

Article

Experimental Multi-Metric Health Assessment of Second-Life Electric Vehicle Batteries for Reuse Pathway Classification

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Abstract

Second-life electric vehicle (EV) batteries are increasingly recognized as valuable resources for stationary energy storage. However, the heterogeneous degradation of retired batteries makes reliable and application-oriented reuse decisions challenging. Existing studies primarily focus on battery health estimation or degradation characterization, while limited attention has been given to systematically translating experimentally measured health indicators into practical second-life deployment decisions. To address this gap, this study proposes an experimental multi-metric battery health assessment and decision-support framework for application-oriented screening and reuse pathway allocation of retired EV batteries. A total of 91 s life lithium-ion battery cells were experimentally characterized through standardized laboratory charge–discharge testing. Multiple complementary health indicators, including State of Health (SoH), discharge capacity, round-trip energy efficiency, and voltage–current time-series characteristics, were extracted and statistically analyzed to evaluate residual battery performance and degradation behavior. The experimental results reveal substantial variability among retired batteries, with SoH values ranging from approximately 22% to 96%, while more than half of the tested cells exhibit SoH below 60%. Furthermore, batteries with comparable SoH frequently demonstrate different energy efficiencies, indicating that capacity retention alone is insufficient for reliable second-life battery assessment. Building upon these findings, a transparent rule-based decision-support framework is developed to map experimentally measured battery health indicators to application-oriented reuse pathways, including grid-support systems, residential energy storage, backup applications, and recycling. The proposed framework establishes a practical bridge between laboratory battery characterization and deployment-oriented second-life decision-making, providing an interpretable and experimentally grounded methodology for scalable battery screening and sustainable reuse planning.

Keywords: second-life EV batteries; battery health assessment; state of health; round-trip energy efficiency; reuse pathway classification; stationary energy storage



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1. Introduction

The rapid expansion of the electric vehicle (EV) market has led to a significant increase in the number of lithium-ion batteries reaching the end of their automotive service life [1]. Although these batteries are typically retired when their capacity decreases to approximately 70–80% of their original nominal value, they often retain sufficient residual capacity

for use in less demanding stationary applications [2]. Consequently, second-life utilization of retired EV batteries has attracted considerable attention as a promising strategy to reduce battery waste, extend material value, and enable cost-effective energy storage solutions. In addition to its economic benefits, battery repurposing supports circular economy principles by promoting resource conservation, reducing environmental impact, and improving the lifecycle sustainability of battery technologies [3].

Despite these advantages, the practical deployment of second-life batteries remains challenging because retired batteries exhibit highly heterogeneous degradation characteristics [4]. Battery ageing is governed by multiple degradation mechanisms, including loss of active material, internal resistance growth, and parasitic side reactions, all of which are influenced by operating conditions such as duty cycles, temperature exposure, and depth of discharge [5]. Consequently, retired batteries demonstrate considerable variability in State of Health (SoH), usable capacity, and round-trip energy efficiency [5]. This heterogeneity complicates battery screening and reuse decision-making, making it difficult to reliably determine the most suitable second-life application for individual batteries. Therefore, reliable and comprehensive health assessment methodologies are essential not only for identifying batteries suitable for reuse but also for distinguishing those that should be directed toward recycling [6].

A substantial body of research has investigated battery degradation mechanisms, SoH estimation techniques, and the technical feasibility of second-life applications. However, many existing studies rely on limited experimental datasets, simulated degradation scenarios, or single-parameter evaluation approaches, most commonly capacity-based SoH assessment. While these studies provide valuable insights into battery degradation, they often evaluate health indicators independently and provide limited support for practical reuse decision-making. In real-world second-life deployment, battery suitability depends on multiple complementary performance indicators. For example, round-trip energy efficiency directly influences energy losses, heat generation, and operational cost, whereas voltage and current characteristics provide additional insight into internal resistance growth and electrochemical degradation [7]. Consequently, evaluating battery condition using a single indicator may not adequately represent its residual functional capability for specific second-life applications.

To address these limitations, this study experimentally characterizes a heterogeneous population of retired EV batteries using a comprehensive set of complementary health indicators. Standardized charge–discharge experiments are conducted under controlled laboratory conditions to extract State of Health, maximum discharge capacity, round-trip energy efficiency, and voltage–current time-series characteristics [8]. The resulting dataset enables population-level statistical characterization, cross-metric analysis of battery degradation behavior, and systematic evaluation of relationships among multiple health indicators.

Building upon these experimentally derived health indicators, this study further develops an application-oriented battery screening framework for second-life deployment. Rather than evaluating battery condition solely from an analytical perspective, the proposed framework translates measured battery health characteristics into structured reuse pathway recommendations. Based on the combined assessment of SoH, discharge capacity, and round-trip energy efficiency, batteries are classified into application-oriented categories, including grid-support systems, residential energy storage, backup applications, and recycling. In this way, the framework establishes a practical link between laboratory battery characterization and deployment-oriented decision-making, providing decision support for industrial battery screening, repurposing, and lifecycle management.

The primary contribution of this work is an experimentally grounded framework for assessing heterogeneous retired EV batteries using multiple complementary health indicators and systematically relating these indicators to application-oriented reuse decisions. The study quantitatively examines the relationships among SoH, discharge capacity, and round-trip energy efficiency, demonstrating that capacity retention alone does not fully characterize residual battery performance. By integrating experimentally measured capacity-based and energy-based indicators within a transparent and interpretable classification methodology, the proposed framework provides a practical approach for supporting scalable second-life battery screening and reuse pathway determination. Rather than proposing a new predictive model or learning-based algorithm, this work addresses an important practical gap by bridging comprehensive laboratory battery characterization with application-oriented second-life deployment decisions.

2. Related Work

Second-life utilization of electric vehicle (EV) batteries has attracted increasing research attention in recent years, driven by the rapid global expansion of EV adoption and the resulting accumulation of retired traction batteries [9]. Previous studies have investigated this topic from multiple perspectives, including battery degradation characterization, State of Health (SoH) estimation, second-life application feasibility, and ageing model development. These studies have significantly advanced the understanding of battery degradation and repurposing strategies. However, existing research has largely addressed these aspects independently, while comparatively limited attention has been given to integrating experimentally derived battery health indicators into a unified framework that directly supports application-oriented second-life deployment decisions using heterogeneous retired EV battery populations.

2.1. Degradation Characterization and State of Health Estimation

A substantial body of research has focused on estimating battery SoH for both on-board monitoring and laboratory diagnostics [10]. Existing approaches commonly rely on individual degradation indicators, including capacity fade, internal resistance growth, and incremental capacity analysis. Among these, capacity-based SoH estimation remains one of the most widely adopted methods because of its simplicity and clear physical interpretation [11]. Nevertheless, capacity alone does not fully characterize battery degradation, as it does not adequately reflect changes in round-trip energy efficiency, voltage stability, energy losses, or thermal behavior that directly influence operational performance [12].

Another limitation of many reported SoH estimation studies is their reliance on simulated degradation trajectories or relatively small and homogeneous experimental datasets. Although these studies provide valuable insights into battery ageing, they may not adequately represent the diverse operational histories and degradation characteristics of retired EV batteries intended for second-life deployment [13].

Recent research has further explored the integration of second-life batteries into broader energy systems. Studies on multi-station EV charging networks have highlighted the operational challenges associated with load balancing and energy management when second-life batteries are incorporated into charging infrastructure [14]. Likewise, hybrid photovoltaic–battery systems have demonstrated the technical feasibility and economic potential of utilizing second-life batteries for stationary energy storage applications [15]. While these studies demonstrate promising application scenarios, they generally assume that battery suitability has already been determined and therefore provide limited guidance on how heterogeneous retired batteries should be systematically screened before deployment.

Impedance-based diagnostic techniques, particularly electrochemical impedance spectroscopy (EIS), have also been extensively investigated for battery health assessment [16]. EIS provides detailed information on internal resistance, charge-transfer processes, and electrochemical kinetics, enabling the identification of degradation mechanisms that cannot always be inferred from capacity measurements alone [17]. However, impedance-based methods typically require specialized instrumentation, longer testing durations, and more sophisticated analysis procedures, limiting their suitability for high-throughput battery screening [18]. Consequently, there remains practical interest in assessment methodologies based on standardized charge–discharge measurements that can be more readily implemented for large-scale evaluation of retired batteries.

2.2. Second-Life Application Feasibility Studies

Recent advances in machine learning and deep learning have significantly improved battery SoH estimation [19]. Methods utilizing incremental energy or state-of-charge (SOC) features combined with machine learning algorithms have demonstrated enhanced sensitivity to battery degradation behavior [20]. Furthermore, deep learning architectures such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and related variants have achieved high estimation accuracy by effectively modelling temporal characteristics of battery data [21].

More recently, transformer-based architectures, including Vision Transformers, together with hybrid approaches combining fractional-order equivalent circuit models and data-driven learning, have further improved prediction accuracy under complex operating conditions [22]. Attention mechanisms and hybrid neural network structures have also enhanced feature extraction and model robustness for battery health prediction [23].

Although these approaches provide powerful predictive capabilities, they are primarily designed for SoH estimation and typically require large, labelled datasets for model development. Their primary objective is accurate prediction rather than practical decision support for allocating heterogeneous retired batteries to appropriate second-life applications. In contrast, the present study focuses on experimentally measured battery health indicators and their systematic interpretation through an application-oriented classification framework that supports practical battery screening without requiring predictive model training.

A parallel research direction has focused on evaluating the feasibility of specific second-life applications, including residential energy storage, renewable energy integration, uninterruptible power supply systems, and microgrid support [24]. Many of these studies assess feasibility using nominal battery specifications or assumed performance characteristics rather than experimentally measured health conditions [25]. Moreover, most investigations evaluate batteries within a single application scenario and do not consider how batteries exhibiting different degradation characteristics may be allocated across multiple second-life applications [26]. Consequently, a practical gap remains between battery health assessment and application-oriented deployment decision-making.

2.3. Ageing Models and Their Limitations for Practical Second-Life Battery Screening

Extensive research has also been devoted to electrochemical, empirical, and semi-empirical models describing lithium-ion battery ageing [27]. These models improve understanding of degradation mechanisms, including solid electrolyte interphase growth, lithium inventory loss, and active material degradation. However, they are generally developed using controlled laboratory experiments and relatively homogeneous battery populations. In practical applications, retired EV batteries experience diverse operating conditions, cycling histories, and environmental exposures, resulting in substantially heterogeneous

behavior [28]. Consequently, simulation-based ageing models require validation using experimentally characterized retired batteries before they can reliably support practical second-life deployment decisions.

Table 1 summarizes representative studies on second-life EV batteries and highlights the research gaps addressed in this work. Existing research has contributed significantly to battery degradation analysis, SoH estimation, simulation-based ageing models, energy efficiency assessment, machine learning prediction, application feasibility evaluation, and impedance-based diagnostics. However, comparatively fewer studies have combined large-scale experimental battery characterization with multi-metric health assessment and an application-oriented decision framework that directly supports systematic reuse pathway allocation for heterogeneous retired EV batteries. The comparison presented in Table 1 provides the foundation for the research gaps discussed in the following subsection.

Table 1. Representative studies related to second-life EV battery characterization and the specific research gaps addressed in this work.

Study Focus	Main Contribution	Limitation/Research Gap	Ref.
SoH estimation (capacity/resistance)	State of Health estimation using capacity or impedance measurements	Primarily focused on capacity or impedance indicators with limited integration of complementary performance metrics	[29]
Simulation ageing models	Empirical and electrochemical models for predicting battery ageing	Limited experimental validation using large, heterogeneous retired EV battery populations	[30]
Energy efficiency studies	Analysis of charge–discharge energy efficiency behavior	Lack of integrated analysis combining SoH, capacity, and efficiency	[31]
Small-scale experimental datasets	Laboratory testing on a limited number of battery cells (typically fewer than 20)	Limited statistical significance and representativeness of real battery populations	[32]
Second-life feasibility analysis	Evaluation of battery suitability for specific second-life applications	Limited linkage between experimentally measured battery health and application-oriented allocation	[33]
Machine learning SoH prediction	Neural network and regression-based SoH estimation models	Often focused on predictive accuracy rather than practical reuse pathway determination	[34]
Impedance and advanced diagnostic methods	Use of impedance spectroscopy and signal-based health indicators	Require specialized equipment and complex analysis; limited scalability	[35]
Pack and module-level studies	Assessment of battery packs and modules	Limited focus on cell-level variability and individual cell performance	[36]
Our work	Experimental characterization of 91 retired EV cells using multi-metric health indicators and reuse pathway classification	Integrates experimentally measured SoH, discharge capacity, and efficiency into an interpretable reuse pathway classification framework	

As summarized in Table 1, existing studies have typically focused on isolated aspects of second-life battery analysis, including SoH estimation, ageing simulation, techno-economic assessment, impedance diagnostics, or application feasibility evaluation. However, rela-

tively few investigations combine experimentally measured multi-metric health characterization with direct application-oriented reuse pathway allocation using heterogeneous retired EV batteries. The present study specifically addresses this intersection by integrating experimentally derived SoH, discharge capacity, and round-trip efficiency indicators into a transparent classification framework for second-life deployment screening.

