable to data-privacy restrictions [39,40], alongside intellectual property concerns and the absence of standardized recording protocols across OEMs—who are highly unlikely to share full Battery Management System (BMS) data for secondary applications, as highlighted by the limitations of draft standards like IEC63330 and IEC63338 [41].

Beyond technical limitations, the second-life battery supply chain departs from a traditional linear model. Retired packs flow through a network of loosely coordinated actors, including original equipment manufacturers, insurers, independent repair shops, and secondary markets. This fragmentation introduces variability in acquisition costs, quality assurance, and lead times that idealized models typically fail to capture [13]. Furthermore, this supply-chain variability is compounded as repurposing costs escalate sharply if intermodular capacity dispersion is not screened prior to deployment [40].

4.1. Scenario Definitions and Methodology

Throughout this section, 'usable DoD' serves as the quantitative proxy through which the 'usable operational capacity' concept introduced in Section 1 is operationalized within the techno-economic model.

To quantify the real-world operational penalties, two distinct technological scenarios are established and compared against the baseline model from Section 3: Scenario A (Realistic First-Life Operation) and Scenario B (Second-Life Battery, SL-BESS). The integration of SL-BESS introduces unique operational dynamics. Retired EV batteries typically enter their second life with an initial State of Health (SOH) of approximately 80% [12,42], which manifests as a reduced initial usable capacity and heightened internal resistance, factors that are reflected in the discounted pricing of second-life systems relative to new units. The $150,000 capital expenditure for Scenario B represents a 40% discount relative to the new system, aligning with literature benchmarks where reported cost reductions range from approximately 25% at the system level [43] to 20–80% at the battery-pack level [44] (with Steckel et al. [12] reporting second-life BESS upfront capital costs at 64.3–78.9% of new systems, representing an effective 21.1–35.7% discount), while explicitly encompassing module procurement, testing, and repurposing costs.

The key techno-economic parameters governing these scenarios are summarized below:

CAPEX: Baseline ($250,000) vs. Scenario A ($250,000) vs. Scenario B ($150,000). Scenario A retains the baseline CAPEX of $250,000, as it represents the same new-battery hardware under a more realistic (non-constant) degradation profile, rather than a distinct technology.

Round-trip efficiency (η): Baseline (85% constant) vs. Scenario A (85% dropping to ~77%) vs. Scenario B (80% constant).

Usable DoD (Proxy for Capacity/SOH): Baseline (100%) vs. Scenario A (90% dropping to 76%) vs. Scenario B (80% dropping to ~68%). Unlike Scenario A, where both efficiency and capacity are assumed to degrade concurrently under continuous first-life-equivalent cycling, Scenario B's round-trip efficiency is held constant (at 80%). This reflects the assumption that second-life packs, having already passed through their steepest efficiency-fade region during first-life use, exhibit comparatively stable internal resistance, with residual capacity (DoD) representing the dominant remaining degradation mode.

Annual O&M Costs: Baseline ($10,000) vs. Scenario A ($12,000) vs. Scenario B ($14,000), with all scenarios strictly maintaining the 0.5% annual escalation rate established in the baseline methodology.

System Lifetime: Baseline (10 years) vs. Scenario A (8 years) vs. Scenario B (7 years).

Availability factor: Baseline (100%) vs. Scenario A (93%) vs. Scenario B (93%).

The product of the starting maximum allowable Depth of Discharge (DoD) and the system availability factor imposes an initial operational capacity penalty. First-life systems operating at an initial 90% DoD with a 93% availability yield an effective usable capacity of 83.7% (a ~16% penalty). In contrast, second-life systems, which are restricted to a more conservative initial 80% DoD to mitigate accelerated aging, yield an effective usable capacity of 74.4% under the same availability assumption (a ~26% penalty). As the batteries degrade over their lifetime, these capacity penalties dynamically increase as the underlying DoD limits decline over time (to 76% and ~68%, respectively). These penalties specifically result from DoD and availability derating, while separate efficiency fade is quantified in Section 4.2. To evaluate relative cost-efficiency independent of absolute revenue scale, the Normalized Cost-to-Revenue Ratio (CRR) is formally introduced as a dimensionless financial proxy for LCOS under market arbitrage operations. Unlike conventional LCOS ($/MWh), which measures unit lifecycle cost over discharged physical energy (MWh), CRR evaluates total

discounted costs against discounted gross arbitrage revenue ($). Consequently, CRR serves as a dimensionless financial indicator rather than a unit generation cost.

This study adopts a less conservative but still literature-bounded 80% initial DoD for Scenario B, compared to the more conservative 60% DoD advocated by Steckel et al. [12] to minimize cyclic aging in second-life applications. This parameter choice mirrors the upper limits reported in recent second-life techno-economic simulations, securing sufficient energy arbitrage revenue potential while adequately mitigating accelerated degradation.

The degradation sub-model underlying the scenario definitions dictates how battery performance evolves over time. Predicting the exact remaining useful life of repurposed packs often involves complex data-driven or stochastic frameworks to address inherited cell heterogeneity [45]. However, such micro-level precision—including cell-format, temperature, C-rate, and cycling-protocol effects—falls beyond the analytical boundaries adopted here, as our focus remains on aggregate, system-level Net Present Value (NPV) analysis rather than pack-level predictive maintenance. Therefore, the macroscopic degradation of LFP batteries under high-throughput daily arbitrage is modeled here using a simplified linear fade formulation. This approach builds upon the generalized semi-empirical degradation framework by Xu et al. [46], who explicitly demonstrated that cycling-induced capacity loss scales linearly with equivalent full cycles (EFCs) and depth-of-discharge (DoD) for LFP chemistries.

