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Trigger-Based PDCA Framework for Sustainable Grid Integration of Second-Life EV Batteries

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Abstract

Second-life electric vehicle batteries (SLBs) represent a promising asset for enhancing grid flexibility and advancing circular economy objectives in the power sector. This paper proposes a conceptual trigger-based PDCA (Plan–Do–Check–Act) framework for the sustainable grid integration of SLBs, enabling adaptive operational control across diverse application scenarios. The framework combines lifecycle KPI monitoring, degradation and performance tracking, and economic feasibility assessment with trigger-driven dispatch logic. Technical, financial, and environmental indicators are systematically integrated into the four PDCA phases, providing a structured basis for adaptive management. To illustrate applicability, indicative KPI calculations are presented for three representative scenarios (HV Backup, RES Smoothing, and Frequency Regulation). These examples demonstrate how the framework supports scenario-based planning, performance evaluation, and decision-making under uncertainty. Compared with existing state-of-the-art approaches, which typically analyse technical or economic aspects in isolation, the proposed framework introduces a modular, multi-model architecture that aligns operational triggers with long-term sustainability goals. By embedding reuse-oriented strategies into an adaptive PDCA cycle, the study offers a clear and practical methodology for maximising SLB value while minimising degradation and environmental impacts. The framework provides a valuable reference framework for structured SLB deployment, supporting more resilient, cost-effective, and low-carbon energy systems.

Keywords: second-life batteries; PDCA; KPI monitoring; trigger-based dispatch; electric vehicles; grid flexibility; energy systems; sustainability

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1. Introduction

The global energy transition is gaining momentum, driven by the dual imperatives of mitigating climate change and achieving a sustainable, low-carbon future [1–3]. A core component of this transition is the growing reliance on renewable energy sources (RES), such as solar and wind [3–5]. These sources offer clear environmental advantages, but their inherent variability poses new challenges for balancing energy generation and consumption [6,7]. This increases the demand for flexible, efficient, and scalable energy storage systems capable of stabilising the grid and ensuring energy security [8].

At the same time, the transportation sector is undergoing a significant transformation towards electrification. Supported by climate policies, consumer incentives, and falling

battery costs, electric vehicle (EV) adoption is accelerating worldwide [9]. Global sales of EVs surpassed 10 million in 2023, and projections indicate a tenfold increase in the next decade [10]. As the EV fleet grows, so does the number of retired lithium-ion batteries (LIBs). These batteries typically retain 60–80% of their initial capacity after their first life in vehicles. They can be repurposed in stationary applications such as energy storage systems, backup power, and renewable energy integration [11].

The reuse of automotive batteries in second-life applications aligns with the principles of the circular economy. It reduces the need for new raw materials such as lithium, cobalt, and nickel, decreases waste, and extends the value chain of battery production. Numerous studies project that by 2030, approximately 3.4 million EV batteries globally will be retired from transportation use, representing nearly 950 GWh of technically accessible second-life capacity [10,11].

In Ukraine, the dominance of imported EVs—often retired at 60–80% of their initial capacity—creates both a challenge and an opportunity for developing a circular battery management system [12–17]. The National Transport Strategy outlines the rapid growth of the EV market while underscoring the absence of systematic end-of-life management pathways for used batteries [12]. Recent studies confirm that second-life battery deployment in Ukraine is technically viable and economically attractive for grid support, V2G services, and flexible backup applications, providing a pathway to enhance system resilience [13–16]. Moreover, the integration of SLBs within the energy system contributes to decarbonization and circularity objectives under the country's evolving energy landscape [17].

However, integrating second-life batteries (SLBs) into energy systems is not straightforward [18]. These assets exhibit diverse degradation histories, chemical compositions, battery management system configurations, and residual performance characteristics [18,19]. SLBs behave differently under varying load profiles, temperature conditions, and grid dynamics. Some can operate reliably in shallow-cycling modes for up to 10–15 years, while others may degrade rapidly under high-intensity use [17–19]. Moreover, the lack of standardisation, regulatory clarity, and quality assurance mechanisms further complicates their deployment [18,19].

To ensure that SLBs fulfil their potential as flexible, cost-effective, and sustainable energy assets, a new management paradigm is needed—one that embraces uncertainty, adapts to real-time feedback, and enables informed decisions throughout the asset lifecycle. This paper proposes the Plan-Do-Check-Act (PDCA) cycle as a conceptual and operational framework for SLB integration. Initially developed for continuous process improvement, PDCA offers a robust model for dynamic performance monitoring, degradation tracking, and adaptive planning. When coupled with key performance indicators (KPIs), cost-effectiveness metrics (such as LCOS), and event-based trigger logic, PDCA can support both strategic oversight and day-to-day operational control of battery-based energy systems.

Building on this foundation, the specific objectives of this study are:

- to develop a PDCA-based operational management framework for SLB deployment;
- to integrate technical, economic, and environmental KPIs into a trigger-based control loop;
- to test the applicability of the framework through scenario-based simulation;
- to identify key limitations and implementation challenges.

To operationalise the integration of SLBs within circular and flexible energy systems, this study employs a structured research design that connects KPI monitoring with the PDCA cycle and scenario-based analysis. This structured methodology enables systematic evaluation and adaptive management of SLBs across technical, economic, and environmental dimensions while maintaining alignment with circular economy goals. The following flowchart (Figure 1) outlines the stages of the research approach applied in this study.

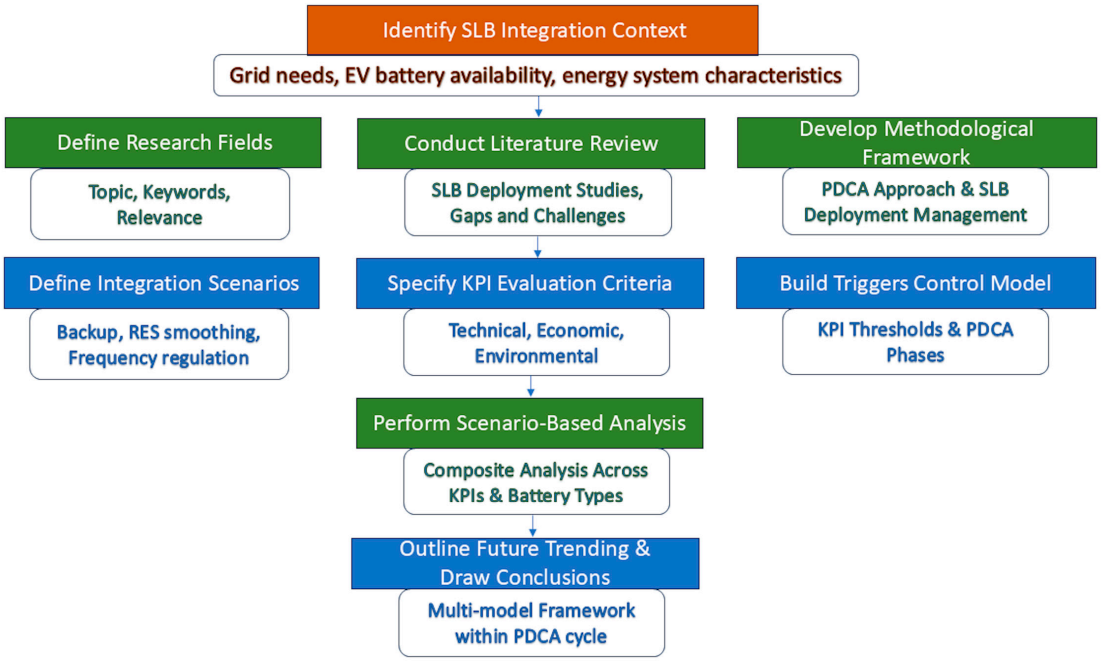


Figure 1. Research framework for SLB evaluation using KPI-PDCA.

The framework integrates KPI monitoring, PDCA cycles, and scenario analysis to support adaptive and circular SLB deployment strategies.

This study focuses on stationary SLB applications in mid-voltage distribution networks, using simulation data for typical renewable variability and load curves. The proposed framework is tailored to lithium-ion EV batteries with partial degradation and targets mid-term planning horizons of approximately 5 to 10 years. While the methodology is generalizable, its assumptions and input parameters reflect the operational conditions of decentralised grid environments with variable generation.

2. Literature Review

To contextualise the scientific background of SLB integration, a targeted bibliometric analysis was conducted using Scopus-indexed publications from 2010 to 2024. The goal was to identify prevailing trends, research dynamics, and thematic clusters within the SLB knowledge domain. The analysis was performed using VOSviewer software (v 1.6.19), applying keyword co-occurrence mapping and temporal evolution tracking. The results are synthesised in Figures 2–4, which capture complementary dimensions of this research landscape.

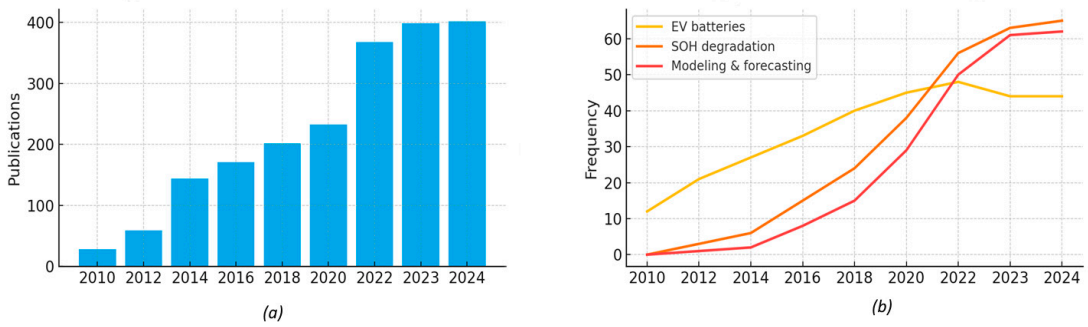


Figure 2. Overview of bibliometric trends and keyword analysis in SLB-related research (2010–2024), based on Scopus-indexed publications and VOSviewer mapping: (**a**) Dynamics of the number of scientific publications for 2010–2024; (**b**) Keywords evolution over time for selected concepts.