2.4. Identified Research Gaps

Based on the reviewed literature, several important research gaps remain in the assessment and practical deployment of second-life EV batteries.

First, many existing studies rely primarily on a single health indicator, most commonly capacity-based State of Health (SoH), without incorporating complementary performance metrics such as discharge capacity and round-trip energy efficiency. Although SoH provides a useful measure of capacity retention, it does not fully capture the functional performance of aged batteries. Consequently, batteries exhibiting similar SoH values may differ substantially in energy efficiency, voltage stability, and operational capability, increasing the risk of inaccurate second-life suitability assessment.

Second, large-scale experimental investigations using heterogeneous populations of retired EV batteries remain relatively limited. Numerous studies rely on simulated degradation profiles, newly manufactured batteries, or relatively small laboratory datasets, which may not adequately represent the diverse ageing characteristics encountered in practical second-life applications. As a result, the applicability of many existing assessment approaches to real-world battery repurposing remains insufficiently validated.

Third, although battery health indicators such as SoH, discharge capacity, and round-trip energy efficiency have each been widely investigated, their integrated evaluation remains relatively limited. These indicators reflect different aspects of battery degradation and provide complementary information regarding residual battery performance. Evaluating them independently may therefore overlook important characteristics that influence battery suitability for second-life deployment.

Fourth, relatively few studies establish a systematic framework that translates experimentally measured battery health indicators into application-oriented reuse decisions. Existing research commonly focuses on battery characterization, degradation analysis, or application feasibility independently, without explicitly connecting experimentally derived battery condition to structured reuse pathway allocation. Consequently, a practical gap remains between laboratory battery characterization and deployment-oriented decision-making.

Collectively, these research gaps highlight the need for an experimentally validated and practically applicable assessment framework capable of integrating multiple complementary health indicators while supporting systematic second-life battery screening. Although previous studies have made significant contributions to SoH estimation, degradation analysis, ageing simulation, techno-economic evaluation, and application feasibility assessment, comparatively fewer studies combine comprehensive experimental characterization with application-oriented decision support for heterogeneous retired EV batteries.

Motivated by these gaps, the present study experimentally evaluates 91 retired EV battery cells under standardized laboratory conditions and extracts multiple complementary health indicators, including State of Health, discharge capacity, and round-trip energy efficiency. Building upon these experimentally derived indicators, the study performs cross-metric statistical analysis and develops a transparent classification framework that systematically relates battery health characteristics to application-oriented reuse pathways. Rather than proposing a new predictive or learning-based model, the study aims to pro-

vide an experimentally grounded and practically interpretable methodology that supports scalable second-life battery screening and deployment decisions.

3. Methodology

This section presents the integrated methodological framework developed for the health characterization and application-oriented reuse allocation of second-life electric vehicle (EV) batteries. The proposed framework combines standardized charge–discharge experimentation, time-series signal acquisition, data preprocessing and validation, multi-metric health indicator extraction, statistical degradation assessment, and rule-based decision-making within a unified evaluation architecture.

Unlike conventional battery assessment approaches that rely primarily on a single degradation indicator, the proposed methodology integrates capacity-related and energy-related performance indicators to provide a more comprehensive representation of residual battery condition. Discharge capacity and the derived State of Health (SoH) quantify remaining energy-storage capability, while round-trip energy efficiency captures energy losses associated with internal degradation processes and operational performance limitations.

Following experimental characterization, the acquired voltage and current signals are processed and analyzed to extract key health-related indicators describing battery degradation behavior and residual performance capability. Statistical and cross-metric analyses are subsequently performed to evaluate indicator distributions, interrelationships, and variability across the battery population. Based on the combined evaluation results, a multi-metric decision engine is employed to classify batteries according to their residual functional characteristics and allocate them to suitable second-life application pathways.

The proposed framework supports application-oriented reuse allocation for multiple deployment scenarios, including grid-support systems, residential energy storage systems, backup or low-rate applications, and recycling pathways for severely degraded batteries. By integrating experimental assessment with systematic decision-support logic, the methodology establishes a practical and scalable framework for reliable second-life battery screening and deployment.

The overall integrated system-level framework adopted in this study is illustrated in Figure 1.

Figure 1 illustrates the complete workflow of the proposed multi-metric battery health assessment and reuse pathway classification framework. The process begins with experimental charge–discharge testing of second-life EV batteries under controlled laboratory conditions. Voltage, current, capacity, and energy measurements are continuously acquired and stored as high-resolution time-series data. These raw measurements are subsequently subjected to preprocessing and validation procedures to remove incomplete records, identify anomalous measurements, and improve data quality.

Following preprocessing, key battery health indicators are extracted, including discharge capacity, State of Health (SoH), and round-trip energy efficiency. These indicators provide complementary information regarding capacity retention, energy losses, and overall battery performance. Statistical analysis is then performed to investigate the distribution of degradation characteristics across the battery population and to evaluate relationships among the extracted health indicators.

Finally, the derived health metrics are supplied to a multi-metric decision engine, which applies the proposed classification rules to determine the most suitable second-life deployment pathway for each battery. Based on the combined evaluation of SoH and efficiency-related performance characteristics, batteries are allocated to application categories including grid-support systems, residential energy storage, backup applications,

or recycling. This sequential workflow establishes a direct connection between experimental battery characterization and practical reuse decision-making.

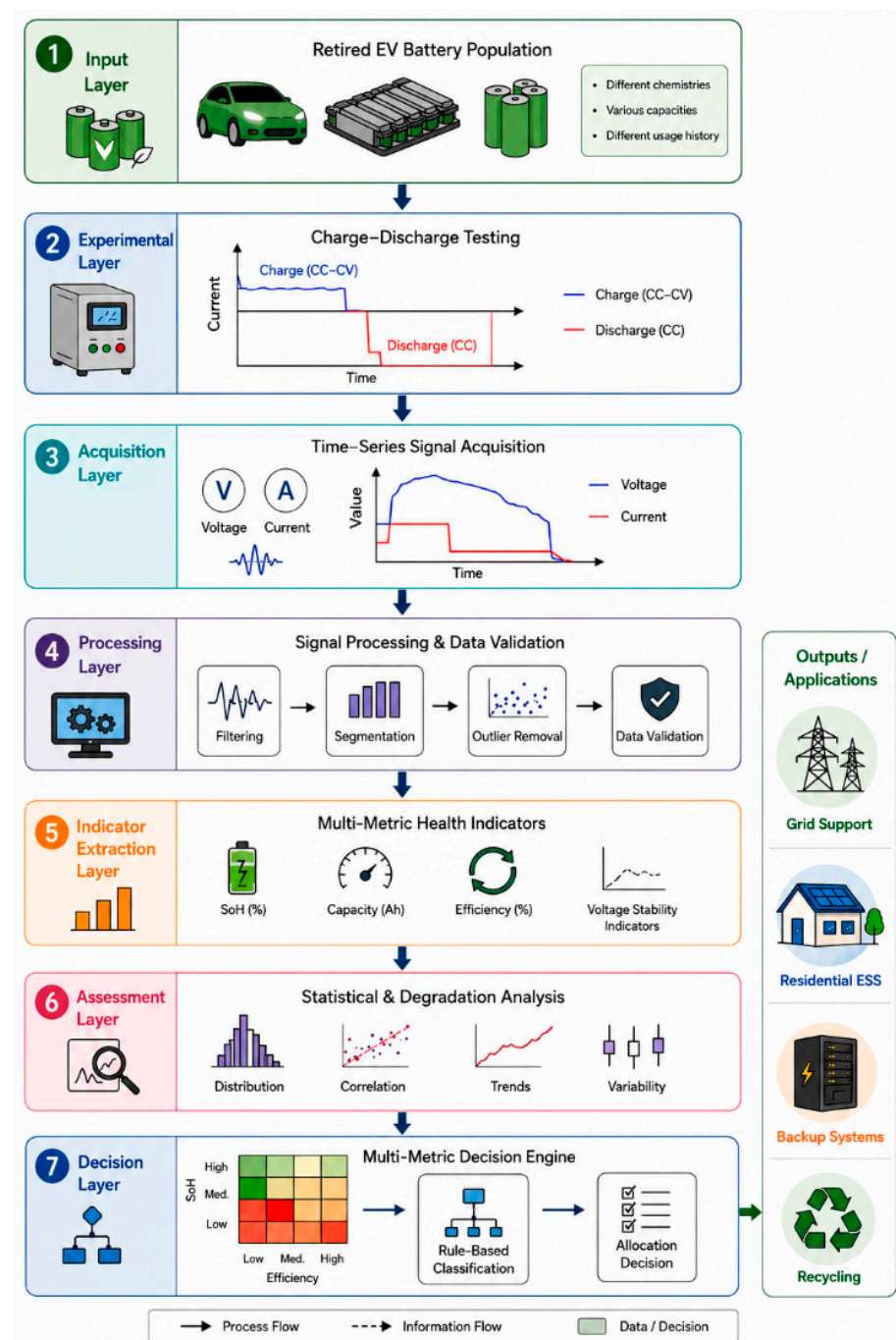


Figure 1. Integrated system-level framework for multi-metric health assessment and application-oriented reuse allocation of second-life EV batteries.

3.1. Experimental Testing and Data Acquisition

A total of 91 s life lithium-ion EV battery cells were experimentally evaluated in this study. The tested cells were obtained from retired electric vehicle battery packs through an academic–industry collaboration with a battery repurposing partner. All batteries originated from commercial EV systems that had reached end-of-service conditions for automotive applications. Due to confidentiality agreements, detailed information regarding vehicle manufacturers, models, and operational histories cannot be disclosed. Nevertheless, the dataset represents a heterogeneous retired battery population subjected to diverse

real-world operating conditions, including variations in cycle aging, depth of discharge, and calendar aging duration.

Although detailed vehicle operating histories, manufacturer information, and usage records could not be disclosed due to confidentiality agreements, all tested cells originated from retired EV battery systems with comparable electrochemical characteristics and nominal specifications. Consequently, the statistical analysis was performed on a relatively homogeneous battery population, allowing meaningful comparison of residual health characteristics despite the absence of detailed first-life operational information.

All experiments were conducted in a controlled laboratory environment at 25 ± 2 °C. The tested cells are lithium-ion EV battery cells with a nominal rated capacity of 180 Ah. A calibrated laboratory-grade battery testing system (Neware BTS series) was used for all charge–discharge experiments, providing voltage measurement accuracy of $\pm 0.05\%$ and current measurement accuracy of $\pm 0.1\%$. The testing system was calibrated prior to experimentation according to manufacturer procedures to ensure measurement accuracy and traceability.

The tested cells were operated under constant-current charge and discharge conditions, with observed current levels of approximately ± 14.4 A and voltage operating limits ranging from approximately 2.8 V to 3.65 V. These profiles illustrate the standardized cycling conditions used for battery characterization and health assessment.

Each battery was subjected to constant-current charging followed by constant-current discharging within manufacturer-specified voltage limits. The experimental design was intended to establish a standardized characterization framework for evaluating the residual functional performance of retired EV batteries for potential stationary second-life applications. Rather than emulating a specific operational profile, such as grid support or low-speed electric vehicle duty cycles, the experiments were designed to obtain consistent and comparable measurements of intrinsic battery health characteristics, including discharge capacity, round-trip energy efficiency, voltage stability, and energy delivery capability.

Voltage, current, capacity, and energy were continuously recorded throughout each charge–discharge cycle using a sampling interval of 1 s. This sampling resolution is consistent with standard laboratory practices for lithium-ion battery characterization and enables accurate numerical integration of current and power signals for capacity and energy computation. The recorded variables are summarized in Table 2.

Table 2. Recorded experimental variables.

Variable	Description
$V(t)$	Terminal voltage as a function of time
$I(t)$	Charge and discharge current as a function of time
Cumulative capacity	Charge and discharge capacity
Energy	Charge and discharge energy

The duration of individual charge–discharge cycles varied according to the State of Health and remaining capacity of each battery cell. Under the applied constant-current protocol, complete charge–discharge cycles typically ranged from approximately 1.5 to 3 h, with more degraded cells generally exhibiting shorter discharge durations due to earlier voltage cutoff conditions.