Our framework adapts Xu et al.'s linear capacity-loss proportionality to model both capacity fade and the associated round-trip efficiency fade. Although capacity fade and internal resistance evolution are influenced by distinct electrochemical mechanisms, dedicated empirical resistance-growth data for the specific dispatch profile is not available in this study. Therefore, we conservatively assume that efficiency degradation co-scales with capacity fade as a simplifying, computationally consistent approximation. This approach avoids introducing additional unverified nonlinear parameters while preserving comparability across scenarios. While semi-empirical frameworks (e.g., Xu et al. [46]) explicitly model calendar aging via a square-root-of-time ($\sqrt{t}$) relationship reflecting decelerating SEI growth, calendar aging is assumed to be negligible relative to cycling-induced degradation under the daily arbitrage operation considered here (an operational separation consistent with established storage dispatch literature, e.g., Schneider et al. [47]; Liu et al. [48]). The sudden non-linear "knee-point" acceleration is also excluded. This omission is methodologically justified since the declining Usable DoD, acting as the direct mathematical proxy for capacity fade, is constrained to keep terminal capacities safely above the 60% end-of-life threshold established in recent second-life aging studies [38,39,42]. For Scenario A, both round-trip efficiency η (A,t) and depth-of-discharge DoD (A,t) degrade linearly over the 8-year project horizon:

$$\eta(A,t) = 0.85 - 0.01125 \times (t-1),\ t = 1, 2, \ldots, 8 \quad (3)$$

$$DoD(A,t) = 0.90 - 0.02 \times (t-1),\ t = 1, 2, \ldots, 8 \quad (4)$$

This corresponds to an absolute annual efficiency drop of approximately 1.12% and an absolute annual usable capacity drop of 2.0%, yielding terminal values of $\eta \approx 0.771$ and DoD ≈ 0.76 at Year 8. It should be noted that this degradation is applied over years 2 through 8 (representing 7 discrete annual steps), consistent with Year 1 reflecting the initial as-installed value. This terminal capacity sits slightly below the traditional ~80% end-of-life threshold typical for first-life EV traction batteries [12,39].

For Scenario B, the battery begins operation at a reduced round-trip efficiency of $\eta = 0.80$, capturing the irreversible capacity fade accumulated during its initial service. Consistent with baseline modeling assumptions in stationary second-life literature (e.g., Casals et al. [38], Steckel et al. [12], which establish a constant 85% round-trip efficiency

baseline across operational scenarios), this parameter remains stable throughout the 7-year operational period. However, to account for accumulated internal resistance, power electronics/inverter efficiencies, and balance-of-plant (BOP) auxiliary losses in second-life configurations, our model utilizes a lower baseline round-trip efficiency (0.80), consistent with but more conservative than reported Li-ion round-trip efficiencies (~85%) [12]. Simultaneously, the usable DoD decreases linearly, functioning as an operational constraint independent of load-driven DoD-SOH relationships:

$$DoD(B,t) = 0.80 - 0.02 \times (t - 1) \quad (5)$$

Tables 2 and 3 present the resulting year-by-year gross revenue (GR) and net revenue (NR) projections under the linear degradation model. Scenario B's operational horizon is limited to seven years, reflecting the assumed end-of-second-life operational lifetime, after which the pack is retired from service.

Table 2. Scenario A: Realistic First-Life Operation.

Year	η(t)	DoD(t)	Gross Revenue ($)	O&M ($)	Net Revenue ($)
1	0.8500	0.90	74,643	12,000	62,643
2	0.8388	0.88	72,009	12,060	59,949
3	0.8275	0.86	69,436	12,120	57,316
4	0.8163	0.84	66,910	12,181	54,729
5	0.8050	0.82	64,431	12,242	52,189
6	0.7938	0.80	61,975	12,303	49,672
7	0.7825	0.78	59,544	12,365	47,179
8	0.7713	0.76	57,208	12,426	44,782
Total			526,156	97,697	428,459

Table 3. Scenario B: Second-Life Battery.

Year	η(t)	DoD(t)	Gross Revenue ($)	O&M ($)	Net Revenue ($)
1	0.80	0.80	62,446	14,000	48,446
2	0.80	0.78	60,885	14,070	46,815
3	0.80	0.76	59,324	14,140	45,184
4	0.80	0.74	57,763	14,211	43,552
5	0.80	0.72	56,202	14,282	41,920
6	0.80	0.70	54,641	14,354	40,287
7	0.80	0.68	53,079	14,425	38,654
Total			404,340	99,482	304,858