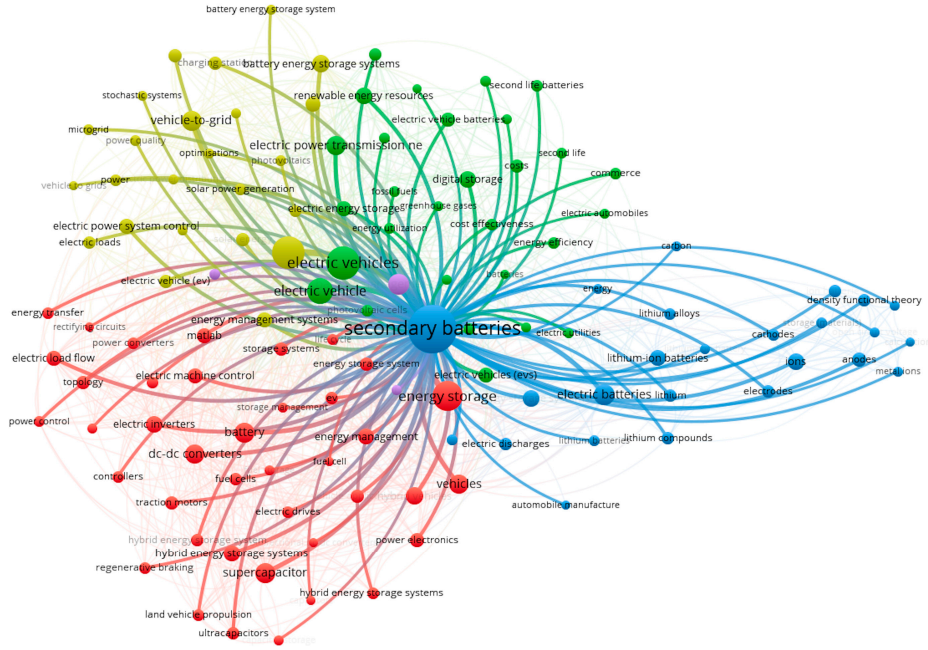


Figure 3. Co-occurrence network of key terms in the SLB domain (VOSviewer).

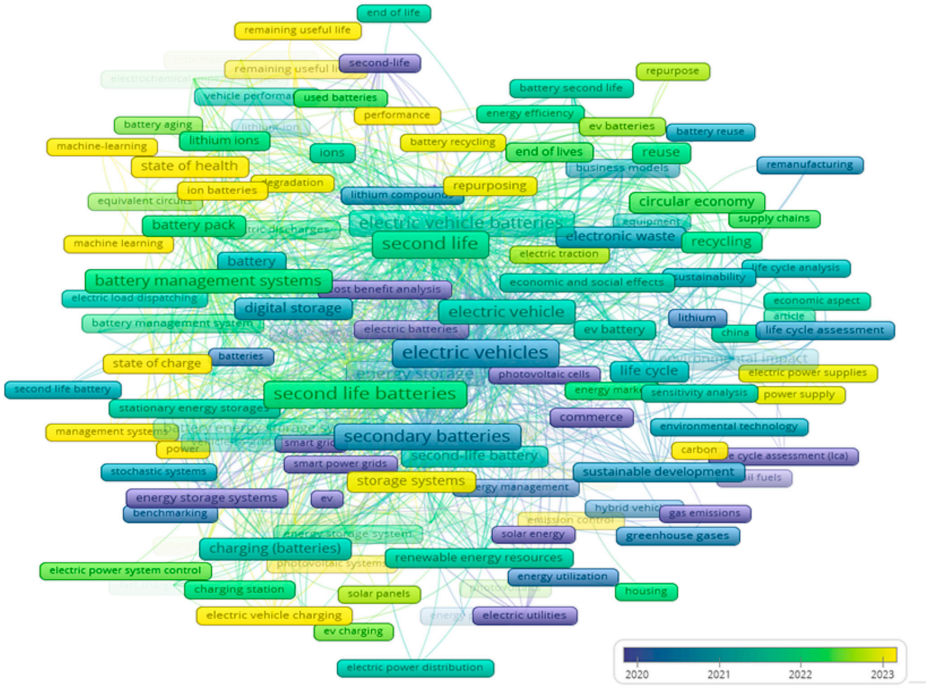


Figure 4. Temporal trends in key term usage in SLB research of 2019–2024 (VOSviewer).

Figure 2a shows the growth trajectory of SLB-related publications over the past decade. The number of peer-reviewed articles has increased from fewer than 30 per year before 2015 to over 400 in 2023–2024, indicating a rapid rise in scientific and technological interest. This reflects not only the maturation of electric vehicle markets but also an intensified global focus on battery reuse, circular economy models, and sustainable storage strategies. Figure 2b tracks the temporal frequency of key research terms—specifically "EV batteries," "SOH degradation," and "modelling & forecasting." While early publications focused primarily on electrochemical design and basic reuse feasibility, recent years have seen a surge in degradation-oriented studies and the development of predictive models for SLB

performance. This shift underscores the growing need for lifecycle-aware and data-driven integration approaches.

Figure 3 in turn, presents a co-occurrence network of keywords based on VOSviewer clustering. Several dense term clusters emerge, notably those centred around "secondary batteries," "electric vehicles," "grid integration," and "hybrid systems." The presence of terms such as "uncertainty," "state of health," and "optimisation algorithm" suggests a clear shift toward dynamic, performance-sensitive control models.

And finally, Figure 4 visualises the temporal evolution of keyword usage from 2019 to 2024. Early keywords such as "reuse" and "battery management" are now joined by emerging terms like "second life batteries," "degradation modelling," and "adaptive control." Notably, "KPI," "trigger mechanism," and "circular economy" appear with increasing frequency since 2021, indicating growing recognition of the importance of structured evaluation and operational responsiveness.

These findings confirm that SLB research is rapidly evolving from conceptual feasibility and engineering design toward complex, multidisciplinary strategies that encompass reliability, cost-effectiveness, policy alignment, and lifecycle optimisation. However, the literature still lacks integrated frameworks that combine performance monitoring, feedback-based control, and economic justification within a unified management model. This gap forms the basis for the PDCA-based approach proposed in this study.

Research on SLBs has rapidly expanded over the past decade, covering a wide range of topics from degradation modelling and lifecycle extension to techno-economic assessment and integration into stationary energy systems [20–22]. Early studies focused on the technical feasibility of repurposing EV batteries for less demanding applications, demonstrating that such reuse can delay battery disposal while reducing storage costs [23–25]. Subsequent work has addressed performance characterisation, with several authors proposing classification schemes based on state-of-health, electrochemical behaviour, and thermal sensitivity, providing systematic criteria for assessing repurposing potential [26–29].

A parallel stream of research has developed cost metrics tailored to SLB deployments. While LCOS remains the most widely used economic indicator for assessing financial viability, recent work emphasises the importance of incorporating broader evaluation parameters, including lifecycle emissions, reuse efficiency, and circular economy perspectives [30–33]. Within this context, new integrated metrics have been proposed, such as the Integral Degradation Index (IDI), aimed at capturing technical and contextual constraints that affect the economic rationality of reuse scenarios under uncertainty [34].

Another line of inquiry has focused on decision-making frameworks and control strategies for SLB deployment. While most existing work emphasises predictive diagnostics, BMS optimisation, and state estimation to extend SLB usability [35–37], there is growing recognition of the need for structured operational models capable of adapting to stochastic degradation and variable load profiles in real-world applications [38–41]. In this context, the use of quality management principles—notably the PDCA cycle—has been proposed as a framework for lifecycle-oriented SLB integration into energy systems, aligning reuse pathways with sustainability and resilience goals [42–44].

While recent studies have emphasised the role of KPIs in assessing the readiness and effectiveness of circular business models for SLB deployment [45–47], two key gaps remain in the literature. First, there is a lack of systematic approaches that combine performance indicators, cost metrics, and adaptive logic into a unified operational management framework for grid integration of SLB systems [48,49]. Second, there is limited guidance on how to practically implement PDCA-based management in systems characterised by high variability and incomplete information. In particular, the integration of KPI monitoring into adaptive PDCA cycles and trigger-based dispatch strategies for real-time grid sup-

port and lifecycle management of SLB systems has not yet been sufficiently explored [33]. Recent contributions have examined the use of trigger-based control and KPI thresholds to structure decision-making loops for SLB applications. Still, these approaches remain underdeveloped and context-dependent, requiring further scenario-based validation and demonstration [50–53]. In the context of Ukraine, regulatory frameworks for second-life battery reuse remain underdeveloped, with no standardised pathways for testing, certification, or integration into national grid strategies [13–19].

High renewable energy penetration, especially from intermittent sources such as solar and wind, has introduced new challenges to grid operation, including congestion and localised imbalances. Recent studies emphasise the importance of deploying flexible energy storage systems to mitigate grid congestion, improve load balancing, and increase hosting capacity for renewables [21,22]. At the same time, some of them [54–56] demonstrate how spatially distributed battery storage can reduce congestion in transmission networks, supporting more stable and efficient system operation.

Large-scale optimisation models (e.g., DIgSILENT PowerFactory [57], TIMES [58], or ENERTILE [59]) provide system-level insights but lack degradation-aware and KPI-triggered operational control, leaving a gap for practical SLB deployment methods. To contextualise the proposed contribution, we compared the KPI–PDCA framework with state-of-the-art (SOTA) methods addressing SLB integration and related energy storage frameworks. The comparison includes both large-scale simulation/optimisation tools and recent SLB-specific studies (2018–2025). Table 1 summarises their scope, strengths, and limitations with respect to SLB deployment.

Table 1. Comparison of SOTA methods and the proposed KPI–PDCA framework for SLB integration.

Method/Authors (Year)	Scope/Strengths	Limitations (Relevance to SLB)	Ref.
Haram et al., IEEE Access (2023)	Techno-economic assessment of SLB lifetime and costs	Focus on cost, lacks PDCA cycle or KPI-trigger control	[31]
Martinez-Laserna et al., IEEE TIA (2018)	Degradation modelling, RUL assessment	Technical focus only, no economic or governance dimension	[32]
Prenner et al., Int. J. Energy Res. (2024)	KPIs for circular business models of SLB	KPI definition only, no integration with PDCA or dispatch logic	[33]
Tadayon & Frey, Energies (2025)	Multi-level degradation-aware operation of BESS	Strong LIB focus, not tailored to SLB variability	[45]
DIgSILENT PowerFactory	Large-scale grid simulation, RES + storage integration	No SLB-specific degradation modelling, no KPI-trigger logic	[57]
TIMES model	Long-term techno-economic optimisation for energy systems	Macro-level only, lacks operational control and lifecycle adaptation	[58]
ENERTILE	RES integration and storage for European grids	No SLB focus, no adaptive PDCA management	[59]
Canals, Casals, & Amante, J. Environ. Manag. (2019)	RUL + environmental impact of SLB	Valuable LCA insights, no integrated PDCA management	[60]
Neigum & Wang, J. Energy Storage (2024)	Review of SLB technology, economy, and environment	Descriptive, no operational management framework	[61]
Hu et al., Renew. Sust. Energy Rev. (2019)	State estimation for advanced BMS	Diagnostics only, no KPI–circular economy integration	[62]
Proposed KPI–PDCA framework	Integrates technical, economic, and environmental KPIs; PDCA cycle; trigger-based logic; 6-model multimodel architecture; scenario evaluation (HV Backup, RES Smoothing, FR)	Proof-of-concept; requires further empirical validation	-

As shown in Table 1, existing approaches provide significant contributions but remain fragmented. System-level tools (e.g., DIgSILENT, TIMES, ENERTILE) capture grid or economic dynamics but neglect SLB-specific degradation and adaptive operation. Recent SLB studies define KPIs, analyse economics, or assess degradation and LCA impacts, but they do not combine these elements into an operational management cycle. The proposed KPI–PDCA framework addresses this gap by integrating technical, economic,

and environmental KPIs with trigger-based control logic and scenario analysis, thereby offering a structured and replicable approach to SLB deployment.