The combination of controlled environmental conditions and high-resolution time-series acquisition enabled reliable extraction of battery health indicators, including discharge capacity, energy efficiency, and voltage-response characteristics for subsequent statistical analysis and reuse pathway classification.

3.2. Data Preprocessing and Validation

The experimental datasets consisted of high-resolution time-series measurements of voltage, current, capacity, and energy acquired during charge–discharge testing. Prior to analysis, a structured preprocessing and validation procedure was implemented to ensure data reliability, internal consistency, and suitability for quantitative battery health assessment.

All charge–discharge records were first screened to identify incomplete, prematurely terminated, or instrument-interrupted cycles. Such records were excluded to prevent inaccuracies in capacity and energy calculations. Measurements exhibiting physically implausible behavior or exceeding operational limits, including abnormal voltage values or irregular current signals, were identified as outliers and removed from further analysis.

Specifically, abnormal records were identified according to three criteria. First, charge–discharge cycles that were incomplete, prematurely terminated, or interrupted due to equipment communication or acquisition errors were excluded. Second, measurements exhibiting physically implausible voltage or current behavior, including abrupt signal discontinuities, missing data segments, or values outside the operational limits defined by the testing protocol, were classified as outliers. Third, derived performance indicators producing physically unrealistic results, such as round-trip energy efficiency values exceeding the theoretical limit of 100%, were flagged for additional validation and treated as potential measurement or preprocessing anomalies. These quality-control procedures were implemented to ensure the reliability and consistency of the dataset used for subsequent statistical analysis and battery health classification.

To reduce the influence of measurement noise while preserving the underlying electrochemical response, a moving-average smoothing filter was applied to the voltage and current time-series signals. The filtered data were subsequently segmented into charge, discharge, and rest phases using threshold-based analysis of the current waveform. For each valid discharge segment, the start and end points were automatically identified according to current transitions and voltage cut-off conditions.

A moving-average filter with a window size of 10 samples was applied to both voltage and current measurements. Given the sampling interval of 1 s, this corresponds to a smoothing window of 10 s. The selected window size was sufficient to suppress high-frequency measurement noise while preserving the overall charge–discharge behavior and voltage-response characteristics required for battery health assessment.

Following preprocessing and quality screening, the validated charge–discharge cycles were retained for feature extraction. For each battery cell, a consolidated dataset was generated containing discharge capacity, computed State of Health (SoH), round-trip energy efficiency, and additional derived performance indicators. This processed dataset formed the basis for the statistical analysis, correlation evaluation, multi-metric classification, and reuse pathway determination presented in the subsequent sections.

All battery cells were tested under identical experimental protocols and sampling conditions to ensure consistency and comparability across the dataset.

In addition, calculated round-trip energy efficiency values exceeding 100% were flagged as potential measurement or preprocessing anomalies and were separately examined during the statistical validation stage to assess their influence on the overall analysis.

3.3. Mathematical Formulation for Health Estimation

This subsection presents the mathematical formulations used to derive the key health indicators of second-life lithium-ion batteries. These indicators include discharge capacity, charge–discharge energy, State of Health (SoH), and round-trip energy efficiency.

The discharge capacity is obtained from the time integral of the discharge current:

$$C_{\text{dis}} = \int_{t_1}^{t_2} I_{\text{dis}}(t) dt \quad (1)$$

where t_1 and t_2 denote the start and end of the discharge period. Numerical integration is carried out using discrete sampled current measurements.

The charge or discharge of energy is calculated from the product of instantaneous voltage and current:

$$E = \int_{t_1}^{t_2} V(t) I(t) dt \quad (2)$$

which reflects both voltage behavior and ohmic losses due to internal resistance. The State of Health (SoH) is defined based on capacity retention:

$$\text{SoH}(\%) = \frac{C_{\text{dis}}}{C_{\text{rated}}} \times 100 \quad (3)$$

where $C_{\text{rated}} = 180$ Ah is the nominal rated capacity of the tested cells.

The round-trip energy efficiency is given by:

$$\eta_{\text{rt}}(\%) = \frac{E_{\text{dis}}}{E_{\text{ch}}} \times 100 \quad (4)$$

and reductions in η_{rt} are associated with resistive, kinetic, and thermal energy losses.

In addition to the primary health indicators defined above, several quantitative features were extracted from the voltage and current time-series profiles to characterize degradation behavior. The maximum discharge capacity and discharge energy were obtained through numerical integration, providing direct measures of charge storage capability and usable energy. The round-trip energy efficiency captures energy losses associated with internal resistance and electrochemical inefficiencies.

Furthermore, voltage profile characteristics were evaluated, including average discharge voltage and discharge duration. Degraded batteries typically exhibit lower average operating voltage and shorter discharge duration due to increased internal resistance and earlier voltage cutoff. These parameters provide additional quantitative indicators of battery degradation and complement the capacity-based State of Health metric.

In addition to the primary health indicators, degradation-sensitive quantitative features were extracted from the time-series voltage and current profiles. Maximum discharge capacity reflects loss of active lithium inventory and electrode degradation. Discharge energy and round-trip energy efficiency capture energy losses associated with internal resistance growth and polarization effects.

Voltage profile characteristics were also evaluated. Degraded batteries typically exhibit lower average discharge voltage and steeper voltage decline under constant current conditions due to increased internal resistance and reduced voltage stability. Discharge duration and usable energy delivery capability were also analyzed, as degraded batteries reach the cutoff voltage earlier. These extracted parameters provide quantitative indicators of degradation and establish a direct link between time-series behavior and underlying electrochemical degradation mechanisms.

The health indicators selected in this study were chosen because they directly reflect key functional degradation mechanisms relevant to second-life battery deployment. State of Health and maximum discharge capacity quantify the remaining charge storage capability, while round-trip energy efficiency captures internal resistance growth and energy dissipation during operation. Voltage profile behavior provides additional insight into polarization effects, voltage stability, and energy delivery performance under load. To-

gether, these parameters provide a complementary evaluation of both capacity-related and energy-related degradation characteristics.

The selection of discharge capacity, State of Health (SoH), and round-trip energy efficiency was motivated by their established relationship with major lithium-ion battery degradation processes reported in the literature. Capacity loss is commonly associated with degradation mechanisms such as loss of active lithium inventory, growth of the solid electrolyte interphase (SEI), and active material degradation, all of which reduce the amount of charge that can be stored and delivered by the battery. Consequently, discharge capacity and the derived SoH metric are widely used indicators of remaining energy-storage capability.

Round-trip energy efficiency provides complementary information because it is influenced by internal resistance growth, polarization effects, and irreversible energy losses occurring during charge–discharge operation. As batteries age, increased resistance and electrochemical inefficiencies typically result in lower energy efficiency, even in cases where capacity retention remains relatively acceptable. Therefore, efficiency degradation may reveal performance limitations that are not fully captured by capacity-based indicators alone.

It is acknowledged that battery ageing is governed by complex and interacting electrochemical mechanisms whose precise evolution depends on operating conditions, temperature history, cycling behavior, and battery chemistry. Since detailed historical operating records, electrochemical impedance measurements, and post-mortem material characterization were not available for the retired batteries investigated in this study, direct identification of specific degradation mechanisms was beyond the scope of the work. Instead, the proposed framework focuses on experimentally measurable performance indicators that serve as practical proxies for overall battery condition and second-life suitability. This approach is consistent with industrial battery screening practices, where rapid and scalable assessment methods are often preferred over detailed mechanistic diagnostics.

Equivalent Full Cycle (EFC)-based lifetime assessment methods have also been widely reported in the literature for battery degradation evaluation. However, EFC estimation typically requires detailed historical cycling records or long-term operational datasets, which were unavailable for the heterogeneous retired EV batteries analyzed in this study. Since the objective of the present work is practical screening and classification of already retired batteries using experimentally measurable indicators, the proposed framework relies on directly observable charge–discharge performance metrics rather than historical cycle-count reconstruction.

Internal resistance is widely recognized as an important degradation indicator because it directly influences power capability, voltage drop, heat generation, and energy efficiency. However, direct resistance measurements, such as DC internal resistance testing or electrochemical impedance spectroscopy (EIS), were not available within the experimental protocol used in this study. Consequently, resistance-based diagnostics could not be incorporated into the proposed framework. Nevertheless, round-trip energy efficiency was included as a complementary performance indicator because efficiency degradation is strongly influenced by internal resistance growth and associated energy losses during charge–discharge operation. Future work may extend the framework by integrating resistance- or impedance-based diagnostics to provide a more comprehensive assessment of second-life battery condition.

3.4. Health Classification Rules

To support practical interpretation of the measured indicators and enable application-oriented decision-making, the tested batteries were grouped into discrete health categories.

Classification thresholds were selected based on commonly accepted practices in electric vehicle warranty policies and second-life deployment guidelines.

The State of Health (SoH) thresholds adopted in this study are consistent with widely accepted industry and research standards. Lithium-ion batteries are typically considered to have reached automotive end-of-life when their capacity falls below approximately 70–80% of the nominal value, as this level no longer satisfies vehicle performance requirements. Batteries with SoH above 80% are generally regarded as suitable for demanding second-life applications, while those between 60% and 80% remain viable for less demanding stationary applications such as residential storage and backup systems. Batteries below 60% SoH are commonly considered unsuitable for most reuse scenarios and are directed toward recycling. The classification ranges used in this work ($\geq 90\%$, 80–90%, 60–80%, and $<60\%$) provide a finer subdivision within these established ranges to enable more detailed application mapping.

Similarly, the round-trip energy efficiency thresholds were defined based on both literature-reported performance ranges and the statistical distribution of the experimental dataset. Previous studies have reported typical efficiency ranges of approximately 80–95% for lithium-ion batteries depending on degradation state and operating conditions [25,26]. In the present dataset, most batteries exhibited efficiencies between 80% and 90%, and therefore efficiency values above 90% were classified as high efficiency, values between 80% and 90% as moderate efficiency, and values below 80% as low efficiency. This approach ensures that the efficiency classification reflects both experimentally observed performance and established operational benchmarks.

The combined SoH and efficiency classification provides a quantitative basis for reuse pathway determination by distinguishing batteries with sufficient capacity and acceptable energy efficiency from those with significant degradation and elevated internal losses.

Based on the calculated State of Health (SoH) values, the tested batteries were classified into four health categories, as summarized in Table 3.

Table 3. SoH-based battery health classification.

Category	SoH Range	Description
Excellent	$\text{SoH} \geq 90\%$	Performance close to the fresh state with minimal degradation
Good	$80\% \leq \text{SoH} < 90\%$	Slightly aged but suitable for demanding second-life applications
Moderate	$60\% \leq \text{SoH} < 80\%$	Noticeable capacity loss, but functional for low-rate or long-duration uses
End-of-life	$\text{SoH} < 60\%$	Below the automotive warranty threshold and unsuitable for most reuse applications

An analogous four-level classification was applied to round-trip energy efficiency to capture losses associated with internal resistance, side reactions, and hysteresis effects. While SoH primarily reflects capacity fade, efficiency is more sensitive to resistive and kinetic degradation mechanisms. Using both metrics enables a richer description of battery condition than either indicator alone.

Cross-classifications of SoH class and the efficiency class were subsequently performed. This two-dimensional assessment distinguishes, for example, batteries that retain capacity but suffer from high internal losses from those that exhibit capacity fade while maintaining acceptable efficiency. This multi-metric strategy is central to the proposed methodology, as it avoids false health attribution arising from reliance on a single degradation indicator.

The classification thresholds used in this study are based on established electric-vehicle battery retirement criteria and on second-life application feasibility reported in the literature. Lithium-ion batteries are commonly retired from automotive applications when their capacity falls below approximately 70–80% of nominal value, but they may

remain technically suitable for less demanding stationary applications such as residential storage and backup systems. Batteries with higher State of Health and efficiency are better suited for applications requiring higher performance and reliability, while those with lower health indicators are more appropriate for low-rate or backup applications. Therefore, the classification ranges used in this work provide a practical and technically justified basis for reuse pathway determination.

The proposed reuse pathway mapping is intended as an initial screening framework that links experimentally measured health indicators to general application suitability based on performance capability. Final deployment decisions would require additional system-level validation under specific operating conditions.