4.2. Year-by-Year Revenue Erosion

Continuous cycling consistently drives capacity fade and internal resistance growth, severely restricting usable DoD and round-trip efficiency over the project horizon [42]. In repurposed packs, cell-to-cell heterogeneity compounds these issues, effectively capping overall pack performance at the limit of its weakest cell [39]. To capture this time-varying performance, the annual gross revenue in year t for scenario s was calculated as follows:

$$GR(s,t) = R_0 \times \left(\frac{\eta(s,t)}{0.85} \right) \times DoD(s,t) \times A \quad (6)$$

where GR(s,t) = gross revenue for scenario s in year t (USD); R_0 = baseline annual revenue of $89,179, calculated in Section 3; η(s,t) = round-trip efficiency for scenario s in year

t; DoD(s,t) = usable depth of discharge for scenario *s* in year *t*; A = availability factor (since the baseline revenue R_0 was calculated assuming 100% availability, this factor is penalized to 93% for Scenarios A and B to account for realistic operational downtime). The term $(\eta(s,t)/0.85)$ normalizes the time-varying efficiency against the baseline 85% nominal efficiency used to establish R_0, ensuring that revenue scales proportionally to internal resistance changes.

While the idealized baseline incorporated a 0.5% annual electricity price escalation, this escalation is deliberately set to 0% for the revenue term R_0 in Scenarios A and B. This methodological choice strictly isolates the financial impact of physical battery degradation from exogenous market inflation, consistent with constant-dollar techno-economic assessments [12]. The impact of varying electricity prices is handled separately through sensitivity analysis in Section 4.4.

The degradation mechanisms require distinct modeling approaches for new versus repurposed systems. New batteries (Scenario A) undergo a progressive, simultaneous decline in both round-trip efficiency and usable DoD. Second-life systems operate under a different reality. Since retired packs enter their second life with already elevated internal resistance, we stabilize their round-trip efficiency at 80% for the duration of the project. This distinction is critical, as it isolates the ongoing performance decay of the SL-BESS entirely to shrinking usable DoD, while escalating O&M costs represent a separate, compounding economic factor affecting net revenue.

Annual net revenue is then derived by subtracting the scenario-specific O&M costs from the gross revenue:

$$NR(s,t) = GR(s,t) - O\&M(s,t) \tag{7}$$

We set the first-year O&M costs at \$12,000 for new packs and \$14,000 for repurposed ones, with both escalating by 0.5% annually. The \$2000 premium for second-life systems is not arbitrary; it represents a pragmatic engineering assumption rather than a direct empirical derivation. Repurposed packs demand advanced integration, thermal balancing, and rigorous continuous monitoring to mitigate the risks of pronounced cell heterogeneity and increased management complexity [39]. These allocated absolute costs (equivalent to 12–14/kW for a 1 MW system) fall within the broader empirical fixed O&M bounds of \$7.78–17.4/kW reported for utility-scale storage systems [12]. O&M premiums for second-life systems here are expressed in absolute annual dollar terms rather than normalized \$/kW-yr, reflecting the fixed-capacity baseline assumptions of this study. Some literature (e.g., Steckel et al., [12]) reports lower normalized O&M bounds for second-life systems (3.15–7.78 \$/kW-yr vs. 7.78–17.4 \$/kW-yr for new BESSs); this apparent reduction is due to normalization against significantly degraded base capacities rather than a decrease in actual absolute maintenance effort or complexity. Steckel et al. [12] explicitly assume identical absolute O&M costs between new and second-life systems in their model, attributing the normalized cost divergence entirely to the lower capacity factor of second-life packs (6.80–7.18% vs. 10.0–11.5% for new BESSs).

For illustration, first-year net revenue for Scenario A is calculated as follows:

$$NR_{(A,1)} = R_0 \times \left(\frac{\eta_{(A,1)}}{0.85}\right) \times DoD_{(A,1)} \times A - O\&M_{(A,1)} \tag{8}$$

$$NR_{(A,1)} = 89,179 \times \left(\frac{0.85}{0.85}\right) \times 0.90 \times 0.93 - 12,000 = \$62,643 \tag{9}$$

For Scenario B, the first-year result explicitly incorporates its reduced round-trip efficiency, lower usable DoD, and higher scenario-specific O&M cost:

$$NR_{(B,1)} = R_0 \times \frac{\eta_{(B,1)}}{0.85} \times DoD_{(B,1)} \times A - O\&M_{(B,1)} \tag{10}$$

$$NR_{(B,1)} = 89,179 \times \frac{0.80}{0.85} \times 0.80 \times 0.93 - 14,000 = \$48,446 \quad (11)$$

The results show a gradual decline in annual net revenue in both scenarios, driven by technical degradation, declining usable operating capacity, and rising O&M costs. Scenario A produces higher cumulative net revenue because of its stronger initial performance and longer operational lifetime. Scenario B generates lower annual and cumulative revenue; however, its lower initial acquisition cost may still improve investment attractiveness when evaluated using discounted indicators such as NPV and IRR.

Scenario A's combined efficiency and DoD degradation yields an annual gross revenue erosion that increases from approximately 3.5% to 3.9% over its lifetime, while Scenario B's DoD-only degradation (assuming efficiency stabilizes at a conservative 80% baseline for secondary use) results in a more moderate erosion of 2.5% to 2.9%. These distinct operational trajectories are directly consistent with the 2.5% to 3.9% generalized impact bounds introduced in Table 1.