3. PDCA Cycle as a Planning Tool

The Plan-Do-Check-Act (PDCA) cycle, initially developed by Walter A. Shewhart and later promoted by W. Edwards Deming, has evolved into a universal framework for continuous process improvement across engineering, quality management, and adaptive systems [63–66]. In the context of SLB integration, the PDCA cycle offers a valuable approach for managing uncertainty, degradation variability, and operational dynamics across the entire battery lifecycle [67–70].

3.1. PDCA Logic for SLB Deployment

Second-life EV batteries are characterised by non-uniform performance, unpredictable degradation rates, and heterogeneous usage histories, requiring a flexible yet structured decision-making process that can respond dynamically to changes in technical condition, economic context, and system demands [69,70]. The PDCA methodology, with its iterative feedback mechanism, is uniquely suited for this task, enabling a shift from static planning toward an adaptive, data-driven operational philosophy [71,72].

To formalise this approach, a conceptual model of SLB deployment based on PDCA logic is proposed (Figure 5). Each PDCA cycle represents a complete loop of planning, operation, monitoring, and adjustment under specific use conditions [63,71]. When performance indicators (such as KPI thresholds or degradation metrics) indicate deviation or risk, reconfiguration is triggered, leading to updated operational baselines and the initiation of a new management cycle [72,73]. This logic enables continuous system-level adaptation and progressive optimisation of SLB integration strategies [74].

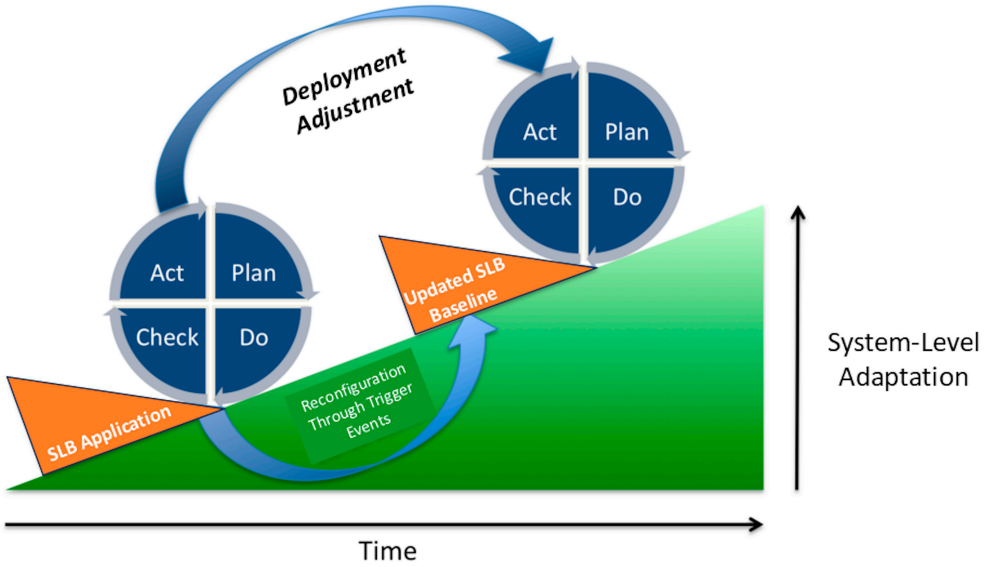


Figure 5. Conceptual visualisation of the PDCA-based management approach for second-life battery (SLB) integration.

The diagram shows how each SLB deployment cycle leads to system-level adaptation through performance-triggered reconfiguration and updated operational baselines. The author developed this interpretation as an adaptation of PDCA for the context of SLB lifecycle control.

3.2. Operationalization of the PDCA Cycle for SLB Integration

Translating the PDCA concept into a practical management tool for second-life batteries requires aligning each phase with concrete decision-making tasks and observable system variables, capturing system uncertainty, enabling real-time feedback, and supporting long-term optimization [75]. Unlike traditional applications of PDCA in manufacturing, where conditions are often stable, SLB integration is dynamic and influenced by degradation variability and evolving grid requirements [76].

The Plan phase serves as the strategic anchor, involving use-case selection, degradation forecasting, KPI target setting, and defining the control environment [77]. The Do phase functions as an experimental implementation stage under monitored conditions, generating empirical data on degradation, thermal behavior, and operational dynamics [33,63]. The Check phase systematically compares observed performance against forecasted values and KPIs, identifying deviations in key indicators such as RTE and LCOS as triggers for recalibration [76]. The Act phase represents adaptive learning, involving operational adjustments, KPI updates, and SLB reassignment while initiating new planning cycles with refined insights [64,74]. By structuring SLB deployment in this way, the PDCA framework enables more than operational control; it supports an evolving integration strategy responsive to real-world conditions. The result is not a static system, but a living one—capable of optimizing itself over time in alignment with both technical and economic performance targets.

3.3. PDCA as a Lifecycle Management Strategy for SLB Deployment

While originally designed for quality assurance, the PDCA cycle evolves in the SLB context into a comprehensive lifecycle-oriented governance strategy, enabling ongoing adaptation to performance deviations, degradation signals, and external constraints [63–66]. When implemented within EMS, BMS, or SCADA systems, the PDCA approach supports proactive control and continuous recalibration, essential for SLBs exposed to price volatility, load fluctuations, and variable renewables [67–71]. Table 2 illustrates how the four PDCA phases map to management actions, monitoring priorities, and decision triggers within an SLB context. Each phase aligns with a performance feedback stream that signals when and how the system should evolve, enabling an evidence-based pathway for SLB optimization.

Table 2. Mapping PDCA phases to SLB management logic.

PDCA Phase	Core Management Actions	Monitoring Priorities	Decision Triggers
PLAN	Define KPI targets, scenario selection, lifecycle and economic modeling	Feasibility, resource efficiency, emission impacts	Regulatory requirements, resource constraints
DO	Deploy and operate SLBs, implement control strategies, real-time data collection	SOH, SOE, utilization rate, operational anomalies	Performance deviation, technical constraints
CHECK	Evaluate KPI compliance, degradation assessment, environmental monitoring	KPI tracking vs. targets, degradation rates	Threshold crossings (SOH drop, LCOS increase)
ACT	Adjust operational parameters, reallocate SLBs, initiate refurbishment or recycling plans	Improvement needs, strategy effectiveness	Economic underperformance, safety margins reached

In this sense, the PDCA methodology becomes not only a planning or diagnostic tool but a lifecycle management philosophy: a system-level discipline that continuously redefines what optimal performance means under uncertainty and system evolution [72–75].

To complement the process-level description, Figure 6 summarizes the functional logic of each PDCA phase for SLB integration, aligning operational activities with key technical and economic indicators such as RTE, LCOS, DoD, and degradation metrics [77–85]. This enables a modular yet dynamic approach to SLB lifecycle management, transforming SLB

integration from static planning into a continuous loop of adaptation to maximize technical performance and ROI across the battery's second life.

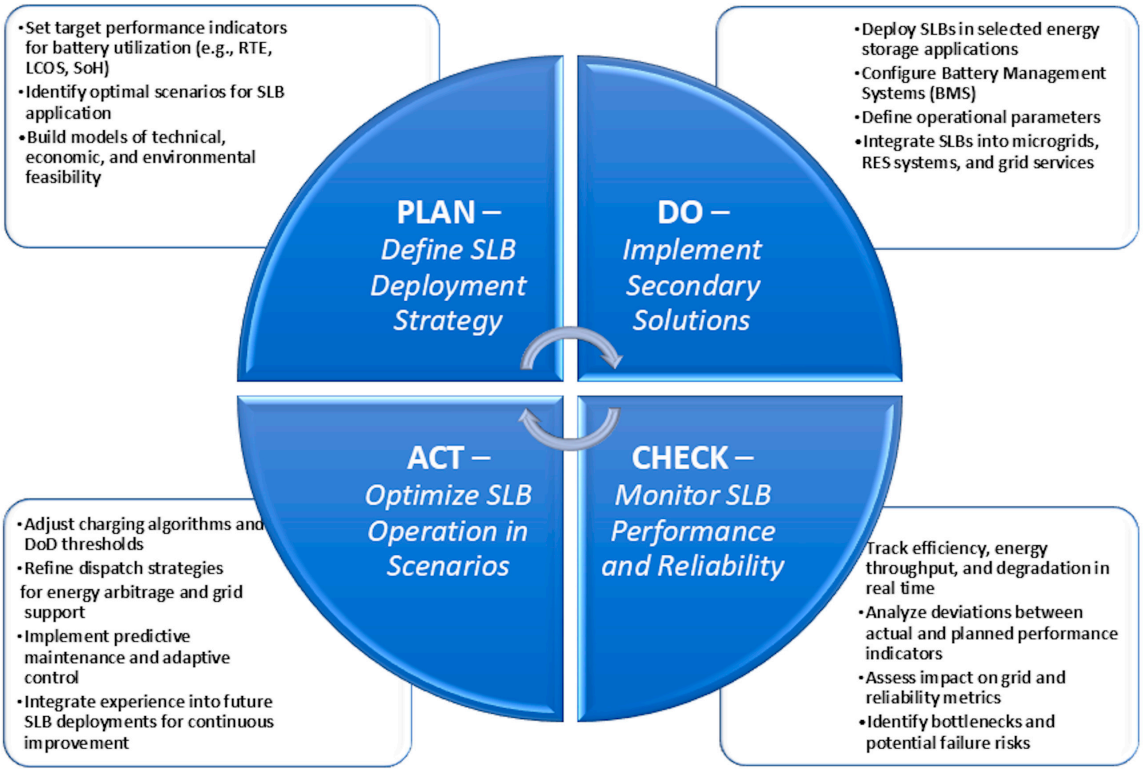


Figure 6. PDCA cycle adapted for second-life battery (SLB) integration in energy systems.

Each quadrant in Figure 6 corresponds to a distinct operational focus—strategic framing (Plan), controlled implementation (Do), performance evaluation (Check), and adaptive optimization (Act)—while aligning typical activities and monitoring tasks with key technical and economic indicators such as round-trip efficiency, LCOS, depth of discharge, and degradation trends. This structure enables a modular yet dynamic approach to SLB lifecycle management, where learning from each phase directly feeds into the next iteration. In this way, the PDCA cycle allows SLB integration to move beyond static project planning and into a continuous loop of adaptation, maximizing both technical performance and return on investment across the battery's second life.

A key challenge during framework formalization was the limited availability of standardized empirical degradation profiles for second-life batteries. Further studies should integrate data from operational pilot projects to enhance model validation and representativeness.

4. Key Performance Indicators for SLB Management Within the PDCA Framework

The effective integration of SLBs into grid applications requires a structured approach to monitoring and evaluation throughout their lifecycle. KPIs act as measurable metrics that translate complex technical, economic, and environmental aspects into actionable insights, supporting adaptive management under the PDCA framework [78,79].

While several studies have proposed KPIs for first-life batteries, there is a research gap in systematically applying KPIs to second-life batteries within operational management frameworks, particularly under circular economy and resilience objectives. This section aims to address this gap by presenting a comprehensive KPI catalogue aligned with the PDCA cycle, allowing operators to track, analyse, and optimize SLB deployments

dynamically. The KPIs were selected and structured based on analytical review and adapted by the author to reflect second-life battery characteristics.