It should be emphasized that the proposed methodology is not intended to introduce a new electrochemical degradation diagnostic model or predictive reuse optimization algorithm. Instead, the contribution of this work lies in the experimentally grounded integration of multiple complementary battery health indicators into a transparent and application-oriented screening methodology for heterogeneous retired EV batteries. The framework is therefore intended as a practical decision-support approach for preliminary second-life battery assessment rather than a fully validated deployment optimization model.

The proposed reuse pathway classification is consistent with established application categories defined in battery energy storage system (BESS) standards and industrial practice. According to international standards such as IEC 62933, repurposed lithium-ion batteries are commonly deployed in grid support services (e.g., frequency regulation and peak load management), residential energy storage systems, and backup or uninterruptible power supply applications.

These applications impose different technical requirements on battery performance. Grid-support applications typically require high power capability, rapid response, and high round-trip energy efficiency to ensure effective participation in grid services. Residential energy storage systems operate under moderate load conditions and prioritize energy capacity and cycle life. Backup power applications generally involve low discharge rates and emphasize reliability rather than high efficiency or power density.

The classification framework proposed in this study aligns with these application-specific requirements by linking higher State of Health and efficiency to high-performance applications while assigning moderately degraded batteries to less demanding use cases. Batteries with low capacity and efficiency are directed toward recycling, consistent with industry practices for end-of-life battery management.

It should be emphasized that the proposed framework provides preliminary screening and decision-support methodology based on experimentally measured battery health indicators. The assigned reuse pathways represent application-oriented suitability recommendations rather than validated deployment outcomes. Practical implementation would require additional application-specific testing, long-term cycling assessment, safety evaluation, and techno-economic analysis before final deployment decisions can be made.

Figure 2 illustrates the mapping between battery health classes and recommended second-life applications based on the proposed multi-metric classification framework. Batteries with higher State of Health are allocated to more demanding applications such as grid support and residential storage, while moderately degraded batteries are assigned to lower power uses such as backup systems. Severely degraded batteries are directed toward recycling and material recovery. This mapping links experimentally measured health indicators to practical reuse pathway determination.

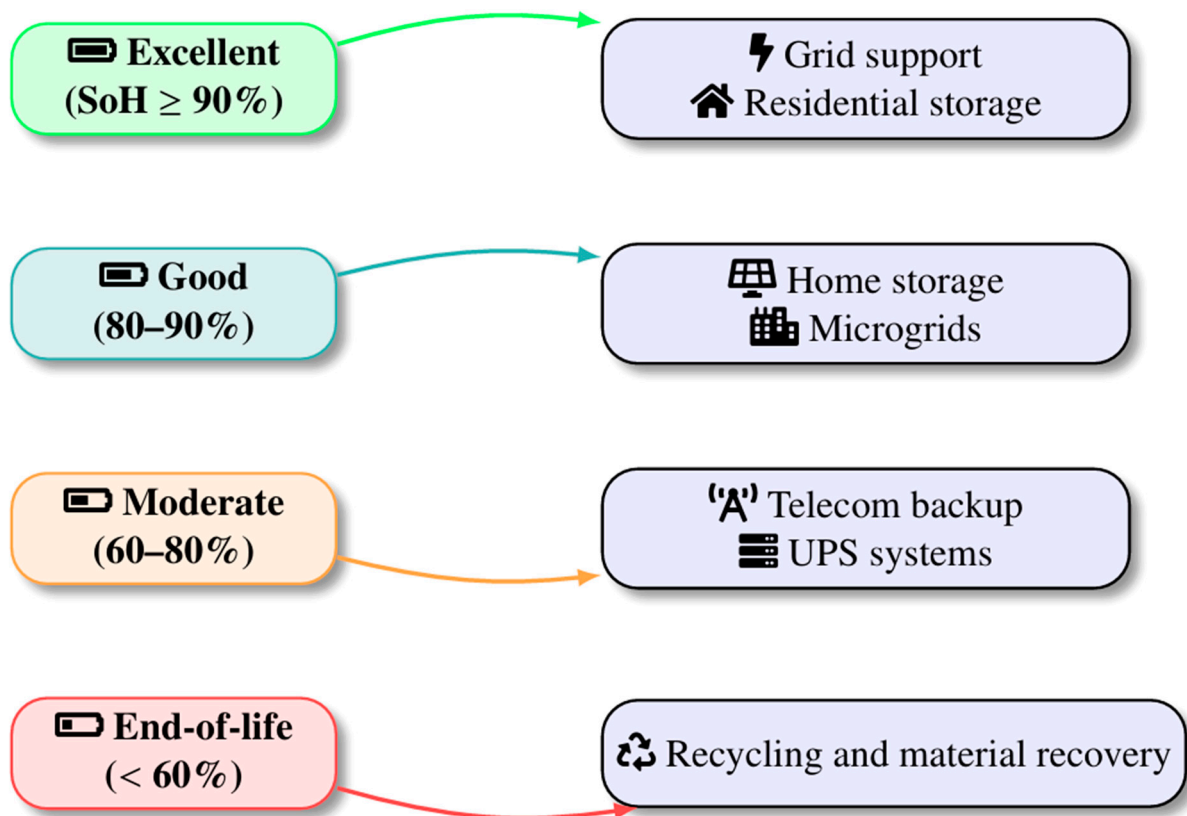


Figure 2. Health-class application mapping of second-life EV batteries based on multi-metric classification.

For clarity, the deterministic classification procedure can be represented as the following mapping function:

$$f : (SoH, \eta) \rightarrow C$$

where SoH represents the State of Health, η denotes the round-trip energy efficiency, and $C \in \{\text{Grid-support, Residential storage, Backup, Recycling}\}$ is the assigned application class.

This formulation highlights that the proposed method is a deterministic multi-parameter classification approach based on experimentally derived health indicators, enabling consistent and interpretable allocation of batteries to application categories.

Different second-life applications impose distinct performance requirements on battery systems. Grid-support applications, such as frequency regulation and peak shaving, typically require high power capability (moderate-to-high C-rate), fast response, and high round-trip efficiency to ensure effective energy delivery and minimal losses. Residential energy storage systems operate under moderate power demand and emphasize usable energy capacity and cycle life. Backup or uninterruptible power supply applications generally involve low discharge rates (low C-rate) and prioritize reliability over efficiency or high-power performance.

The classification proposed in this study is aligned with these general requirements by associating higher State of Health and energy efficiency with applications requiring higher performance while assigning moderately degraded batteries to lower-demand use cases. However, it should be emphasized that this mapping represents an engineering-informed hypothesis based on performance alignment, rather than a validated assignment of batteries to specific applications. Comprehensive validation would require application-level testing, including dynamic load profiles, cycle life assessment, and techno-economic analysis, which are beyond the scope of the present study.

3.5. Contribution Relative to the Existing Literature

Table 4 complements the graphical illustration by providing a structured comparison between representative categories of existing studies and the present work. For each category, the typical limitation reported in the literature is compared with the scope of the proposed framework. Rather than introducing a new battery degradation model or predictive algorithm, this study addresses a practical research gap by integrating experimentally derived battery health indicators into a unified assessment framework that directly supports application-oriented second-life battery screening. The comparison demonstrates that the contribution of this work arises from the systematic combination of comprehensive experimental characterization, complementary health indicator analysis, and interpretable reuse pathway determination within a single decision-support methodology.

Table 4. Novelty of the present study relative to the existing literature.

Study Category	Typical Limitation in Prior Work	Our Work Addresses It by
Capacity-only SoH studies [29]	Efficiency, energy losses, and load performance ignored	Capacity-retention and energy-performance indicators: discharge capacity, derived SoH, and round-trip efficiency.
Simulation or model-only studies [30]	No verification on real retired EV batteries	All results based on 91 experimentally tested second-life cells
Small-sample experiments [32]	Too few samples to capture variability	Analysis of a large heterogeneous retired-cell population
Distribution-only reporting [37]	Statistics not connected to real applications	Mapping health metrics to concrete second-life applications
Single-application evaluation [38]	Only one market segment assessed	Assessment of grid support, residential storage, telecom backup, and recycling
Single-indicator degradation studies [39]	Hidden failure risk when indicators diverge	Cross-classification of SoH and efficiency to reveal hidden degradation states

The primary contribution of this study is the development of an experimentally grounded framework that systematically relates complementary battery health indicators to application-oriented second-life deployment decisions. Using a heterogeneous population of 91 retired EV battery cells, the study evaluates the relationships among State of Health, discharge capacity, and round-trip energy efficiency to investigate how different health indicators collectively describe residual battery performance. The results demonstrate that batteries with comparable capacity retention may exhibit substantially different energy efficiency characteristics, indicating that State of Health alone does not always provide sufficient information for practical reuse assessment.

Building upon these observations, the proposed framework integrates experimentally measured health indicators within a transparent classification methodology to support structured reuse pathway allocation. Rather than evaluating battery degradation solely from an analytical perspective, the framework translates laboratory-derived battery health characteristics into interpretable recommendations for grid-support systems, residential energy storage, backup applications, and recycling. In this way, the study establishes a practical connection between experimental battery characterization and deployment-oriented decision support for second-life battery utilization.

It should be emphasized that the contribution of this work lies in the proposed assessment methodology rather than in the development of a new predictive model, machine learning algorithm, or electrochemical degradation model. Instead, the framework provides a practical and experimentally validated approach for systematically interpreting

complementary battery health indicators to support scalable second-life battery screening and reuse pathway determination.

A limitation of the present study is that the selected health indicators provide an indirect assessment of degradation behavior rather than direct identification of specific electrochemical ageing mechanisms. Future work may incorporate impedance spectroscopy, incremental capacity analysis, differential voltage analysis, or post-mortem material characterization to establish stronger links between observed performance degradation and the underlying electrochemical ageing processes.

4. Results

4.1. Overview of the Tested Battery Population

The experimental dataset consists of 91 s life EV battery cells obtained from retired automotive battery systems with heterogeneous first-life operating histories. For each battery cell, multiple health-related indicators were extracted, including State of Health (SoH), discharge capacity, round-trip energy efficiency, and voltage–current time-series characteristics. Collectively, these complementary indicators provide a comprehensive representation of residual battery condition by capturing both capacity-related and energy-related degradation behavior.

Table 5 summarizes the descriptive statistics of SoH and round-trip energy efficiency for the evaluated battery population. The SoH values range from approximately 22% to 96%, with a mean of 63.6% and a standard deviation of 16.3%. This broad distribution indicates that the dataset encompasses batteries at substantially different stages of degradation, ranging from severely degraded cells to units retaining relatively high residual capacity. Furthermore, the interquartile range shows that 50% of the tested batteries exhibit SoH values between approximately 53% and 75%, highlighting the considerable variability typically encountered in retired EV battery populations.

Table 5. Descriptive statistics of State of Health and round-trip energy efficiency for all tested batteries.

Statistic	SoH (%)	Efficiency (%)
Count	91	91
Mean	63.6	83.7
Standard deviation	16.3	8.7
Minimum	22.1	48
25th percentile	53.2	81.7
Median	57.4	84.3
75th percentile	75.2	86.6
Maximum	96.4	116.3

Round-trip energy efficiency ranges from approximately 48% to 116%, with an average value of 83.7%. A small number of calculated efficiency values exceeded the theoretical upper limit of 100%, which is physically unrealistic. These anomalous observations are most likely attributable to cumulative measurement uncertainty, numerical integration sensitivity, and charge–discharge segmentation inconsistencies during data preprocessing rather than actual battery behavior. To evaluate their influence, additional statistical verification was performed by comparing the overall distribution characteristics and classification outcomes with and without these samples. No significant differences were observed, indicating that the anomalous values did not materially affect the principal findings of this study.

Nevertheless, these observations are acknowledged as a limitation of the experimental dataset and should not be interpreted as physically achievable battery performance.

The substantial variation observed in both SoH and round-trip energy efficiency reflects the heterogeneous operating histories of retired EV batteries, including differences in cycling conditions, depth of discharge, calendar ageing, and operational environments. This variability is particularly important because it demonstrates that retired batteries cannot be adequately represented by a single degradation state, reinforcing the need for assessment methodologies capable of systematically evaluating multiple complementary health indicators.

Due to confidentiality agreements associated with the industrial data source, detailed information regarding battery manufacturers, originating vehicle platforms, and specific battery chemistries cannot be disclosed. Consequently, the evaluated battery population should not be interpreted as statistically representative of the global retired EV battery market. Instead, it provides a heterogeneous experimental dataset suitable for investigating battery degradation characteristics and evaluating the proposed multi-metric battery health assessment framework under realistic second-life conditions.