4.3. Financial Comparison and Second-Life Trade-Off

Section 3 evaluated the preliminary baseline economic viability under an idealized, annualized framework assuming constant operational parameters. To ensure a seamless transition to the degradation-aware analysis, Table 4 explicitly details the baseline. This idealized baseline assumes no material capacity degradation, with an initial annual optimal dispatch revenue of \$89,179 and a base annual O&M cost of \$10,000, both escalating at a nominal 0.5% annual rate.

Table 4. Baseline scenario: idealized battery operation (undiscounted cash flows, 10 years).

Year	Gross Revenue (\$)	O&M (\$)	Net Revenue (Undiscounted, \$)
1	89,179	10,000	79,179
2	89,625	10,050	79,575
3	90,073	10,100	79,973
4	90,523	10,151	80,372
5	90,976	10,202	80,774
6	91,432	10,253	81,179
7	91,889	10,304	81,585
8	92,348	10,355	81,992
9	92,809	10,407	82,402
10	93,274	10,459	82,815
Total	912,126	102,280	809,846

The granular baseline cash flow model detailed in Table 4, incorporating the \$10,000 annual O&M cost with a 0.5% escalation rate, yields a standardized baseline NPV of \$297,972, which remains consistent throughout this study.

To evaluate the economic trade-offs between a new battery energy storage system (BESS) and a repurposed second-life BESS (SL-BESS), this study assessed each scenario's financial performance using Net Present Value (NPV), Internal Rate of Return (IRR), and Discounted Payback Period (DPP). Because the scenarios possess unequal operational lifetimes (10, 8, and 7 years), the Equivalent Annual Annuity (EAA) was also calculated to allow for an unbiased, annualized comparison. All cash flows were discounted at a rate of r = 7.75%. The metrics are governed by the following standard formulations:

$$NPV = \sum_{t=1}^{n} \frac{NR_t}{(1 + r)^t} - CAPEX \quad (12)$$

$$0 = \sum_{t=1}^{n} \frac{NR_t}{(1 + IRR)^t} - CAPEX \quad (13)$$

$$\sum_{t=1}^{DPP} \frac{NR_t}{(1 + r)^t} = CAPEX \quad (14)$$

$$EAA = \frac{r \cdot NPV}{1 - (1 + r)^{-n}} \quad (15)$$

As shown in the equations, the IRR is the discount rate (r) that sets the NPV to zero. In these formulas, NR_t represents the net revenue in year t, and the DPP is the exact duration required for the cumulative discounted cash flows to equal the initial CAPEX. Table 5 summarizes the absolute financial indicators for the idealized baseline and the two degradation-adjusted scenarios.

Table 5. Comparative financial performance of baseline, first-life, and second-life BESS scenarios (present values discounted at 7.75%).

Metric	Baseline Case (10 Yrs)	Scenario A (Realistic First-Life, 8 Yrs)	Scenario B (Second-Life, 7 Yrs)
Initial CAPEX	$250,000	$250,000	$150,000
NPV	$297,972	$66,490	$81,219
Equivalent Annual Annuity (EAA) *	$43,910/year	$11,462/year	$15,476/year
IRR	30.0%	14.8%	22.8%
DPP	3 years 9 months	5 years 7 months	3 years 11 months
Total PV of Net Revenue	$547,972	$316,490	$231,219

Note: Net Present Value (NPV) is calculated as the Total PV of Net Revenue minus the Initial CAPEX. * Equivalent Annual Annuity (EAA) is calculated using the aggregate NPV to standardize the unequal lifespans of the scenarios (10, 8, and 7 years) into a comparable annual metric. Additionally, the Discounted Payback Period is reported to the nearest completed month, consistent with the convention established in Section 3.

The baseline case represents a simplified investment environment in which the system operates over a 10-year horizon without availability constraints or degradation-related reductions. Under these idealized conditions, the project achieves an NPV of $297,972 and an IRR of 30.0%.

Introducing realistic operational constraints severely impacts the financial performance of the first-life BESS (Scenario A). Compared to the idealized baseline, the NPV drops by 78% to $66,490. This steep decline stems from the combined effects of the 7% availability penalty, progressive efficiency and capacity fade, escalating O&M costs, and the truncation of the economic operating life to eight years. As a result, the investment requires 5 years and 7 months to break even, and the IRR drops to 14.8%.

The results for Scenario B demonstrate the practical trade-offs of repurposing used batteries. Although the SL-BESS starts with inferior technical specifications, demands higher maintenance costs, and lasts only seven years, it yields an NPV of $81,219 and an IRR of 22.8%. The explicit $100,000 reduction in capital expenditure (CAPEX) for repurposed batteries more than offsets the operational revenue lost to efficiency and capacity degradation over time. Ultimately, this capital advantage enables the second-life system to surpass Scenario A's NPV by approximately 22% and exceed its Equivalent Annual Annuity (EAA) by 35%.

The end-of-life salvage value adds another variable to this economic evaluation. LFP batteries, lacking high-value metals like cobalt and nickel, yield minimal recycling revenues compared to NMC or NCA chemistries. The base NPV of $81,219 for Scenario B strictly excludes any end-of-life residual value. Even if a nominal 5% salvage value ($7500) were realized, its discounted contribution would only increase the NPV to $85,666. Since

the final scrap value contributes marginally to overall profitability, extending the operational life of LFP cells through second-life applications remains the primary lever for their economic utility.