4.1. Scenario Definitions and Assumptions

To illustrate the implementation of the proposed PDCA-based framework, three representative deployment scenarios for second-life batteries (SLBs) are defined. These scenarios reflect distinct operational roles within power systems and require tailored KPI configurations and trigger conditions to support adaptive lifecycle management:

(a) Scenario 1: HV Backup. SLBs are deployed as reserve power sources at medium-voltage substations, providing support during outages and unplanned events. Performance is characterised by infrequent deep discharges with long idle periods. The primary KPIs include State of Health (SOH) and Round-Trip Efficiency (RTE). Planning targets are SOH > 70% and RTE > 85%. Real-time monitoring ensures that, when SOH falls below 65% (trigger threshold), the SLB is reallocated to a less demanding application to extend residual value and defer disposal.

(b) Scenario 2: RES Smoothing. In this case, SLBs are integrated to mitigate fluctuations in photovoltaic (PV) and wind power output, absorbing surplus generation and smoothing short-term variability. Operational patterns involve moderate cycling with medium depth-of-discharge (DoD). Key KPIs include DoD range (target 60–70%) and the Integral Degradation Index (IDI). When the IDI exceeds 0.85 (trigger threshold), the battery is reassigned to low-cycling roles such as frequency regulation or strategic reserve to preserve functionality and mitigate further degradation.

(c) Scenario 3: Frequency Regulation. Here, SLBs provide rapid-response ancillary services, balancing short-term frequency deviations through intensive cycling. This scenario places greater stress on battery lifespan, requiring close tracking of cost-effectiveness. Economic KPIs, such as Levelized Cost of Storage (LCOS) and Return on Investment (ROI), guide performance evaluation. A dynamic LCOS threshold (180–200 USD/MWh) serves as a trigger for re-evaluation. If exceeded, the SLB is shifted to services with lower cycling intensity or retired if no viable use remains.

All scenarios are designed for mid-voltage grid applications and assume partial battery degradation at the time of integration. The planning horizon for each use case spans 5–10 years. Load profiles are derived from historical public data and synthetic reconstructions based on Ukrainian modelling studies [80–88], while renewable generation variability is modelled using international benchmarks, including IEA-PVPS. The trigger-based mechanism in each scenario supports responsive control aligned with PDCA phases, maximising the operational utility and sustainability of second-life battery systems.

4.2. Technical KPIs for SLB Integration

Selection of technical performance indicators is critical for ensuring the operational readiness and longevity of second-life batteries (SLBs) within energy systems [89–93]. Metrics such as RTE, DoD, SOH, and IDI provide quantifiable insights into the core functional capabilities of SLBs under dynamic operational conditions [94–96]. These KPIs help in evaluating conversion efficiency, usable capacity, degradation progression, and charge/discharge behaviour, aligning operational control with grid support requirements and degradation mitigation strategies [60,97–100].

SOH is a key indicator that characterises the current performance of a battery relative to its initial condition [28–30]. It is commonly evaluated from two main perspectives: the remaining capacity and the internal resistance of the battery.

When calculated based on remaining capacity, *SOH* is expressed as [28]:

$$SOH = \frac{C_{current}}{C_{initial}} \cdot 100\% \quad (1)$$

When evaluated based on internal resistance, *SOH* is defined as [27]:

$$SOH = \frac{R_{\max} - R_{current}}{R_{\max} - R_{initial}} \cdot 100\% \quad (2)$$

In these formulas, $C_{current}$ and $C_{initial}$ represent the battery's current and nominal capacity as specified by the manufacturer. R_{max}, $R_{current}$, and $R_{initial}$ correspond to the internal resistance at the beginning of life, current state, and end-of-life threshold, respectively.

To capture the complex degradation dynamics of second-life batteries (SLBs), including both deterministic and stochastic ageing effects, this study employs the Integral Degradation Index (IDI) developed by the authors in previous works [34]. This composite indicator accounts for capacity loss from calendar ageing, cyclic ageing, and random operational variability such as temperature fluctuations, variable DoD, SOC swings, and inconsistent C-rate conditions. The *IDI* formula integrates the deterministic degradation models with a stochastic uncertainty term [34]:

$$\begin{aligned} IDI(T) &= Q_{total}(t) = Q_{calendar}(t) + Q_{cycle}(t) \pm \Delta Q(t) \\ &= k_{calendar} \cdot e^{\frac{E_a}{RT}} \cdot t \cdot f(SOC) + k_{cycle} \cdot (DOD)^{\alpha} \cdot (C_{rate})^{\beta} \cdot e^{\frac{E_a}{RT}} \cdot N_{cycle}(t) \\ &\pm \sqrt{\left(\frac{\partial Q}{\partial T}\Delta T\right)^2 + \left(\frac{\partial Q}{\partial SOC}\Delta SOC\right)^2 + \left(\frac{\partial Q}{\partial DOD}\Delta DOD\right)^2 + \left(\frac{\partial Q}{\partial C_{rate}}\Delta C_{rate}\right)^2} \end{aligned} \quad (3)$$

where $Q_{calendar}(t)$—loss of capacity due to calendar aging; $k_{calendar}$—reaction rate constant; E_a—activation energy; R—universal gas constant; T is the temperature; t is the time; $f(SOC)$ is a function that describes the dependence on the *SOC*; $Q_{cycle}(t)$—loss of capacity due to cyclic aging; k_{cycle}—reaction rate constant for cyclic aging; *DOD*—depth of discharge; C_{rate}—charging/discharging speed; α and β—model parameters; $N_{cycle}(t)$—the number of charge/discharge cycle; $Q_{total}(t)-$ total loss of battery capacity, taking into account the factors of calendar and cyclic aging; Δ*Q*(t)—taking into account the uncertainty of the state/behaviour of secondary batteries under operating conditions; ΔT, ΔSOC, ΔDOD, ΔC_{rate} are random variables, respectively, temperature, state of charge, depth of discharge, charge/discharge rate with a particular distribution (e.g., normal), derivatives represent $\frac{\partial Q}{\partial T}$ $\frac{\partial Q}{\partial SOC}$, $\frac{\partial Q}{\partial DOD}$, $\frac{\partial Q}{\partial C_{rate}}$ the sensitivity of the battery capacity to changes in each of these parameters.

The Remaining Useful Life (RUL) of a battery denotes the projected operational duration remaining before the battery's state of health (SOH) declines to a predefined critical threshold. For SLB applications, lifespan prediction must capture usage- and context-dependent uncertainty. Beyond baseline calendar/cyclic aging curves, recent studies show that RUL accuracy improves when (i) temperature and depth-of-discharge dependencies are explicitly modeled, (ii) diagnostic features at end-of-charge/impedance are leveraged to track health trajectory, and (iii) data-driven or hybrid (physics-informed) prognostics are used to fuse sparse field data with prior electrochemical knowledge [31,41–50]. In this work, we treat these methods as modular options within the KPI–PDCA framework: their outputs (e.g., probabilistic RUL bands) feed the *Check* phase and inform trigger thresholds for reassignment, derating, or refurbishment in the *Act* phase. This alignment allows uncertainty-aware operational decisions for SLBs while keeping empirical model selection open to site-specific data availability [19,51–53].

Provided the initial *SOH* at the beginning of the second-life application and a critical *SOH* limit for acceptable performance, the *RUL* can be estimated as:

$$RUL = \frac{SOH_0 - SOH_{critical}}{IDI}, \quad (4)$$

where SOH_0—the initial state of health of the battery when it starts its secondary use; $SOH_{critical}$—the critical state of health at which the battery is considered no longer adequate for the intended application, IDI—the integral degradation index, which represents the rate of degradation per unit time.

This index enables more realistic modelling of SLB behaviour in operational environments. It improves accuracy in SOH and RUL predictions, making it particularly suitable for adaptive control and trigger-based decision-making within the PDCA framework. Cross-validation was performed using synthetic datasets reflecting three representative SLB ageing scenarios. The results were compared to degradation patterns reported in [34].

In addition, it is essential to account for the reliability indicator $R(t)$, which reflects the actual ability of the battery to operate without interruptions during its second-life application. This indicator is defined as the ratio of uninterrupted operating time to the total operating time:

$$R(t) = \frac{T_{uptime}}{T_{total\ operating}}. \quad (5)$$

Its value decreases in the presence of frequent faults, shutdowns, or failure events, and it is critically important for assessing the long-term effectiveness of second-life battery applications in power systems.

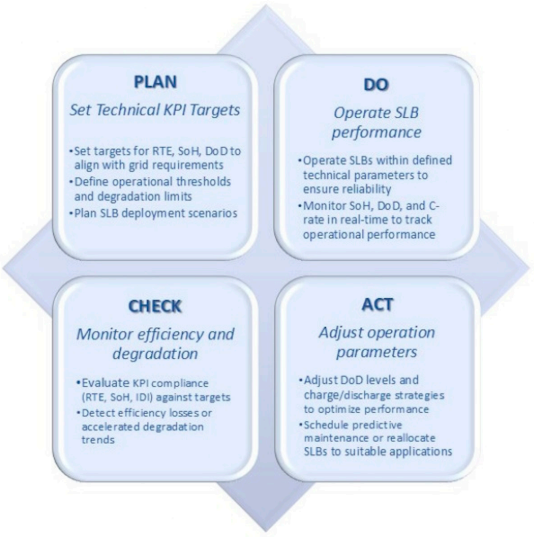
Integrating these technical KPIs within the PDCA cycle enables systematic monitoring and adaptive management, providing the data foundation for trigger-based decision-making, scenario planning, and lifecycle extension strategies under the principles of the circular economy [101,102]. The KPI values used for Scenarios 1–3 are based on indicative benchmarks reported by [9,99] and peer-reviewed studies [35–37,60]. Where direct data for SLBs were unavailable, values were derived from literature ranges for LIBs and adjusted for typical second-life performance (SOH ≈ 70–80%, RTE ≈ 85%). Table 3 summarises the selected technical KPIs relevant to SLB deployment and their connection to PDCA phases.

Table 3. Technical KPIs for SLB Integration.