Overall, the statistical characteristics presented in Table 5 demonstrate considerable diversity in both capacity retention and operational efficiency across the evaluated battery population. This diversity provides an appropriate experimental basis for investigating relationships among complementary battery health indicators and for evaluating how multi-metric assessment can support application-oriented second-life battery screening and reuse pathway determination.

The statistical summary confirms that the evaluated battery population spans a wide spectrum of degradation conditions, providing a suitable experimental basis for subsequent multi-metric health assessment and application-oriented battery classification.

4.2. Distribution of State of Health and Round-Trip Energy Efficiency

The distributions of State of Health (SoH) and round-trip energy efficiency for the tested battery population are presented in Figures 3 and 4. As illustrated in Figure 3, the SoH values span a broad range from approximately 20% to 97%, with many batteries exhibiting SoH values between 50% and 80%. This wide distribution demonstrates the heterogeneous degradation characteristics of retired EV batteries and confirms that the evaluated population includes cells ranging from severely degraded units to batteries retaining relatively high residual capacity. The skewed distribution further indicates that many batteries are retired from automotive service while still preserving a substantial proportion of their original charge-storage capability, highlighting their potential suitability for selected second-life applications.

Figure 4 presents the distribution of round-trip energy efficiency. Most batteries exhibit efficiencies between approximately 75% and 90%, while a smaller subset demonstrates substantially lower efficiency values. Unlike the SoH distribution, the efficiency distribution reflects the influence of internal resistance growth, polarization losses, and irreversible energy dissipation during charge–discharge operation. Consequently, batteries with comparable SoH values may still display noticeably different energy efficiencies, indicating that the mechanisms governing efficiency degradation are not identical to those responsible for capacity fade.

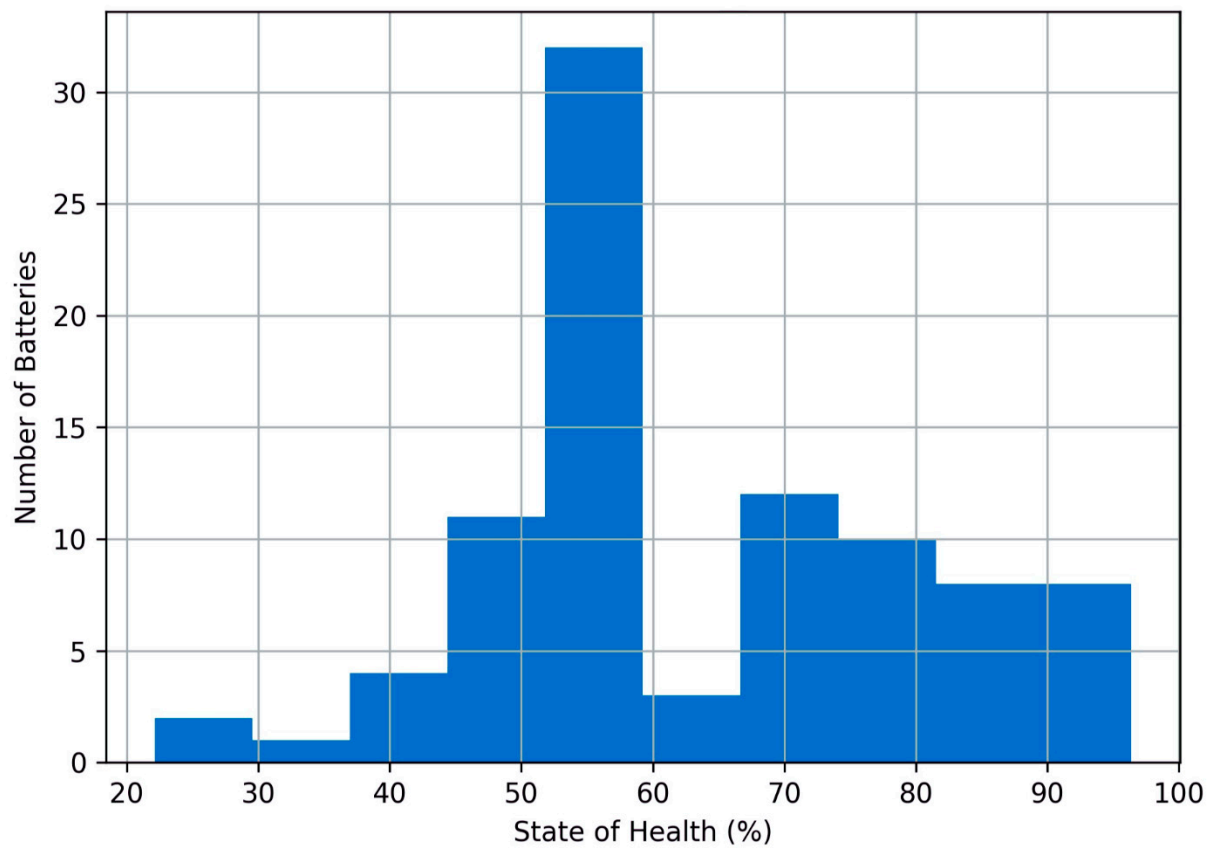


Figure 3. Histogram of State of Health values for all tested batteries.

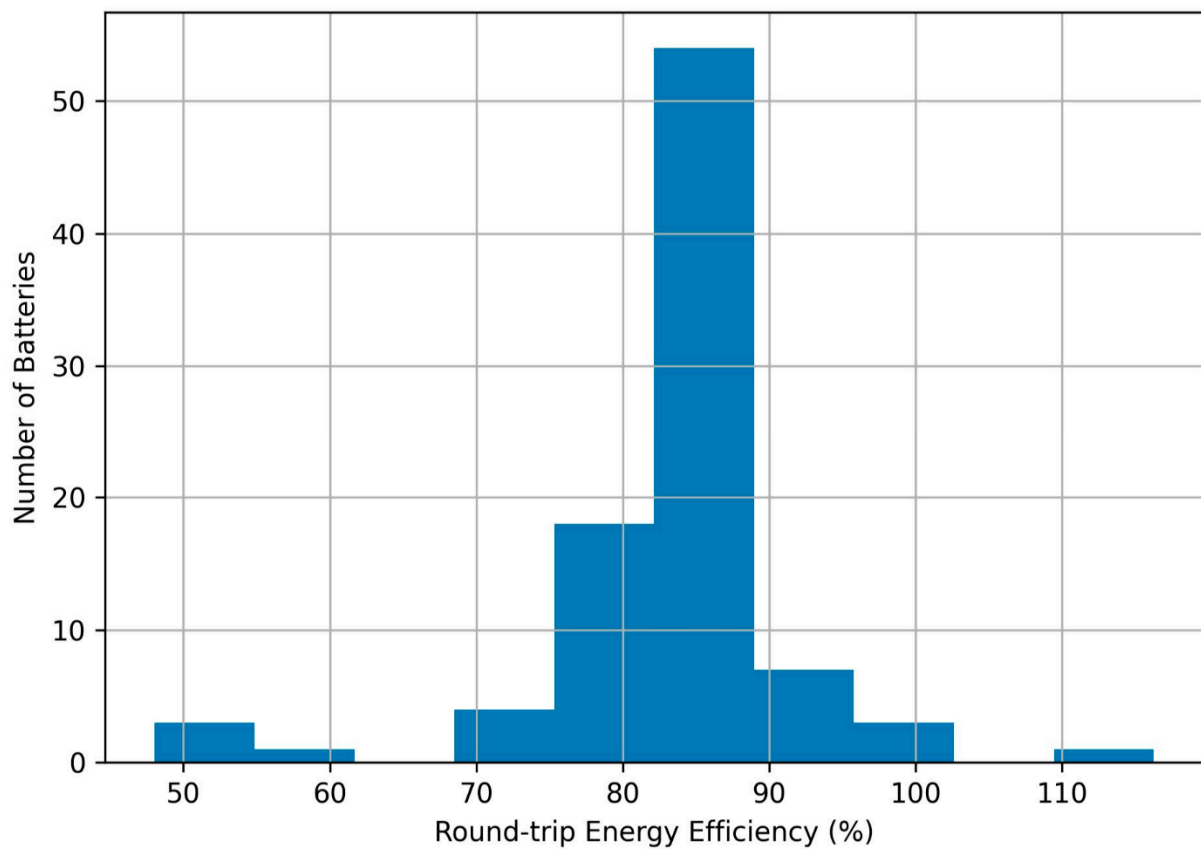


Figure 4. Histogram of round-trip energy efficiency values.

A comparison of Figures 3 and 4 further demonstrates that capacity degradation and efficiency degradation do not necessarily evolve at the same rate throughout battery ageing. Some batteries experience significant capacity loss while maintaining relatively stable energy efficiency, whereas others retain moderate capacity but exhibit pronounced efficiency degradation resulting from increased internal losses. These observations indicate that evaluating battery condition solely based on capacity retention may overlook important aspects of residual functional performance. Consequently, experimental results support the use of complementary health indicators for second-life battery assessment and provide experimental evidence for the multi-metric evaluation framework proposed in this study.

The SoH values range from approximately 20% to 97%, with most cells between 50 and 80%. Efficiency is generally between 75 and 90%, although several degraded units exhibit much lower values. These two distributions indicate that capacity loss and efficiency loss do not occur at identical rates.

A small number of calculated round-trip energy efficiency values exceeded the theoretical upper limit of 100%. Since energy output cannot exceed energy input under normal operating conditions, these values are physically unrealistic and are attributed to cumulative measurement uncertainty, numerical integration sensitivity, and charge–discharge segmentation inconsistencies during data preprocessing. Consequently, these observations are interpreted as measurement-related artifacts rather than actual battery performance characteristics. Despite their presence, the overall statistical trends and classification outcomes remain dominated by most samples exhibiting physically realistic values.

Overall, the distributions of SoH and round-trip energy efficiency demonstrate that retired EV batteries exhibit substantial variability in both capacity retention and operational efficiency. More importantly, the observed differences between the two distributions indicate that capacity-based assessment alone does not fully represent residual battery performance. This experimental observation provides the foundation for the subsequent multi-metric health classification and application-oriented reuse pathway determination developed in this study.

4.3. SoH-Based and Efficiency-Based Health Classification

The numerical distributions of batteries according to the proposed SoH-based and efficiency-based classification schemes are summarized in Tables 6 and 7. The SoH-based classification indicates that more than half of the evaluated batteries (51 out of 91) fall within the End-of-life category, whereas only a small proportion remain in the Excellent health category. This distribution is consistent with current automotive retirement practices, where batteries are typically removed from vehicle service once their remaining capacity no longer satisfies performance requirements.

The efficiency-based classification exhibits a noticeably different distribution. Most batteries are classified within the Medium-efficiency category, whereas relatively few batteries exhibit either High or Low efficiency.

The differences between the two classification schemes demonstrate that State of Health and round-trip energy efficiency characterize different aspects of battery degradation. While SoH primarily reflects capacity retention associated with lithium inventory loss and active material degradation, round-trip energy efficiency is more sensitive to internal resistance growth, polarization effects, and energy dissipation during charge–discharge cycling. Consequently, batteries exhibiting comparable SoH values may still demonstrate substantially different operational performance.

For example, a battery with moderate SoH but relatively high energy efficiency may remain suitable for applications requiring frequent cycling and efficient energy transfer. Conversely, another battery with a similar SoH but lower efficiency may experience greater

energy losses and heat generation, reducing its suitability for demanding second-life applications. These observations demonstrate that relying exclusively on SoH may lead to an incomplete assessment of residual battery performance.

Table 6. Distribution of batteries according to SoH-based health classes.

SoH Class	Count
Excellent	8
Good	9
Moderate	23
End-of-life	51

Table 7. Distribution of batteries according to efficiency-based classes.

Efficiency Class	Count
High ($\geq 90\%$)	10
Medium (80–89%)	68
Low ($< 80\%$)	13

The combined evaluation of SoH and round-trip energy efficiency therefore provides a more comprehensive representation of battery condition than either indicator considered independently. By integrating complementary health indicators, the proposed classification framework enables more informed battery screening and supports application-oriented reuse pathway allocation according to the residual performance characteristics of individual batteries.

Overall, the comparison between the two classification schemes provides experimental evidence that capacity retention and operational efficiency do not degrade uniformly throughout battery ageing. This finding reinforces the central premise of the proposed framework: multi-metric battery health assessment provides a more reliable basis for second-life battery screening than evaluation based on a single health indicator alone.

4.4. Correlation Analysis of Battery Health Metrics

The correlation analysis presented in this study is based on the Pearson correlation coefficient, which quantifies linear relationships between continuous variables. Pearson correlation was selected due to its suitability for assessing the expected linear dependency between State of Health and discharge capacity, as capacity retention directly defines SoH.