Finally, Scenario B secures a highly competitive Discounted Payback Period (3 years and 11 months), driven entirely by its lower initial capital barrier rather than higher lifetime revenues. It is slightly longer than the idealized baseline (3 years 9 months) but significantly faster than the first-life system (5 years 7 months). For second-life batteries to be financially viable, the upfront CAPEX discount must outweigh the cumulative costs of elevated O&M and degraded operational performance. In this specific arbitrage application, the lower $150,000 acquisition cost of the SL-BESS effectively achieves this, delivering a stronger financial return than a new battery.

The cumulative discounted cash flow trajectories for the Baseline, Scenario A, and Scenario B are illustrated in Figure 8. The baseline case (solid blue line) exhibits continuous NPV growth over the full 10-year analysis period, reaching $297,972 in Year 10. Scenario A (dashed red line) generates positive cumulative NPV until its end of life in Year 8, after which it remains constant at $66,490 through Year 10. Similarly, Scenario B (dotted green line) accumulates NPV until Year 7 and subsequently plateaus at $81,219 for the remainder of the analysis period.

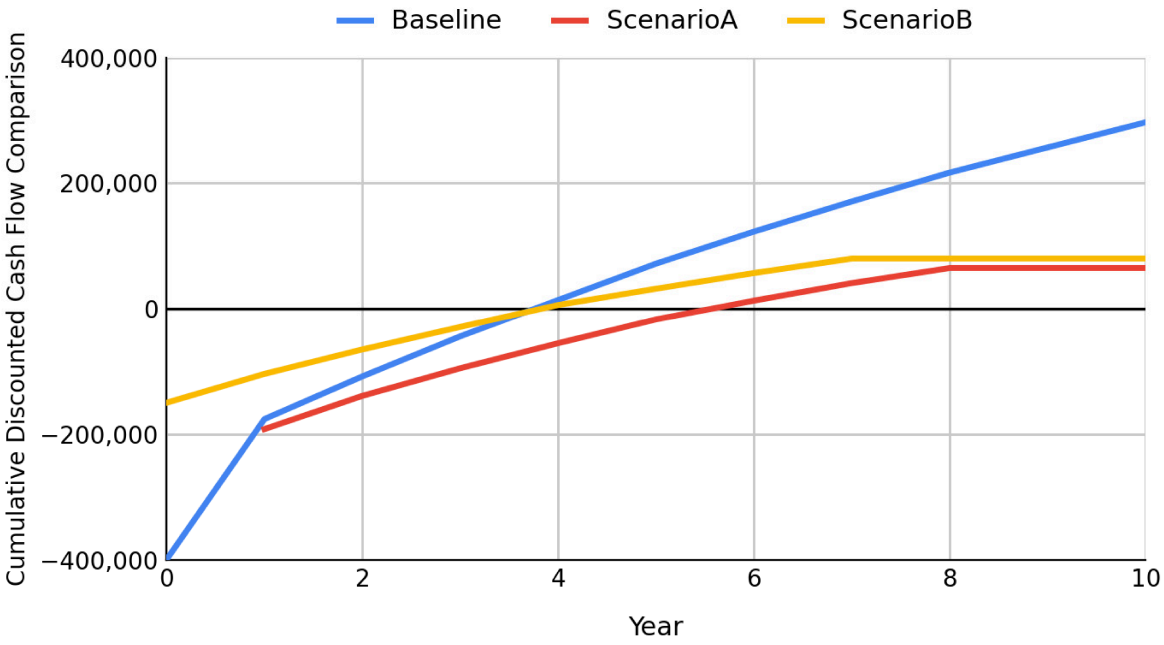


Figure 8. Cumulative discounted cash flow trajectories for Baseline, Scenario A and Scenario B.

The post-retirement plateaus visually reflect the absence of additional operating cash flows after each system reaches its assumed end of life; therefore, the cumulative NPV remains unchanged rather than declining. The vertical reference lines at Years 7 and 8 mark the end-of-life points for Scenario B and Scenario A, respectively, visually separating the active operating period from the post-operation plateau. (The aforementioned EAA metric structurally resolves the analytical disparity of plotting unequal lifespans). Scenario B's shorter horizon reflects its assumed seven-year end-of-second-life retirement, as established in Section 4.1 and consistent with the operational boundary applied throughout this analysis.

To complement the absolute financial comparison, we define a Normalized Cost-to-Revenue Ratio (CRR) as a dimensionless financial proxy for LCOS under market arbitrage operations. Unlike conventional unit-cost LCOS ($/MWh), which incorporates lifecycle

charging and overhaul expenses over physical throughput, CRR evaluates total lifecycle costs against gross arbitrage revenue:

$$CRR_{proxy} = \frac{CAPEX_s + PV(\text{O\&M}_s)}{PV(GR_s)} \quad (16)$$

where $PV(GR_S)$ denotes the discounted sum of annual gross revenue reported for scenario s; $PV(O\&M_S)$ is the discounted sum of annual operation and maintenance costs; and $CAPEX_S$ is the undiscounted initial capital expenditure incurred at t = 0 (computed at the 7.75% discount rate). Because both scenarios face identical market price signals, comparing CRR values (CRR_B/CRR_A) reflects the relative financial cost-efficiency measured by this proxy. This indicates that the second-life BESS achieves an 11.3% reduction in the Normalized Cost-to-Revenue Ratio (from 0.828 in Scenario A to 0.734 in Scenario B), inclusive of both CAPEX and discounted O&M. This model-projected 11.3% CRR reduction is directionally aligned with the 13.8% lower operational LCOS ($LCOS_{OP}$, \$/MWh) reported by Cao et al. [49] using real-world operational data, providing empirical support for the projected magnitude of savings despite differences in metric definitions. Conversely, this CRR reduction is not directly comparable to the unit-cost LCOS findings of Steckel et al. [12], who reported second-life BESS LCOS to be 11–32% higher than new systems. This methodological divergence arises because Steckel et al. evaluated a multi-replacement 15-year lifecycle LCOS (\$/MWh) requiring significant reinvestment CAPEX, whereas our single-horizon CRR proxy assesses the relative financial efficiency of the upfront capital discount against operational arbitrage revenues over the initial 7-year second-life span. Table 6 summarizes the discounted cost and revenue components underlying this comparison.

Table 6. Normalized CRR (LCOS Proxy) calculation components for Scenario A and Scenario B.

Component	Scenario A (Realistic First-Life)	Scenario B (Second-Life)
PV (Gross Revenue)	\$387,213	\$305,737
PV (O&M)	\$70,724	\$74,518
CAPEX	\$250,000	\$150,000
PV (Total Cost) = CAPEX + PV(O&M)	\$320,724	\$224,518
Normalized CRR (LCOS Proxy)	0.828	0.734

4.4. Sensitivity Analysis

To assess the robustness of the second-life battery investment (Scenario B), we performed a sensitivity analysis on key technical and economic parameters. The tested variables include initial capital expenditure (CAPEX), discount rate, round-trip efficiency, initial depth of discharge (DoD), and electricity price escalation rate.

Parametric Sensitivity: As summarized in Table 7, the NPV of the SL-BESS is highly sensitive to both financial variables and core technical performance. A ±15% variation in CAPEX alters the NPV linearly by ±\$22,500. Varying the discount rate by ±2 percentage points shifts the NPV by +\$17,590/−\$15,837, underscoring the project's vulnerability to the cost of capital. On the technical side, a ±5 percentage point change in round-trip efficiency directly scales the annual gross revenue, causing an NPV swing of approximately ±\$20,391. Similarly, variations in the initial DoD dictate the total volume of energy dispatched, resulting in a nearly identical NPV impact. Finally, positive electricity price escalation acts as a compounding multiplier on the arbitrage spread, with a 2.0% annual escalation adding \$17,526 to the baseline NPV.

Table 7. Sensitivity of Scenario B NPV to key technical and economic parameters.

Parameter	Base Value	Variation (Tested Values)	NPV Change (Δ USD)		
Initial CAPEX	$150,000	$127,500/$172,500	+$22,500/−$22,500		
Discount Rate	7.75%	5.75%/9.75%	+$17,590/−$15,837		
Round-trip Efficiency	80%	75%/85%	−$20,391/+$20,391		
Initial DoD	80%	75%/85%	−$20,495/+$20,495		
Price Escalation Rate *	0.0%	0.5%/2.0%	+$4281/+$17,526		
Parameter	**Base Value**	**Variation**	**NPV ($)**	**IRR (%)**	**EAA ($/yr)**
Operational Lifetime (Scenario B)	7 Years	5 Years	$32,576	15.9%	$8,105
Operational Lifetime (Scenario B)	7 Years	6 Years	$58,318	20.1%	$12,520
Operational Lifetime (Scenario B)	7 Years	7 Years (Base)	$81,219	22.8%	$15,476
Operational Lifetime (Scenario B)	7 Years	8 Years (Upper Bound) *	$101,617	24.6%	$17,516
Operational Lifetime (Scenario B)	7 Years	9 Years (Upper Bound) *	$119,693	25.7%	$18,962

* Hypothetical upper-bound sensitivity cases with relaxed retirement threshold.

ΔNPV values for price escalation are calculated by applying the factor $(1 + g)^{(t-1)}$ to the annual gross revenue series and discounting at 7.75%. The escalation rate was tested exclusively for non-negative values, as persistent electricity price deflation is considered economically implausible over the project horizon.

Taken together, these results indicate that technical boundaries (efficiency and DoD) limit the maximum revenue potential, while the ultimate economic viability of the SL-BESS depends equally on the upfront acquisition cost and the macroeconomic environment.