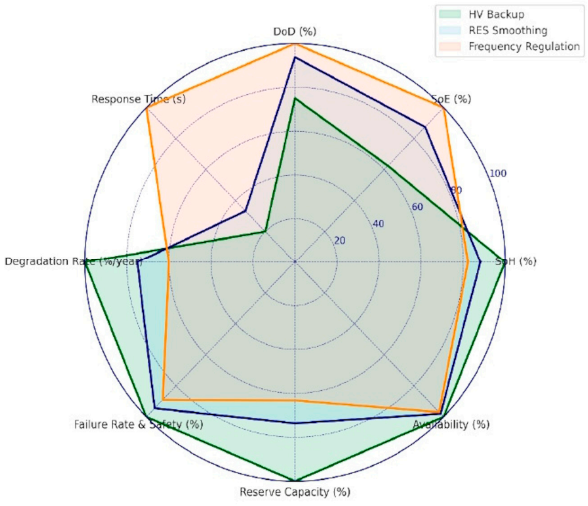
KPI	Description	Measurement Method	Reference Values	Data Source	PDCA Phase
Round-Trip Efficiency (RTE)	Ratio of energy discharged to energy charged, indicating the conversion efficiency of SLB system	% calculated from charge/discharge energy over time	>85% for optimal operation	BMS, EMS logs	Check, Act
Depth of Discharge (DOD)	Proportion of battery capacity used during a cycle, affecting degradation rate	% of nominal capacity	60–80% for balanced degradation and usability	BMS	Do, Check
State of Health (SOH)	Remaining capacity and performance relative to initial state	% of initial capacity; impedance analysis	>70% for active grid applications	BMS diagnostics	Check
Integral Degradation Index (IDI)	Composite metric combining calendar, cyclic, and stochastic ageing	Dimensionless index (0–1 scale)	<0.85 for continued use in active roles	Calculated from operational data	Check, Act
C-rate	Charge/discharge current relative to capacity, impacts ageing	0.2–0.5 C for typical SLB use	≤0.5 C in grid support	BMS	Do, Check
Internal Resistance (IR)	Resistance within the battery, indicating degradation level	measured under load	Threshold increases with degradation; monitor trend	BMS	Check
Remaining Useful Life (RUL)	Projected operational lifespan under current usage	Cycles or years forecast	3–7 years in grid	Prognostic algorithms	Plan, Check
Reliability indicator R(t)	Ratio of uninterrupted operation time to total operating time during SLB use	calculated	≥0.95 for critical applications	SLB system logs, monitoring systems	Check, Act

In practice, these technical KPIs guide operational decisions across different SLB deployment scenarios [93,94]. For instance, in frequency regulation services, maintaining an RTE above 85% and SOH above 70% ensures rapid and reliable system response while preserving SLB health [103]. In renewable energy smoothing applications, DOD levels are strategically managed to balance energy flexibility and degradation rates. At the same time, the IDI can be monitored to assess the combined effects of cyclic and calendar ageing [29,104].

By integrating the selected technical KPIs into the PDCA cycle, operators can implement a structured and adaptive approach to SLB management. This enables ongoing monitoring, threshold-based trigger control, and scenario-specific planning, aligning operational strategies with circular economy goals and performance sustainability [105–107]. The diagram in Figure 7a illustrates how key technical indicators (such as RTE, SOH, DOD, and IDI) are embedded within each PDCA phase to support continuous performance improvement and degradation mitigation. To visualise how these indicators manifest in different system roles, Figure 7b presents a comparative radar chart of three SLB deployment scenarios—HV Backup, RES Smoothing, and Frequency Regulation—highlighting scenario-specific KPI profiles and trade-offs.



(a)



(b)

Figure 7. Technical KPIs for SLB integration within the PDCA framework: (**a**) Integration of key performance indicators into the PDCA cycle for managing second-life batteries; (**b**) Comparative radar chart of three SLB deployment scenarios based on normalised technical KPI scores.

4.3. Economic KPIs for SLB Deployment

Economic feasibility is a critical dimension of SLB deployment, influencing investment decisions, operational strategies, and long-term project viability [62,107]. Economic KPIs such as LCOS, Payback Period (PBP), Return on Investment (ROI), and Revenue Stacking Potential provide structured tools for evaluating the cost-effectiveness of SLB systems while aligning them with market and policy frameworks [62,108,109]. These indicators allow for quantifying economic benefits, managing operational expenditures, and assessing profitability under various market conditions, including in residential, backup, and grid-support contexts [108–110].

To quantify the financial viability of SLB deployment across scenarios, two key economic indicators are applied: *ROI* and *LCOS*.

ROI is calculated as:

$$ROI = \frac{Net\ Profit}{Total\ Investment} \cdot 100\% \tag{6}$$

LCOS reflects the total cost per unit of stored and delivered energy across the project lifetime:

$$LCOS = \frac{\sum_{t=1}^{T} \frac{C_t + O_t}{(1+r)^{t-1}}}{\sum_{t=1}^{T} \frac{E_t}{(1+r)^{t-1}}} \tag{7}$$

where C_t—capital expenditures in year t; O_t—operational and maintenance costs; E_t—delivered energy; r—discount rate; T—project lifetime.

These formulas allow for comparative financial assessment across applications such as backup power, microgrids, and renewable integration. As noted in prior work [32–34], SLB deployment in RES smoothing shows an ROI of 15–22%, while LCOS values vary strongly with utilisation and degradation rate. ROI is initially assessed at the investment stage and is subsequently re-evaluated during later stages of SLB operation, reflecting updated performance and financial conditions.

Incorporating economic KPIs within the PDCA cycle ensures that financial considerations are systematically monitored and integrated into adaptive decision-making, enabling project stakeholders to align operational control with profitability and circularity goals [107,111]. Table 4 summarizes the key economic KPIs relevant to SLB integration and their linkage to PDCA phases.

Table 4. Economic KPIs for SLB Integration.

KPI	Description	Measurement Method	Reference Values	Data Source	PDCA Phase
Levelized Cost of Storage (LCOS)	Average cost per kWh stored/discharged over SLB lifetime	USD/MWh calculated from total costs and energy throughput	<150–200 USD/MWh for economic viability	Financial analysis, EMS data	Plan, Check
Payback Period (PBP)	Time to recover initial investment from operational savings	Years calculated from cash flow	4–6 years typical	Financial tracking	Plan, Check
Return on Investment (ROI)	Profitability measure over project lifetime	% calculated from net profit/investment	>10–15% desirable	Financial reports	Check
Revenue Stacking Potential	Ability to generate multiple revenue streams (e.g., FR, arbitrage)	Qualitative + USD tracking	Scenario-dependent	EMS, market data	Plan, Do
Operational Expenditure (OPEX)	Ongoing costs for maintenance and operation	USD/year	Minimized within system reliability constraints	O&M logs, financial	Do, Check
Amortization Period	Period over which investment cost is spread	Years	Typically 5–10 years	Financial planning	Plan
Internal Rate of Return (IRR)	Discount rate making NPV zero	%	>8–12% acceptable	Financial calculation	Check

In application, these economic KPIs support scenario-specific financial optimization of SLB systems [62,108]. For example, in HV Backup scenarios, LCOS calculations can be used to compare SLB integration with alternative backup solutions, while PBP and ROI provide critical benchmarks for project viability under cost-constrained conditions [107,110]. In RES smoothing and frequency regulation scenarios, revenue stacking potential allows operators to leverage multiple income streams, improving economic performance and reducing reliance on a single service revenue [108,111].

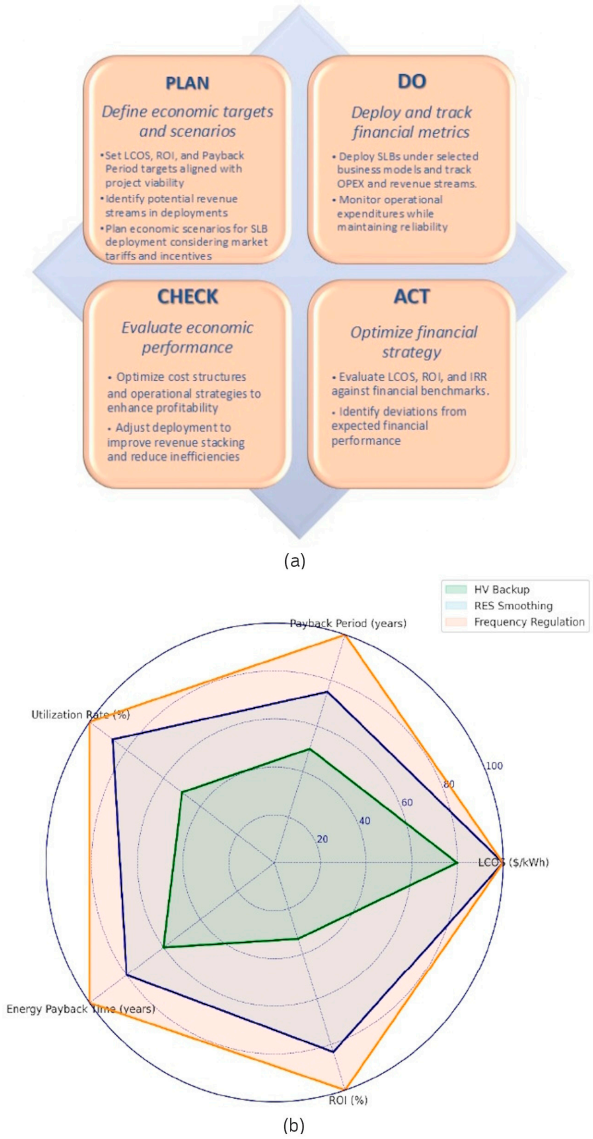


Figure 8. Economic KPI-driven SLB management within the PDCA framework: (**a**) Integration of economic performance indicators into the PDCA cycle to support adaptive financial planning and control; (**b**) Radar chart comparing economic KPIs across three SLB deployment scenarios.

Integrating economic KPIs into the PDCA cycle enables continuous assessment of project viability and profitability across SLB deployment scenarios [107,109,110]. By embedding indicators such as LCOS, ROI, PBP, and Utilization Rate into financial planning and monitoring workflows, stakeholders can identify cost deviations, anticipate revenue fluctuations, and adjust strategies in response to market conditions. Figure 8a presents the economic dimension of the PDCA logic, illustrating how each phase contributes to financial control and optimization. To contextualize these indicators within specific system roles, Figure 8b visualizes the economic KPI profiles of the

three representative SLB scenarios—HV Backup, RES Smoothing, and Frequency Regulation. The radar chart highlights scenario-specific performance trade-offs, enabling comparative evaluation and scenario-driven financial strategy design.

4.4. Environmental KPIs for Evaluation of SLB Sustainability

Environmental sustainability indicators are essential for evaluating the circularity potential and climate impact of SLB deployment in energy systems [112,113]. Metrics such as Lifecycle GHG Emissions Reduction, Resource Savings, and End-of-Life Recyclability Readiness quantify the environmental benefits of reusing batteries compared to first-life systems and conventional fossil-based alternatives [114–116].

Environmental KPIs provide critical insight into the circular value of SLBs. For instance, carbon footprint reduction is expressed as:

$$\Delta CO_2 = \Delta CO_2^{new} - \Delta CO_2^{SLB} \tag{8}$$

where ΔCO_2^{new} and ΔCO_2^{SLB} represent lifecycle emissions for new and second-life battery production, respectively.

A 40 kWh SLB pack can save over 2200 kg CO_2 compared to a new battery.

Material efficiency (ME), indicating energy return on material input, is given by:

$$ME = \frac{E_{out}^{SLB}}{E_{material}^{new}} \tag{9}$$

where E_{out}^{SLB} represents useful output energy in second life, and $E_{material}^{new}$ reflects embodied energy in raw materials.