However, battery degradation processes are governed by multiple electrochemical mechanisms, and certain relationships, particularly those involving round-trip energy efficiency, may exhibit nonlinear behavior. The observed dispersion in the scatter plots reflects these nonlinear effects, indicating that efficiency degradation does not scale linearly with capacity fade.

The correlation analysis demonstrates that the examined health indicators are not redundant but capture complementary degradation characteristics. Consequently, no single indicator provides a complete representation of residual battery performance.

A correlation analysis was carried out to quantify the relationships between State of Health (SoH), maximum discharge capacity, and round-trip energy efficiency. The resulting correlation matrix is presented in Figure 5. As expected, a strong positive correlation was observed between SoH and maximum discharge capacity because SoH is directly derived from discharge capacity according to Equation (3). Therefore, this relationship should not

be interpreted as an independent degradation finding, but rather as a validation of the consistency of the experimental measurements and health-indicator extraction procedure.

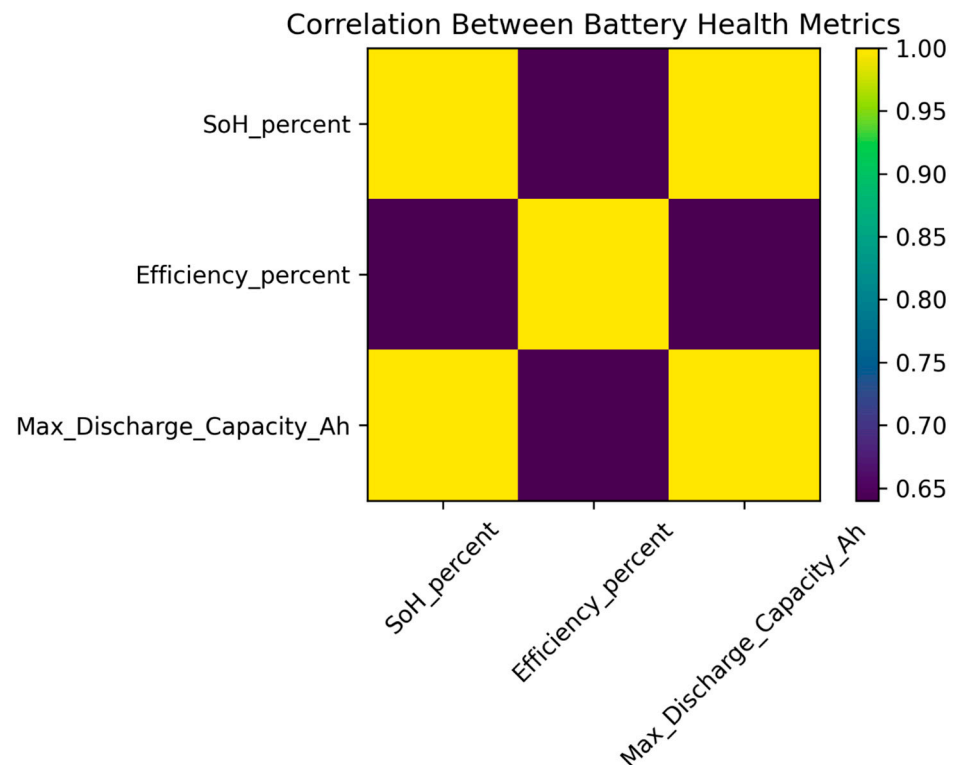


Figure 5. Correlation heatmap showing pairwise relationships among State of Health (SoH), maximum discharge capacity, and round-trip energy efficiency for 91 retired EV cells.

In contrast, the correlation between SoH and round-trip energy efficiency is noticeably weaker, indicating that efficiency degradation does not necessarily progress in parallel with capacity fade. This suggests that batteries exhibiting similar SoH values may still differ substantially in terms of energy losses and operational performance. Consequently, capacity-based SoH alone does not fully represent functional battery health, highlighting the importance of incorporating complementary indicators such as round-trip energy efficiency within the proposed multi-metric assessment framework.

4.5. Cross-Classification of SoH and Efficiency

Table 8 presents the cross-classification of batteries according to both SoH class and efficiency class. This two-dimensional representation allows simultaneous evaluation of capacity-related and efficiency-related degradation and reveals patterns that are not visible when each metric is considered independently.

Table 8. Cross-classification of batteries by SoH class and efficiency class.

SoH Class	High	Medium	Low
Excellent	7	1	0
Good	0	8	1
Moderate	3	19	1
End-of-life	0	40	11

The results show that most batteries classified as Excellent in terms of SoH also fall into the High-efficiency category, indicating consistently strong overall performance. However, clear divergences appear in the Moderate and End-of-life SoH ranges. The presence of Moderate–High and Good–Low combinations demonstrates that batteries with comparable remaining capacity may exhibit substantially different operational behavior. These mixed health states would not be identified through capacity-based assessment alone. Even among End-of-life cells, a large subset remains in the Medium-efficiency class, demonstrating that reduced capacity does not automatically imply poor energy efficiency.

Conversely, Low-efficiency cells are distributed across multiple SoH classes, including Good and Moderate categories. These cases represent batteries that retain appreciable remaining capacity but suffer from high internal resistance or polarization losses, which reduce round-trip energy efficiency. Such batteries would be poorly characterized if SoH were used as the sole health indicator.

Overall, the cross-classification confirms that SoH and efficiency describe distinct, complementary aspects of degradation. The presence of batteries spanning mixed classes (for example, Moderate–High efficiency or Good–Low efficiency) underscores the necessity of multi-metric assessment. This finding provides strong justification for the integrated methodology proposed in this work and demonstrates its relevance for accurate screening and assignment of retired EV batteries to appropriate second-life applications.

This table shows that some Moderate and even End-of-life cells still retain medium efficiency, while several low-efficiency cells appear across multiple SoH ranges.

4.6. Population Variability and Dispersion

Figures 6 and 7 illustrate the population variability of State of Health and round-trip energy efficiency using boxplots. The SoH boxplot shows a wide interquartile range together with several outliers toward both high and low values. This indicates substantial dispersion in remaining capacity among the tested cells and reflects the highly diverse first-life operating histories of the batteries, including different duty cycles, temperatures, calendar aging contributions, and depth-of-discharge patterns.

In contrast, the spread in round-trip energy efficiency is comparatively narrower, although outliers are still present. The smaller dispersion suggests that efficiency tends to remain clustered for much of the population, with significant declines occurring primarily in a subset of cells that have undergone pronounced internal resistance growth or polarization losses. The presence of outliers in both metrics confirms that some batteries deviate strongly from the central population behavior and therefore require careful individual assessment rather than reliance on average values.

Overall, the boxplots highlight that SoH exhibits greater variability than efficiency, implying that capacity fade is more strongly influenced by heterogeneous usage histories than efficiency degradation alone. These observations reinforce the importance of using a multi-metric framework: batteries with similar efficiency may have very different remaining capacities, and vice versa. Capturing this dispersion is essential for realistic modeling of second-life battery populations and for designing robust classification and application-allocation strategies.

SoH exhibits greater dispersion and more outliers compared with efficiency, indicating diverse degradation histories among the retired batteries.

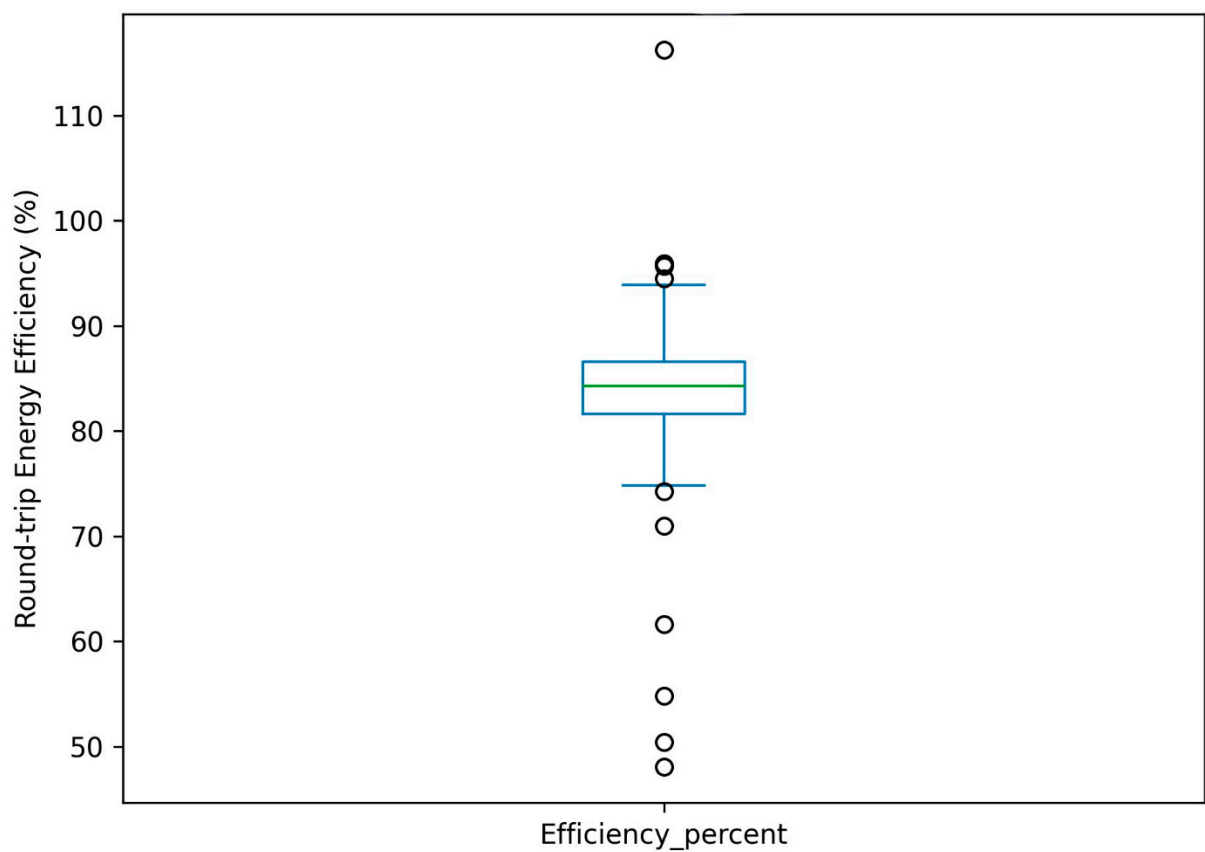


Figure 6. Boxplot of State of Health across all batteries.

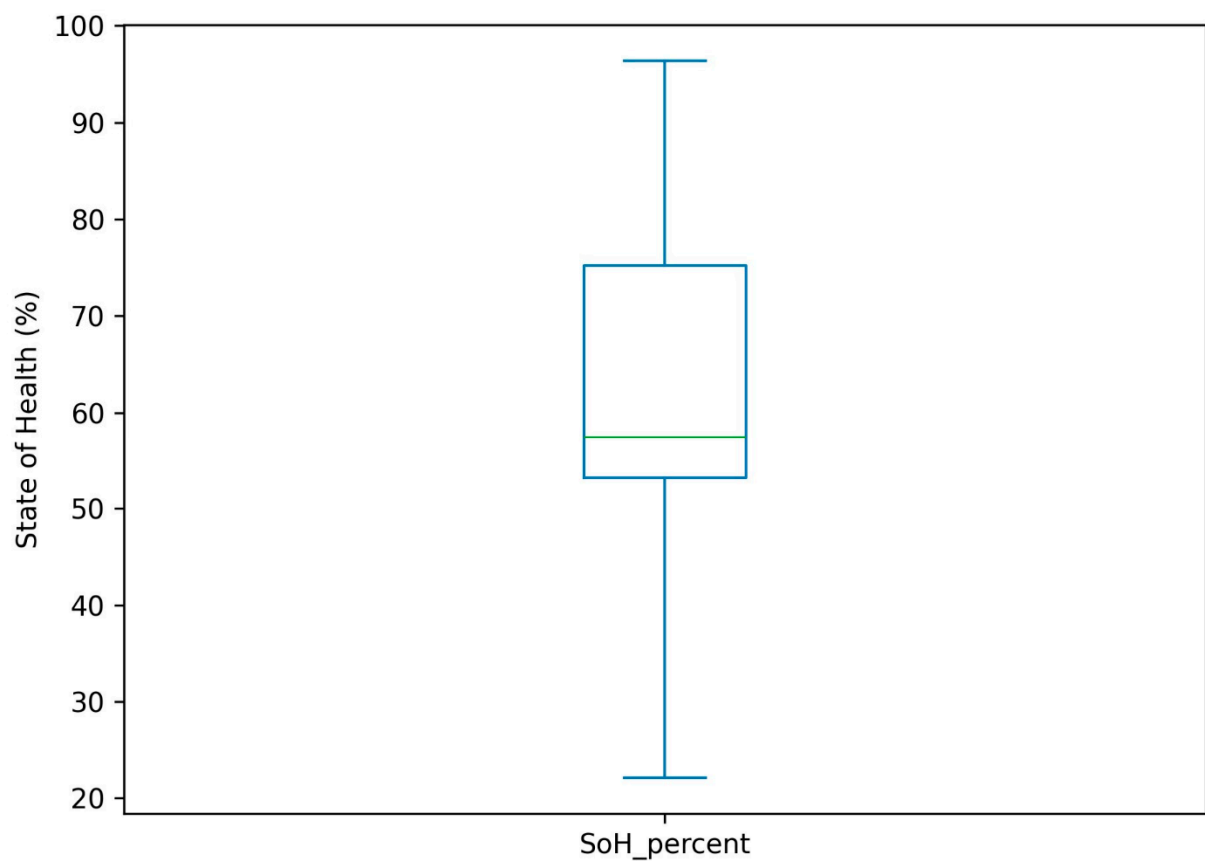


Figure 7. Boxplot of round-trip efficiency across all batteries.