To evaluate the economic robustness of second-life systems against degradation and lifetime uncertainties, an expanded sensitivity analysis was conducted for Scenario B across operational lifetimes ranging from 5 to 9 years (baseline = 7 years; 5 years: NPV = $32,576, EAA = $8105; 8 years: NPV = $101,617, EAA = $17,516; 9 years: NPV = $119,693, EAA = $18,962) and varying degradation conditions. The 8- and 9-year lifetime extensions are presented as hypothetical upper-bound sensitivity cases to test the model's response to a relaxed retirement threshold, rather than representing a revised baseline assumption about second-life battery longevity. The results confirm that even under an accelerated failure scenario where battery lifetime drops to 6 years, Scenario B maintains a strongly positive NPV ($58,318) and achieves an EAA of $12,520, which remains higher than the 8-year first-life baseline (Scenario A EAA = $11,462, IRR = 14.8%). Furthermore, under accelerated annual capacity fade (up to 3%/year) and round-trip efficiency variations (75–85% around the 80% baseline), NPV remains robust, ranging from $61,500 to $101,000 across the tested degradation and efficiency conditions, confirming that the 40% upfront CAPEX discount provides substantial economic insulation against operational degradation penalties. To evaluate the full outer boundary of repurposing costs reported in the literature (20% to 80% discount range relative to first-life CAPEX), extreme sensitivity cases were also evaluated: under an aggressive discount reducing CAPEX to $50,000 (an 80% discount relative to the first-life $250,000 baseline, or a 66.7% reduction from the second-life baseline), Scenario B NPV increases to $181,219, whereas under a conservative 20% discount ($200,000 CAPEX relative to first-life), the system maintains a robust positive NPV of $31,219. This sensitivity range evaluates variations of ±5 percentage points applied directly to the initial (Year 1) DoD baseline (75–85%), with the secondary annual degradation rate of 2.0%/year held constant across the operational timeframe. Full numerical breakdowns across operational lifetimes are detailed in Table 7.

Chemistry Sensitivity: The previous parameters dictate operational boundaries; the underlying battery chemistry introduces a fundamental structural sensitivity. The baseline adoption of Lithium Iron Phosphate (LFP) cells is crucial; substituting LFP with Nickel Manganese Cobalt (NMC) or Nickel Cobalt Aluminum (NCA) chemistries would accelerate capacity fade, consistent with chemistry-dependent degradation patterns reported by Xu et al. [46] (e.g., ~4000–5000 cycles for NMC versus 5000–8000 cycles for LFP before reaching 80% remaining capacity, with NCA assumed equivalent to NMC). In our model, this substitution reduces the SL-BESS project NPV by $11,000–$19,000 depending on chemistry, confirming the importance of chemistry selection in second-life profitability.

In all evaluated chemistry cases (LFP, NMC, and NCA), the negative electrode (anode) is assumed to be pure graphitic carbon, isolating the cathode active material as the primary variable and maintaining consistency with the baseline LFP capacity-fade modeling framework adapted from Xu et al. [46]. While graphite remains the dominant commercial baseline, alternative anode chemistries introduce distinct degradation pathways that directly affect second-life viability. For instance, silicon-graphite (Si-C) composite anodes enhance energy density, but while the silicon active material component within the composite undergoes substantial volumetric expansion (>300%) upon lithiation [50] compared to ~20% for graphite, it leads to particle cracking, continuous SEI rupture, and accelerated cell-level capacity fade that reduces second-life reliability. Conversely, lithium titanate (LTO) anodes operate via a ~1.55 V zero-strain insertion mechanism with minimal lattice volume change (<0.1%) [51], providing superior structural stability and extreme cycle longevity. However, LTO-based full cells (e.g., when paired with conventional cathodes) exhibit a lower nominal cell operating voltage (typically ~1.9–2.4 V depending on cathode pairing) and higher initial capital cost, which offset these longevity gains under market arbitrage operations. Standardizing the anode to pure graphite thus reflects the current second-life supply-chain reality while maintaining a predictable degradation baseline.

4.5. Circular Supply-Chain Dynamics and Business Model Implications

Although Scenario B demonstrates the financial potential of second-life BESS through lower initial acquisition costs, its practical implementation depends on the development of an effective circular supply chain. Repurposing retired EV batteries involves multiple stages, from initial collection and transportation to state-of-health assessment and testing. In some cases, it also requires physical module reconfiguration [13,39]. These activities introduce additional logistics, labor, safety, and quality-assurance costs that directly affect the economic performance of the SL-BESS [12]. In this study, Scenario B assumes higher annual O&M costs than Scenario A ($14,000 versus $12,000), reflecting the upper bound of the anticipated premium range relative to the baseline ($4000 vs. $2,000 for Scenario A), consistent with the greater operational complexity and active cell balancing requirements of second-life systems. This assumption is intended to reflect the potentially greater operational complexity of second-life systems; however, the specific costs associated with reverse logistics and repurposing were not modeled separately.

The efficiency of this reverse logistics network is highly dependent on geographical factors and information transparency. For emerging EV markets like Turkey, the current lack of decentralized collection and testing facilities necessitates long-distance transportation of hazardous retired batteries. This spatial challenge elevates logistics costs and safety risks. The current economic model relies on a generalized premium, it does not incorporate a Turkey-specific logistics cost multiplier; future work should quantify this geographically driven component separately. Information asymmetry regarding the historical State of Health (SOH) of retired batteries presents a major barrier. The implementation of traceability mechanisms, such as the “Battery Passport” mandated by the recently adopted EU

Battery Regulation [39,52], offers a critical regulatory solution. By providing transparent, standardized life-cycle data, Battery Passports can lower the testing and sorting costs within the reverse supply chain, fostering a more reliable SL-BESS market.

The commercial viability of second-life batteries also requires shifting away from traditional asset-sale business models. Due to technical uncertainties and perceived degradation risks associated with used batteries, conventional sales models may deter potential investors. The industry is increasingly transitioning toward service-oriented frameworks, such as Battery-as-a-Service (BaaS) or Energy-as-a-Service (EaaS) [39]. Under these circular models, original equipment manufacturers (OEMs) or specialized Battery Service Providers (BSPs) retain ownership of the battery, and the end-user simply pays for the energy storage service provided [13]. This structure mitigates financial risks for the end-user and guarantees that the batteries are professionally monitored, maintained, and safely channeled into proper recycling streams at their actual end-of-life.