Another indicator, Energy Payback Time ($EPBT$), reflects the time to recover the energy invested in SLB repurposing:

$$EPBT = \frac{E_{repurpose}}{E_{delivered,annual}} \tag{10}$$

For typical SLB deployments, $EPBT \approx 0.1$ years (≈1.2 months), significantly outperforming new LIBs.

Finally, the Circularity Score (CS) is used for comparative circularity evaluation:

$$CS = \frac{W_{reused} + W_{recycled}}{W_{total}} \tag{11}$$

where W_{reused}—the mass of components reused in the second-life battery application; $W_{recycled}$—the mass of components recyclable after the end of the second life; W_{total}—the total mass of materials in the battery.

This indicator reflects the proportion of materials that are either reused or returned into the production cycle, thus serving as a key metric for assessing circular economy performance, and for SLBs achieving scores up to 0.9 versus 0.6 for new batteries.

These KPIs align SLB operations with decarbonization pathways, material circularity, and regulatory sustainability targets [117,118]. Integrating environmental KPIs within the PDCA cycle enables real-time tracking of sustainability outcomes, allowing operational strategies to be adapted to enhance SLB contributions to circular economy goals while maintaining alignment with system performance and economic feasibility [119,120]. Table 5 summarizes key environmental KPIs applicable to SLB management and their placement within PDCA phases.

Table 5. Environmental KPIs for SLB integration.

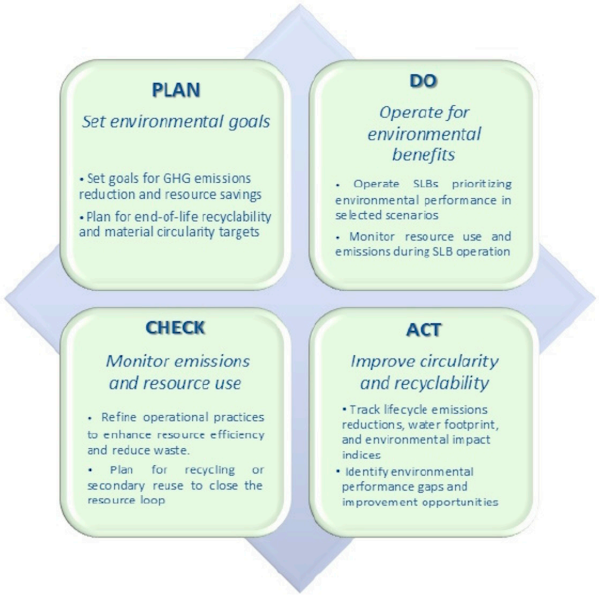
KPI	Description	Measurement Method	Reference Values	Data Source	PDCA Phase
Lifecycle GHG Emissions Reduction	Reduction in CO_2-eq emissions vs. new batteries or fossil alternatives	kg CO_2-eq saved per kWh	>30% reduction target	LCA studies, EMS data	Plan, Check
Material Efficiency	Ratio of energy delivered to embodied material energy	Dimensionless ratio	>1.5	LCA, material input data	Check, Act
Energy Payback Time (EPBT)	Time needed to repay energy used for SLB repurposing	Years	<0.2 years	Repurposing data, use profile	Do, Check
Circularity Score (CS)	Combined indicator of reuse and recyclability	Normalized score (0–1)	>0.8	Material flow analysis	Act, Check
Environmental Pollution Reduction	Reduction in harmful emissions and waste during SLB usage	% reduction compared to baseline	>50%	Emissions inventory, LCA	Do, Check

In practical deployment, these environmental KPIs guide sustainability-aligned operational management of SLBs [112,113]. For instance, in RES smoothing scenarios, monitoring lifecycle GHG reductions enables quantifying emissions savings achieved by displacing fossil-based peak plants, while resource savings metrics provide insights into the materials preserved through reuse instead of new battery production [114–117]. End-of-life recyclability readiness supports planning for circular re-entry of materials, closing the loop in battery resource cycles [118–126]. Utilizing these KPIs within PDCA-based operations enables evidence-based scenario prioritization, allowing SLB operators to select and adjust use cases that maximize environmental benefits while sustaining system reliability and cost-effectiveness.

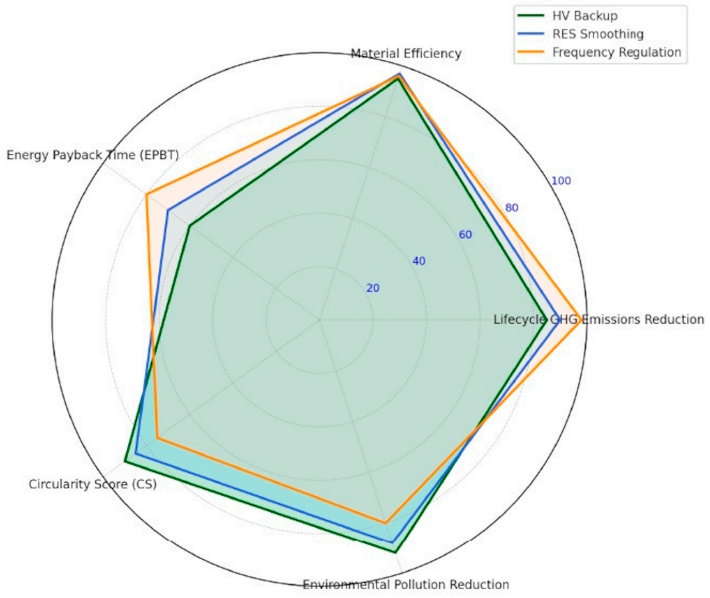
To enable environmentally sound integration of SLBs into energy systems, environmental KPIs must be operationalized within a structured management framework. The PDCA cycle provides such a structure, supporting scenario-specific sustainability goals, tracking real-time emissions and resource use, and informing end-of-life strategies. Figure 9a outlines how environmental considerations are embedded into each PDCA phase—from planning circularity targets to acting on emissions trends and recyclability readiness. To assess how various SLB deployment scenarios contribute to sustainability goals, Figure 9b presents a comparative radar chart of environmental KPIs across three application types: HV Backup, RES Smoothing, and Frequency Regulation. The chart highlights the environmental strengths and trade-offs of each use case, facilitating evidence-based decision-making aligned with decarbonization and circular economy objectives.

While technical, economic, and environmental KPIs each offer valuable insights into second-life battery (SLB) performance, none of them alone is sufficient for making informed deployment decisions. Technical indicators such as SOH, RTE, or IDI characterize the physical capability and health of the battery, but they do not reflect whether continued use is financially viable or environmentally justified. Conversely, a deployment scenario with favorable ROI or LCOS may involve rapid degradation or poor reliability, ultimately compromising system performance. Similarly, scenarios with strong environmental impact—such as carbon footprint reduction or circularity gains—may underperform economically or technically, limiting their practical relevance.

Each KPI dimension becomes more or less critical at different stages of the SLB lifecycle. In the initial screening and repurposing phase, technical KPIs dominate decision-making to ensure safe and viable operation. During scenario matching and early deployment, economic KPIs such as LCOS and ROI take precedence to confirm financial feasibility. As the battery progresses through its operational phase, degradation trends and usage profiles shift the emphasis toward trigger-based technical monitoring. Toward the end of life, environmental and circularity KPIs become crucial in guiding reallocation, recycling, or disposal planning.



(a)



(b)

Figure 9. Environmental KPI integration into the PDCA cycle for SLB sustainability management: (**a**) PDCA cycle stages applied to environmental goals, emissions tracking, and recyclability planning in SLB operations; (**b**) Radar comparison of environmental KPIs across SLB deployment scenarios (HV Backup, RES Smoothing, Frequency Regulation), illustrating sustainability performance profiles.

This evolving relevance of KPIs necessitates a composite, dynamic evaluation framework that allows weighting, tracking, and balancing of competing priorities. Integrating these KPIs within the PDCA management cycle enables scenario-specific optimization, supports lifecycle governance, and ensures alignment with circular economy principles.

4.5. Composite Scenario-Based KPIs Visualization

To support balanced and adaptive deployment of SLBs, a composite radar-based visualization approach is employed. Unlike separate assessments of technical, economic, and environmental indicators, this integrated view enables holistic comparison of SLB perfor-

mance across representative operational scenarios—high-voltage backup, RES smoothing, and frequency regulation.

Figure 10 presents a composite radar chart that consolidates normalized KPI values across all three dimensions, offering a multidimensional overview of scenario-specific strengths, weaknesses, and trade-offs. This includes metrics such as round-trip efficiency, SOH, degradation rate, LCOS, payback period, lifecycle carbon footprint, material resource efficiency, and more—each normalized to a 0–100 scale to allow joint visualization.

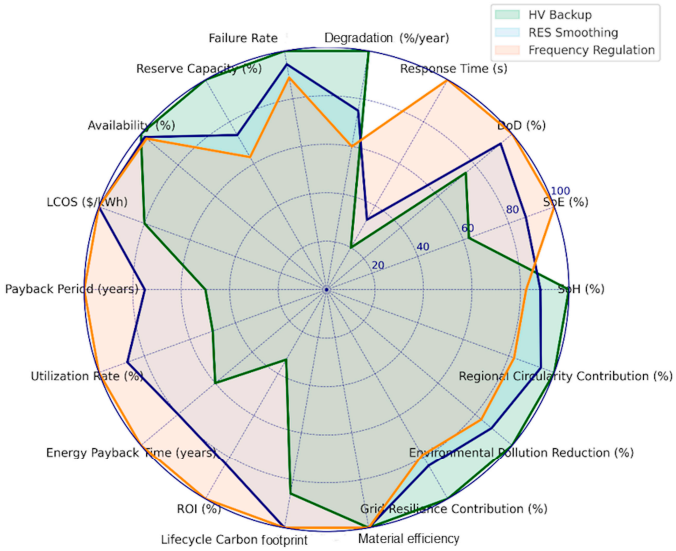


Figure 10. Scenario-based KPI Radar Analysis of Second-Life Batteries (SLBs): Composite KPI overview.

The chart reveals that Frequency regulation delivers strong technical responsiveness but faces challenges from accelerated degradation and increased LCOS, reflecting intensive cycling stress. HV backup excels in safety, availability, and reserve capacity, with moderate financial returns and limited cycling intensity—making it suitable for longevity-oriented roles. RES smoothing offers the most balanced profile, with stable performance across environmental and economic KPIs, positioning it as a versatile option in grid-interactive applications.

This visual comparison directly supports PDCA-based SLB management by making trade-offs explicit and scenario selection more transparent. It enables stakeholders to align deployment strategies with system priorities—whether optimising for resilience, economic return, or circularity gains.

In addition to comparing SLB scenarios, Figure 11 presents a reference radar chart contrasting SLBs and new LIBs across selected KPIs. While SLBs demonstrate clear advantages in lower LCOS and circularity benefits, they underperform in capacity retention, depth of discharge, and degradation rate, emphasising the need for context-specific planning and lifecycle-aware operation.

Together, Figures 10 and 11 anchor the KPI framework in practical insights, enabling adaptive, evidence-based SLB deployment aligned with performance targets and sustainability goals.