4.7. Relationships Among SoH and Efficiency

The relationship between State of Health and round-trip energy efficiency is shown in Figure 8, and the corresponding correlation coefficients are reported in Table 9. A moderate positive correlation ($r \approx 0.64$) is observed between the two metrics, indicating that, in general, batteries with higher SoH tend to exhibit higher round-trip efficiency. This trend is physically consistent, since both capacity retention and efficiency are influenced by underlying degradation phenomena such as loss of active material and growth of internal resistance.

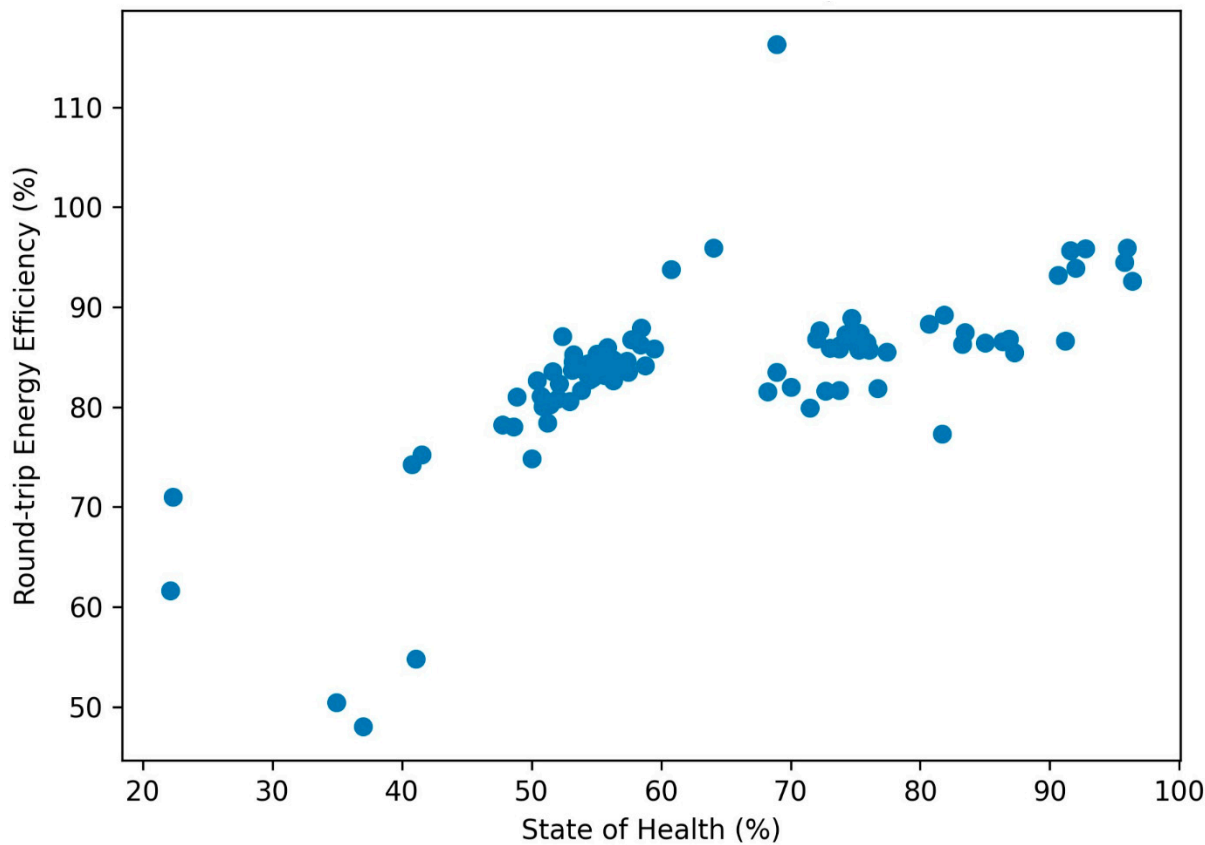


Figure 8. Relationship between State of Health and round-trip energy efficiency.

Table 9. Correlation coefficients between SoH and round-trip energy efficiency.

	SoH (%)	Efficiency (%)
SoH (%)	1.000	0.640
Efficiency (%)	0.640	1.000

The few data points with efficiencies exceeding 100% correspond to measurement-related artifacts discussed previously and are retained only to illustrate the full distribution of the experimental dataset.

However, the scatter plot reveals a substantial degree of dispersion around the overall trend. Batteries with similar SoH values may have markedly different efficiencies, and conversely, batteries with comparable efficiencies can span a broad range of SoH values. This spread reflects the fact that different degradation mechanisms contribute unequally to capacity fade and efficiency loss. For example, growth of internal resistance can significantly reduce efficiency without severely affecting remaining capacity, while loss of cyclable lithium primarily reduces SoH with comparatively smaller impact on efficiency.

The moderate correlation coefficient ($r = 0.64$) indicates that although capacity retention and energy efficiency are related, a considerable proportion of battery performance variability remains unexplained by SoH alone. Therefore, substituting one metric for the other would lead to misclassification of certain batteries, particularly those exhibiting atypical combinations such as low SoH but medium efficiency or high SoH but low efficiency. These observations strongly support the multi-metric assessment strategy adopted in this study and justify the use of cross-classification frameworks for second-life decision-making.

A moderate positive correlation exists between SoH and efficiency, but the dispersion in the scatter plot demonstrates that one metric cannot replace the other.

To further quantify the observed nonlinear relationship between State of Health (SoH) and round-trip energy efficiency, a second-order polynomial regression model was fitted to the experimental data. The fitted relationship is expressed as:

$$\eta = -0.0029 \text{ SoH}^2 + 0.48 \text{ SoH} + 62.1$$

where η denotes the round-trip energy efficiency. The fitted model achieved a coefficient of determination of $R^2 = 0.46$, indicating a moderate nonlinear association between SoH and efficiency. The relatively modest R^2 value confirms the substantial dispersion observed in the experimental data and suggests that efficiency degradation is influenced by additional degradation mechanisms beyond capacity fade alone. These results quantitatively support the need for a multi-metric health assessment of retired EV batteries.

4.8. Time-Series Experimental Behavior

Figures 9–12 present the time-series behavior of representative batteries during the laboratory charge–discharge experiments. The voltage–time profile in Figure 9 shows the typical shape of lithium-ion cell operation, with distinct charge, rest, and discharge segments. The corresponding current–time profile in Figure 10 confirms that testing was performed under controlled current conditions, ensuring consistency of operating stress across all samples. These profiles validate the experimental procedure used to derive the capacity, energy, SoH, and efficiency metrics analyzed in the previous subsections.

Beyond qualitative visualization, these time-series profiles were used to extract quantitative degradation-sensitive features, including discharge capacity, discharge energy, round-trip efficiency, average discharge voltage, and discharge duration. These parameters reflect fundamental degradation mechanisms such as loss of active material and internal resistance growth, which influence energy delivery capability and voltage stability.

In addition to visual interpretation, these time-series profiles were used to extract quantitative degradation indicators, including maximum discharge capacity, discharge energy, round-trip energy efficiency, average discharge voltage, and discharge duration. These parameters provide objective measures of performance loss and enable differentiation between healthy and degraded batteries based on their energy delivery capability and voltage stability.

Figures 11 and 12 show the evolution of discharge capacity and energy as functions of time. Both quantities increase monotonically during discharge, as expected. The slope and final values of these curves vary across batteries, reflecting differences in usable capacity and internal losses. Batteries with reduced SoH reach lower final capacity and energy values, while more degraded cells also tend to deliver energy over shorter discharge times due to voltage drop and higher polarization.

Figure 13 directly compares the voltage profiles of a healthy battery and a degraded battery under similar testing conditions. The degraded cell exhibits a consistently lower operating voltage, a steeper voltage drop under load, and an earlier termination of discharge. These characteristics indicate increased internal resistance and reduced voltage stability, which

are typical signatures of advanced aging. In contrast, the healthy cell maintains a higher and more stable voltage plateau, corresponding to lower ohmic and polarization losses.

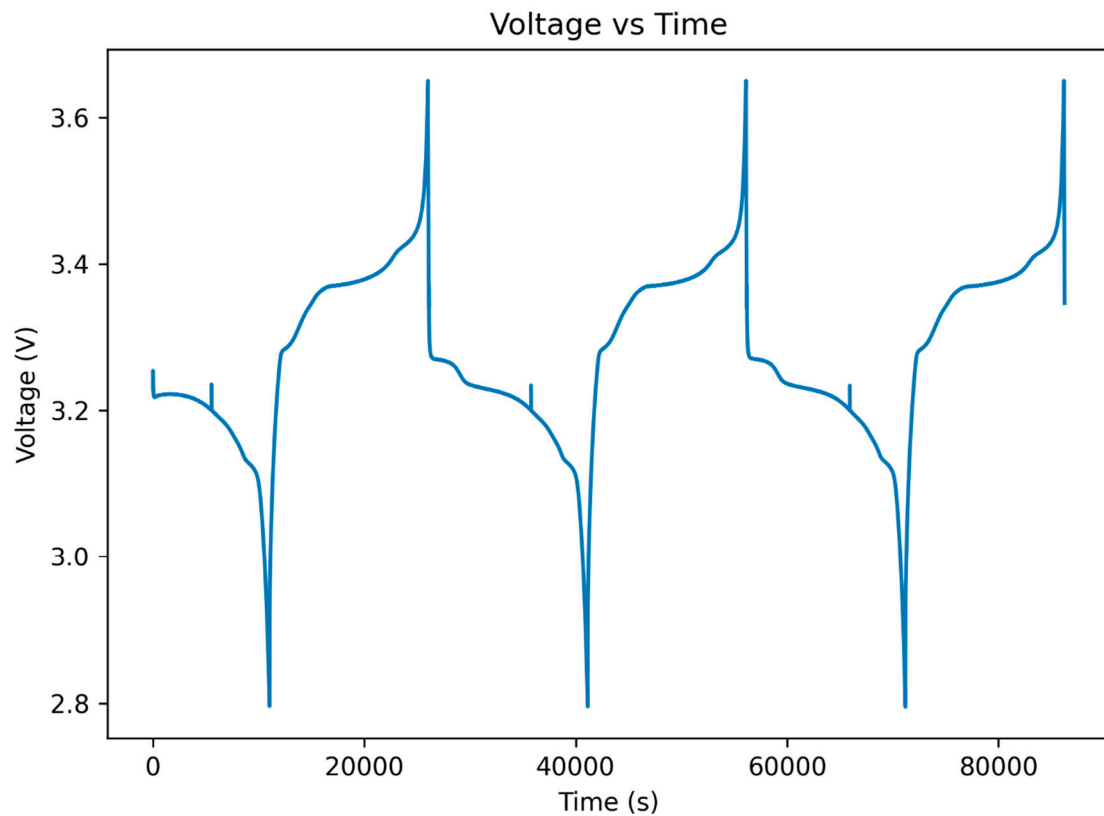


Figure 9. Voltage versus time during charge–discharge testing.