Macroeconomically, deploying second-life batteries extends the useful life of EV components before recycling [43]. This strategic delay reduces the immediate demand for newly manufactured storage assets and defers the need for virgin battery materials [53,54]. Realizing these environmental and economic benefits, however, depends on the condition of the retired batteries, repurposing requirements, transport distances, electricity-market conditions, and the establishment of robust regulatory and safety frameworks [12].

5. Conclusions

This study demonstrates that a BESS can enhance the economic performance of a baseload power plant in Turkey through price arbitrage. The implementation of a fundamental daily-average trading strategy, incorporating a 1 MW BESS, has been demonstrated to generate approximately $89,179 in augmented annual revenue. Financial analysis undertaken under conservative assumptions yielded an NPV of $297,972, an IRR of 30%, and a DPP of under 4 years, thereby confirming the project's strong investment attractiveness.

The findings reveal the pronounced seasonal impact on arbitrage value, with heightened returns observed during the winter months attributable to elevated price volatility. This reinforces the notion that BESS serves as a flexibility asset, effectively decoupling generation from real-time pricing and mitigating market risk. However, the analysis also identifies limitations: a basic operational strategy was used, and system sizing was not optimized. It is recommended that future research focuses on exploring advanced trading algorithms, optimal sizing, and revenue stacking with ancillary services.

The idealized baseline model confirms the strategic viability of battery storage in Turkey's volatile electricity market; however, incorporating empirical degradation trajectories, actual O&M costs, and sub-unity efficiency reveals a stark difference between theoretical and practical performance. Specifically, the transition from idealized assumptions to these realistic operational constraints results in a substantial decrease of $231,482 in the Net Present Value (NPV) of the first-life system (from $297,972 to $66,490). Notwithstanding the considerable decline in baseline profitability, the findings indicate that repurposed second-life batteries (SL-BESSs) continue to demonstrate financial superiority in comparison to newly installed systems. Despite exhibiting lower round-trip efficiency (80%), requiring higher annual O&M costs, and offering a shorter operational lifespan (7 years), the SL-BESS achieved a Net Present Value (NPV) of $81,219 and an Internal Rate of Return (IRR) of 22.8%. Conversely, the realistic first-life system yielded an NPV of merely $66,490 and an IRR of 14.8%. This performance discrepancy can be attributed primarily to the 40% lower initial capital expenditure (CAPEX) of the repurposed system, which effectively compensates for its diminished technical specifications. The second-life BESS reduces the Normalized Cost-to-Revenue Ratio (CRR) by 11.3% (from 0.828 to 0.734), serving as a

dimensionless financial proxy for LCOS under market arbitrage conditions, confirming that upfront capital savings effectively offset operational degradation penalties.

The sensitivity analysis confirms that the economic viability of SL-BESSs is highly robust to technical variations. However, it is also deeply dependent on upfront acquisition costs, macroeconomic variables, and battery chemistry. The initial adoption of Lithium Iron Phosphate (LFP) cells is of pivotal significance; replacement of LFP with Nickel Manganese Cobalt (NMC) or Nickel Cobalt Aluminum (NCA) chemistries would accelerate capacity fade, consistent with chemistry-dependent degradation patterns reported by Xu et al. [46] (e.g., ~4000–5000 cycles for NMC/NCA versus 5000–8000 cycles for LFP before reaching 80% remaining capacity). In the model under consideration, the substitution in question has been shown to result in a reduction in the SL-BESS project NPV by a range of $11,000 to $19,000, the precise amount depending on the specific chemistry selected. This outcome serves to confirm the importance of chemistry selection in ensuring second-life profitability.

Finally, rather than quantifying a standalone reverse-logistics optimization model, this study highlights through parametric representation that the widespread commercialization of second-life batteries cannot rely on theoretical cost advantages alone. The financial erosion demonstrated by these operational constraints implies that establishing decentralized reverse logistics networks, standardized state-of-health assessment protocols, and data transparency mechanisms—such as the EU Battery Passport [39,48]—will be essential to overcome information asymmetry [13]. To mitigate the perceived technical risks of degraded assets, the industry must shift from traditional ownership structures to circular business models like Battery-as-a-Service (BaaS) [39]. Future research should build upon this parametric framework by incorporating empirical BMS-derived degradation datasets and Turkey-specific reverse-logistics cost data (e.g., local recycling infrastructure capacity and customs factors) to further refine the techno-economic parameters adopted here. Additionally, expanding the four-week representative sampling approach into a full 8760 h annual dispatch model would help eliminate potential selection bias and fully capture extreme weather-driven price volatility.

Consistent with our economic and operational findings, integrating retired EV batteries into stationary storage offers a practical and immediate pathway to advance the circular economy [43]. By extending battery life before recycling, this approach delays demand for virgin raw materials, reduces the carbon footprint of energy storage, and provides a cost-effective flexibility mechanism for modern power grids, ultimately facilitating broader integration of renewable energy [53].

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