This scenario-based KPI analysis supports system planners, operators, and researchers in evaluating SLB deployment strategies, enabling informed decision-making on scenario prioritisation while managing trade-offs between operational performance, financial considerations, and sustainability objectives within adaptive PDCA-based management frameworks.

Beyond scenario-based comparisons, KPI roles evolve dynamically across the SLB lifecycle—from early-stage screening to portfolio-level optimisation. Table 6 summarises this evolution by mapping KPI functions to distinct integration phases and strategic decisions. This complements radar-based evaluations with a temporal logic, clarifying not only what to monitor but also when and why it matters for SLB integration.

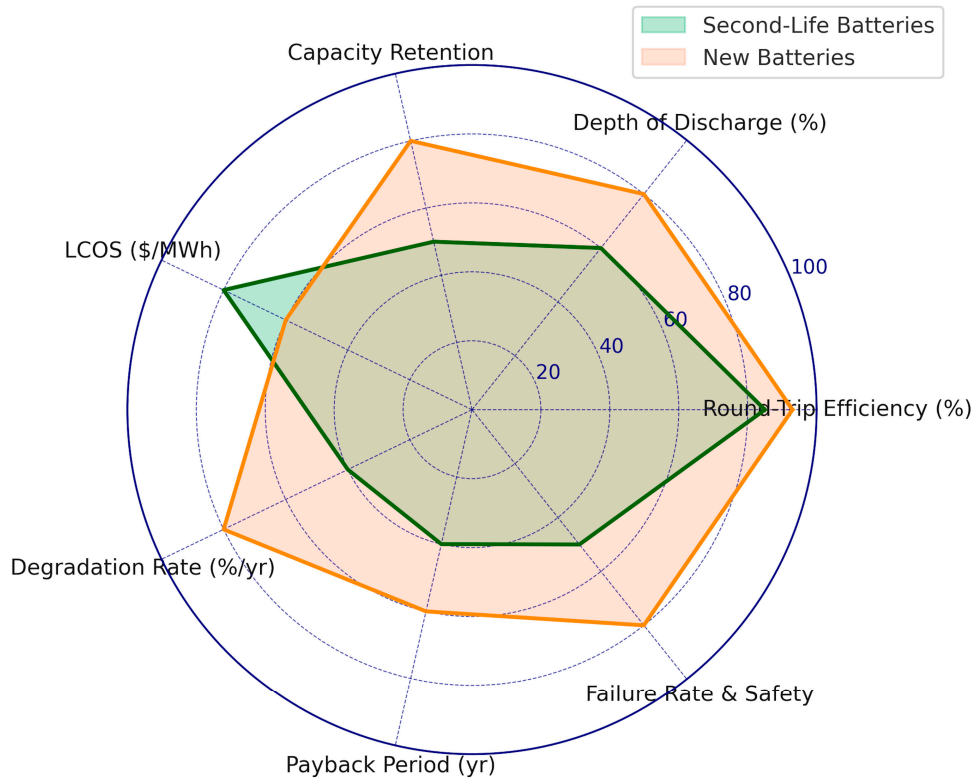


Figure 11. Comparative radar chart of SLBs and new LIBs across KPIs.

Table 6. Application of KPIs in SLB Lifecycle Management.

Stage of SLB Integration	Dominant KPI Role	Example Metrics	Typical Trade-Offs	Strategic Purpose
Initial Screening	Filtering Indicator	SOH, RUL Estimate	Risk of underutilization vs. safety	Select technically viable units
Scenario Matching	Suitability Scoring	DoD, LCOS, Payback	High revenue vs. fast degradation	Match batteries to optimal use cases
Pilot Operation	Performance Benchmark	RTE, Thermal Profile	Efficiency vs. complexity of monitoring	Identify systemic weaknesses
Mid-Term Assessment	Threshold Evaluation	IDI, SOH Drift	Conservative operation vs. underuse	Adjust cycle depth or duty profile
Portfolio Optimization	Decision Trigger	Degradation Rate, LCOS	Short-term gains vs. asset longevity	Reallocate or retire based on ROI decline

Integrating KPIs within the PDCA framework enables systematic continuous improvement in SLB operation: Plan (define KPI targets), Do (deploy with monitoring), Check (track deviations), Act (adjust operational strategies). This structured feedback loop aligns SLB performance with grid requirements, economic objectives, and sustainability goals.

4.6. Trigger-Based Control Logic

To operationalise the PDCA-based integration of second-life batteries (SLBs), a trigger-based control mechanism is introduced, linking key performance indicators (KPIs) to adaptive decision rules. This approach transforms KPI monitoring into actionable logic, enabling timely interventions in response to technical degradation, economic inefficiencies, or environmental deviations. By defining threshold values and corresponding actions, SLB deployment strategies can dynamically evolve while maintaining alignment with system-level objectives, circular economy principles, and reliability standards.

Within this logic, each KPI serves as a sentinel for a specific type of risk or opportunity. When thresholds are breached, corrective or preventive actions are triggered in the Do or Act phases of the PDCA cycle, ensuring that performance deterioration does not become irreversible.

Representative examples of such KPI-driven triggers include:

SOH Trigger: If the state of health drops below 65%, the SLB is reassigned from high-intensity applications (e.g., frequency regulation) to low-stress roles (e.g., backup), thereby extending usable life and deferring replacement.

IDI Trigger: When the Integral Degradation Index exceeds 0.85, indicating cumulative calendar, cyclic, and stochastic wear, the battery's operational load is reduced or it is prepared for secondary reassignment or recycling.

RTE Trigger: A decline in RTE below 75% prompts adjustments in depth-of-discharge (DOD) or cycling frequency to reduce further degradation.

LCOS Trigger: An increase in the LCOS beyond predefined viability thresholds initiates strategic reassessment, including possible changes to use-case scenarios or business models.

Environmental Triggers: If lifecycle GHG reduction falls below 25% or resource savings become negligible, ecological performance is flagged for review, triggering redesign or exit strategies.

Table 7 provides a consolidated KPI–trigger matrix with indicative benchmark values derived from IEC standards, NREL/IEA reports, and peer-reviewed studies. They serve as reference ranges for scenario-specific SLB management rather than prescriptive limits. The matrix links each KPI to corresponding trigger conditions and operational responses, structured in alignment with the PDCA cycle.

Table 7. KPI-Based Trigger and Action Matrix Integrated with PDCA cycles.

KPI	Threshold Value	Sources	Trigger Condition	Action (Do/Act)	Data	PDCA Phase
RTE	>85%	[9,23,99]	Drop below 80%	Adjust DOD, review charge rates	EMS, BMS	Check, Act
DOD	60–80%	[95,96]	Deviates >10% from plan	Limit cycles, adjust dispatch	BMS	Do, Check
SOH	>70%	[48,98]	Drop to 65–70%	Reassign to a low-stress application	BMS diagnostics	Check, Act
IDI	<0.85	[34]	Exceeds 0.85	Trigger reassessment, reallocation	Calculated	Check, Act
LCOS	<200 USD/MWh	[28,45,93,100]	Exceeds threshold	Evaluate cost drivers, optimise ops	Financial analysis	Plan, Check
PBP	4–6 years	[100,113]	Extends beyond 7 years	Recalculate financial plan	Financial tracking	Plan
ROI	>10–15%	[9,44]	Falls below 8%	Adjust business model	Financial reports	Check
GHG Reduction	>30%	[33,127,128]	Drops below 25%	Investigate inefficiencies	LCA data	Check
Resource Savings	20–40%	[98,127,128]	Drops significantly	Review reuse logistics	LCA analysis	Check

This trigger-based logic empowers SLB operators to implement data-driven, scenario-aware interventions, ensuring performance stability, economic feasibility, and sustainability. By embedding KPI thresholds directly into the PDCA cycle, this approach facilitates predictive governance, reduces degradation risks, and supports lifecycle extension—reinforcing the broader goals of circular energy systems. The trigger-based control structure reflects a custom event-driven logic devised specifically for adaptive SLB dispatch under scenario variability.

4.7. KPI-Triggered Operational Model

To operationalise trigger-based SLB management within the PDCA cycle, we propose a formalised control model in which real-time values of selected KPIs determine appropriate system-level actions. These actions aim to maximise performance while minimising degradation, economic loss, or sustainability compromise. The model builds upon the KPI-action matrix and embeds decision logic into an adaptive control rule applicable to SLB deployment.

Let the following KPIs be monitored at time t: SOH(t)—state of health, LCOS(t)—levelized cost of storage, U(t)—utilisation rate, R(t)—reliability indicator.

We also define key thresholds and acceptable minimum values: T_{SOH}—SOH threshold, L_{LCOS}—LCOS threshold, U_{min}, R_{min}—minimum acceptable values for utilisation and reliability, respectively.

Then the control action $A(t)$ is selected according to the rule:

$$A(t) = \begin{cases} \text{Replace}, & \text{if } SOH(t) < T_{SOHi} \text{ or } LCOS(t) > L_{LCOS}, \\ \text{Reallocate}, & \text{if } SOH(t) \geq T_{SOHi},\ LCOS(t) \leq L_{LCOS},\ U(t) < U_{min} \\ \text{Reoptimize}, & \text{if } SOH(t) \geq T_{SOHi},\ LCOS(t) \leq L_{LCOS},\ U(t) \geq U_{min},\ R(t) < R_{min} \\ \text{Continue}, & \text{if } SOH(t) \geq T_{SOHi},\ LCOS(t) \leq L_{LCOS},\ U(t) \geq U_{min},\ R(t) \geq R_{min} \end{cases} \quad (12)$$

This logic yields four distinct operational strategies:

Replace: If technical or economic thresholds are violated, the SLB is retired or moved to end-of-life processing.

Reallocate: If utilisation is too low despite acceptable SOH and LCOS, the SLB is reassigned to a more suitable use case.

Reoptimize: If reliability drops, operational parameters are adjusted (e.g., dispatch frequency, DoD) to mitigate further risk.

Continue: If all KPIs remain within target bounds, the current scenario is maintained.

Each action is mapped to PDCA phases:

- Plan: Define KPI targets and thresholds based on scenario evaluation.
- Do: Deploy batteries and begin monitoring.
- Check: Evaluate deviations using real-time KPI inputs.
- Act: Apply A(t) based on logic rule to modify or continue the operational strategy.

This model ensures that SLB deployment remains data-driven, dynamically adaptive, and aligned with both technical feasibility and circular economy objectives. Moreover, it enables the formalisation of transition logic between deployment roles, bridging operational monitoring with actionable system-level responses.

This study relies on simulated data rather than operational logs. The degradation model assumes uniform calendar and cyclic decay, which may not capture real-world thermal or charging variability. The KPI weights are expert-based and may vary across systems. Scalability and interoperability with existing dispatch platforms require further verification.

4.8. Future Research: Multi-Model Framework for SLB Deployment

Building on the presented KPI-based control approach, future research will focus on the development of an integrated multi-model framework for SLB deployment. This framework will support comprehensive decision-making throughout the battery lifecycle by combining technical performance monitoring, economic feasibility analysis, spatial allocation, operational optimisation, and replacement planning—all aligned with the PDCA cycle. Such an approach aims to enhance the efficiency and reliability of SLB integration into energy systems under diverse grid and microgrid scenarios.

In the PLAN phase, target KPIs are defined across technical (SOH, SOE, DOD, IDI), economic (LCOS, ROI, PBP), and environmental (lifecycle carbon footprint, material resource efficiency) dimensions. Degradation and RUL models are employed to assess the technical suitability of SLBs for intended applications. Economic feasibility is evaluated using LCOS and financial performance indicators, while scenario-based planning identifies optimal use cases considering system flexibility and resilience requirements.

In the DO phase, SLBs are deployed within selected applications such as renewable energy integration, backup power, or frequency regulation. Operational parameters are configured using cluster-based deployment and optimisation models, ensuring efficient system integration while monitoring degradation trends through the IDI and SOH metrics.

In the CHECK phase, real-time monitoring of KPIs allows comparison of actual performance with planned targets. Trigger conditions, based on thresholds for degradation, utilisation rates, and economic parameters, initiate system checks for operational adjustments, maintenance scheduling, or reconfiguration of deployment scenarios.

In the ACT phase, corrective actions are implemented to optimise SLB operation, including adjusting charging/discharging strategies, transitioning to alternative operational scenarios, or planning replacements. Feedback from operational performance informs iterative improvements in future SLB deployment strategies.

To operationalise the KPI-PDCA framework, a set of interconnected models supports scenario-based deployment and adaptive management of SLBs within energy systems. Table 8 summarises these models, detailing their inputs, outputs, applied methods, and integration within the PDCA cycle to align SLB deployment with circular economy goals and system flexibility requirements.

Table 8. Models within the SLB Deployment Framework and their PDCA Phases.

Model Name	Input Parameters	Outputs	Methods Used	PDCA Phase
Degradation Assessment Model	Calendar age, cycle count, temperature, load history	Integral Degradation Index, capacity fade rates	Empirical modelling, regression, and machine learning	PLAN, DO
Remaining Useful Life Forecasting Model	SOH(t), IDI, operational history	Estimated RUL, projected service lifetime	Time series forecasting, exponential smoothing, threshold-based rules	PLAN, CHECK
Economic Feasibility Model	Costs, service life, efficiency, tariffs/profits	LCOS, NPV, IRR, payback period	Financial modelling, scenario analysis, LCOS calculation	PLAN
Optimisation Model for SLB Allocation	Costs, reliability, location, and environmental impacts	Optimal SLB deployment across scenarios	Multi-criteria optimisation, mathematical programming	PLAN, DO
Spatial Deployment Model	Load profiles, infrastructure, RES share, regional risks	Feasibility maps, object ranking for deployment	GIS analysis, spatial multi-criteria assessment	PLAN
Replacement Planning Model	SOH, IDI, degradation thresholds	Replacement timing, reuse or disposal recommendations	Threshold rules, dynamic replacement planning	CHECK, ACT

The models presented in Table 8 function as an integrated system supporting the systematic deployment and adaptive management of SLBs within the KPI-PDCA framework. By combining degradation analysis, lifetime forecasting, economic feasibility, spatial and operational optimisation, and replacement planning, these models enable informed decision-making across planning, operation, monitoring, and corrective phases. Trigger-based control logic is embedded within this structure, using KPI thresholds to initiate adjustments in dispatch strategies, scenario allocations, or replacement timing as SLBs progress through different stages of use. This multi-model approach ensures that SLB deployment aligns with circular economy principles by extending asset lifecycles, improving resource efficiency, and reducing waste while maintaining operational flexibility and economic viability within energy systems. Figure 12 visually summarises this integrated multi-model framework, illustrating how the individual models interact within the PDCA cycle to support scenario-based SLB deployment and adaptive management.

Together, these models enable comprehensive scenario-based evaluation and operational management of SLBs within energy systems, supporting decision-making aligned with circular economy principles, system flexibility needs, and sustainability objectives.

In Ukraine, active research is underway to develop advanced models supporting SLB deployment within energy systems, covering frequency regulation applications, distributed generation integration, and scenario-based optimisation under technological and environmental constraints [129–134]. These models address both the technical dynamics of SLB operation and the economic-environmental dimensions of system-level deployment planning, aligning with the broader goals of grid flexibility and low-carbon transition path-

ways [125–128]. Notably, the author has contributed to this field through the development of integrated degradation modelling, cluster-based SLB allocation frameworks, and circular economy-oriented operational scenarios for the Ukrainian power system [17–19,34,118]. Future work will focus on calibrating these models using real-world operational and degradation datasets to refine scenario-based analyses and trigger thresholds. Additionally, the integrated use of these models offers the potential for developing digital twin systems for SLB management, enabling predictive diagnostics, adaptive dispatch strategies, and continuous optimisation within energy systems.

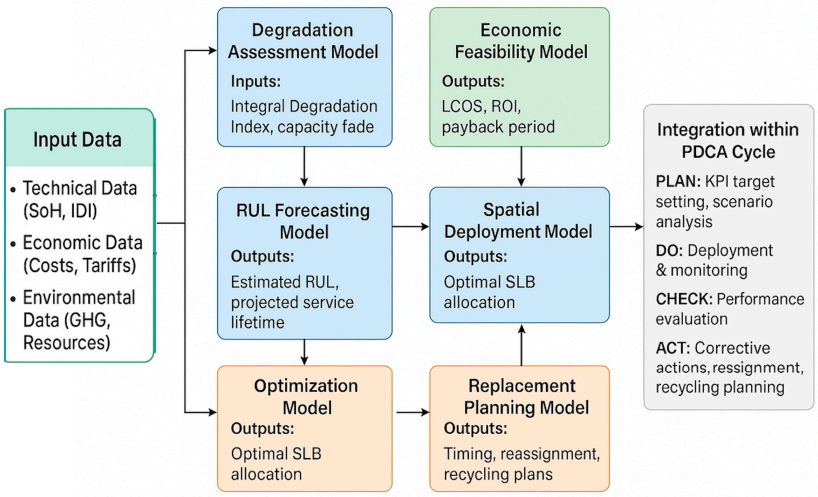


Figure 12. Integrated multi-model framework for second-life battery deployment within the PDCA cycle.

5. Discussion

5.1. Benchmarking with SOTA Methods

While large-scale optimisation tools such as DIgSILENT PowerFactory [57], TIMES [58], and ENERTILE [59] provide valuable insights for system-level planning and long-term economic assessment, they typically lack the granularity required for real-time operational control and do not account for SLB-specific degradation patterns or KPI-triggered decision logic. Similarly, recent SLB-oriented studies (e.g., [33,61,100]) have emphasised techno-economic feasibility or KPI categorisation, but they remain fragmented, with no unified management cycle. The proposed KPI–PDCA framework complements these approaches by embedding operational indicators, adaptive trigger logic, and scenario-specific deployment within an iterative PDCA structure. This positions the framework as a bridging methodology between macro-level system planning and micro-level operational decision-making.

Evaluation consistency across framework components was ensured by cross-checking KPI definitions and threshold logic, so that technical, economic, and environmental indicators were aligned and scenario calculations remained internally coherent.

5.2. Environmental KPIs and Sustainability Implications

Beyond technical and economic indicators, the framework also incorporates environmental KPIs such as lifecycle greenhouse gas (GHG) emissions, carbon footprint per MWh stored, and resource savings from reuse and recycling. For instance, achieving a GHG reduction of >30% relative to primary battery deployment is aligned with benchmarks reported in [33] and [60]. Embedding these KPIs within the PDCA cycle allows environmental performance to be continuously monitored (Check phase) and acted upon (Act phase), ensuring that sustainability targets are integrated into operational decision-making

rather than considered only retrospectively. This reinforces the role of SLBs in advancing circular economy objectives and decarbonization pathways.

5.3. Limitations

This study is conceptual in scope and presents a proof-of-concept framework rather than fully validated empirical results. While scenario-based KPI illustrations have been provided (HV Backup, RES Smoothing, Frequency Regulation), detailed numerical case studies and algorithmic simulations were not included. Another limitation is the absence of hardware-in-the-loop validation, which may reveal implementation constraints such as communication latency or inverter control delays. Additionally, the framework currently assumes indicative KPI thresholds based on standards and literature benchmarks; refining these thresholds with real-world operational datasets remains a priority for future research.

5.4. Future Work

Future research will focus on computational implementation and validation of each model using field data and pilot projects. This will include refining degradation modelling under variable operating conditions, optimising dispatch strategies for cost and emission reductions, and evaluating resilience contributions under grid contingencies. In parallel, collaboration with utilities and regulators will be critical to overcome adoption barriers and ensure that SLB deployment strategies are harmonised with evolving policy frameworks.

6. Conclusions

This study presents a conceptual KPI–PDCA framework for the sustainable deployment of second-life batteries (SLBs) in energy systems. The framework integrates technical (SOH, RTE, DOD, RUL), economic (LCOS, ROI, PBP, NPV), and environmental (GHG reduction, resource savings) KPIs into an adaptive management cycle that links monitoring with trigger-based operational responses. By doing so, the approach provides a structured, replicable, and flexible methodology for guiding SLB integration under conditions of uncertainty.

Benchmarking against state-of-the-art methods shows that while system-level models such as DIgSILENT, TIMES, and ENERTILE offer valuable insights for long-term planning, they do not capture degradation-aware operation or KPI-triggered lifecycle decisions. Recent SLB studies define KPIs or assess economic and environmental feasibility, but remain fragmented, without an operational management cycle. The proposed framework addresses this gap by linking KPI thresholds to PDCA phases and scenario-based deployment strategies, thereby enabling continuous adaptation of SLB utilisation across use cases.

Illustrative KPI calculations for three representative scenarios (HV Backup, RES Smoothing, and Frequency Regulation) demonstrate how the framework can guide practical decision-making. The results highlight trade-offs: backup applications enhance resilience, renewable smoothing balances grid variability, and frequency regulation offers technical value but requires careful degradation management. Across all scenarios, SLBs show economic advantages in LCOS and payback, despite lower efficiency compared to new batteries.

By embedding environmental KPIs, such as lifecycle GHG reduction and resource savings, the framework aligns SLB deployment with circular economy principles. This ensures that technical and economic optimisation does not overlook sustainability performance.

Future research will focus on empirical validation with real-world datasets and pilot projects, refinement of KPI thresholds, and exploration of hybrid SLB–new battery configurations.

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Abbreviations

The following abbreviations are used in this manuscript:

BESS	Battery Energy Storage System
BMS	Battery Management System
DOD	Depth of Discharge
EMS	Energy Management System
EV	Electric Vehicle
GHG	Greenhouse Gas
HV	High Voltage
IDI	Integral Degradation Index
IRR	Internal Rate of Return
KPI	Key Performance Indicator
LCOS	Levelized Cost of Storage
LIB	Lithium-Ion Battery
NPV	Net Present Value
O&M	Operation and Maintenance
PBP	Payback Period
PDCA	Plan-Do-Check-Act
RES	Renewable Energy Sources
ROI	Return on Investment
RTE	Round-Trip Efficiency
RUL	Remaining Useful Life
SLB	Second-Life Battery
SOH	State of Health

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