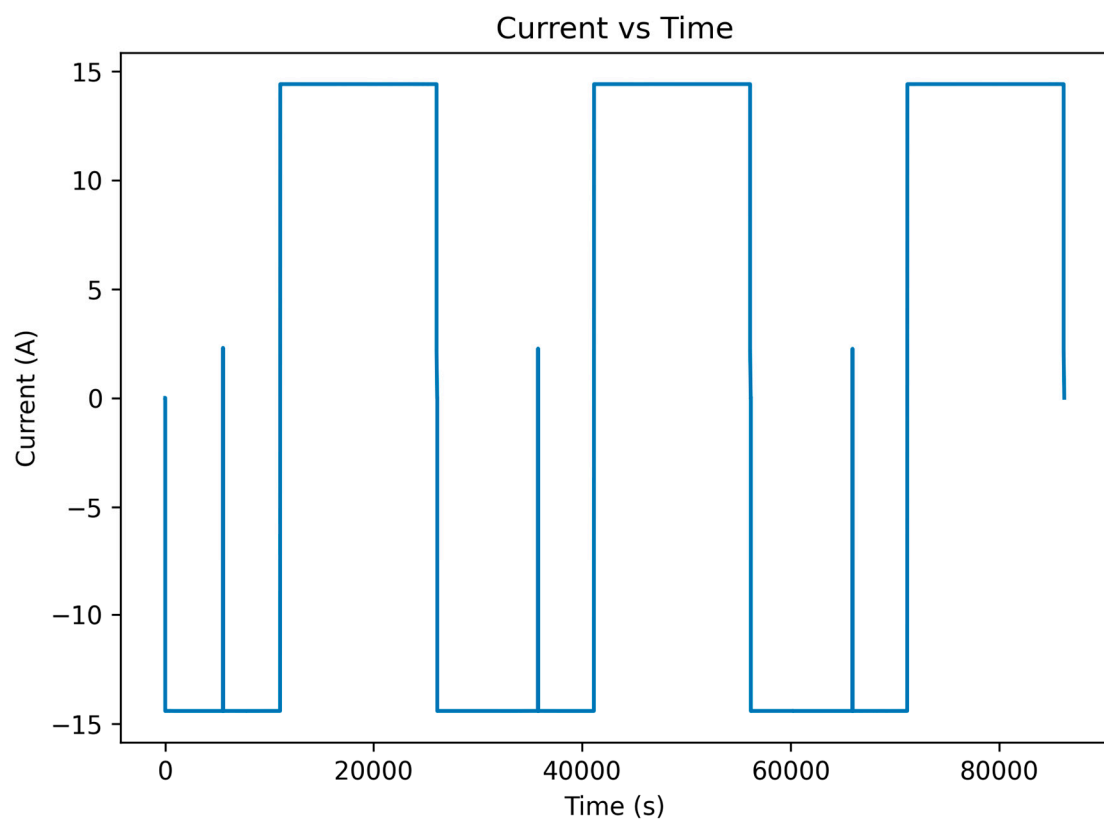


Figure 10. Current versus time during testing.

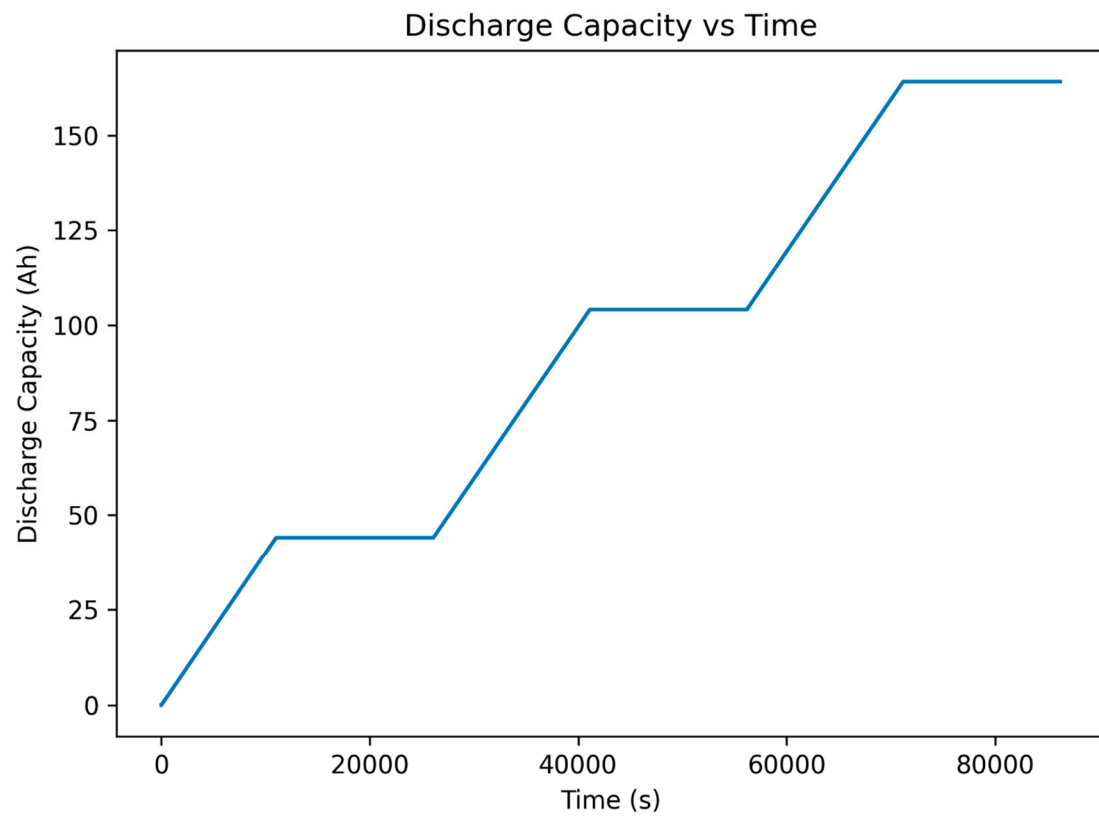


Figure 11. Discharge capacity as a function of time.

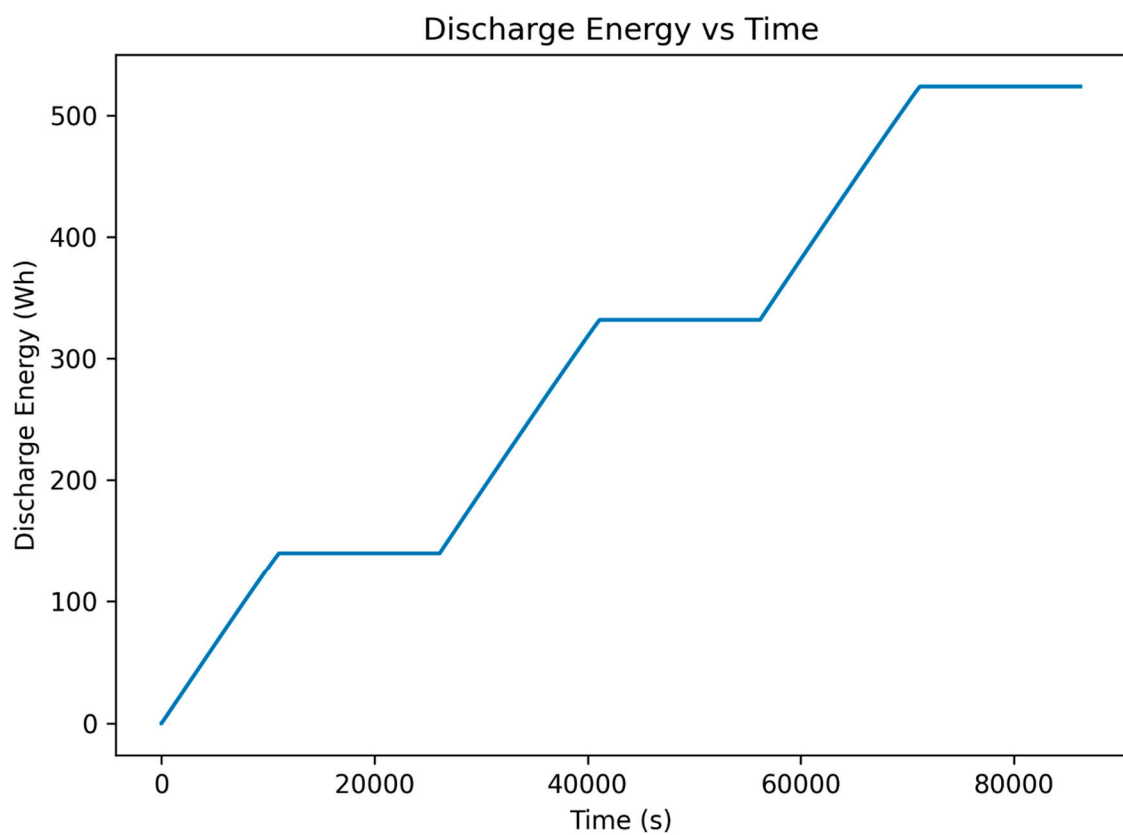


Figure 12. Discharge energy as a function of time.

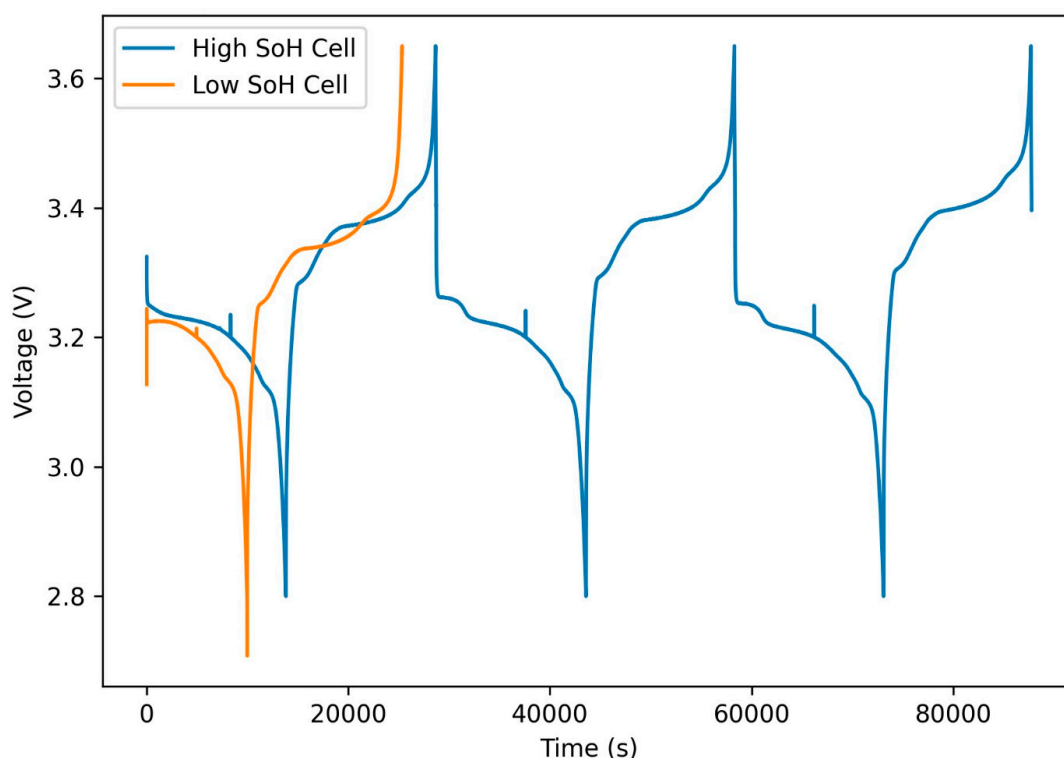


Figure 13. Comparison of voltage profiles for a healthy and a degraded battery.

The degraded battery shows stronger voltage drops and lower operating voltage, indicating increased internal resistance.

Together, the time-series results provide physical insight that complements the statistical and correlation analyses. They visually confirm that degraded batteries suffer from both capacity reduction and efficiency loss arising from resistance growth. These behaviors explain the dispersion observed in the SoH-efficiency relationship and further justify the use of multi-metric health indicators in assessing second-life battery suitability.

The experimental results demonstrate that relying exclusively on capacity-based State of Health may oversimplify the condition of retired EV batteries intended for second-life deployment. Batteries exhibiting similar SoH frequently demonstrate different operational efficiencies, indicating that degradation mechanisms affect multiple performance dimensions. By integrating complementary health indicators within a structured assessment framework, the proposed methodology supports more reliable battery screening and application-oriented deployment decisions. Although further validation under application-specific operating conditions is required, the framework provides a practical basis for industrial battery repurposing and large-scale second-life battery management.

5. Discussion

The proposed classification methodology is based on experimental measurements obtained under controlled laboratory conditions at 25 ± 2 °C. While this ensures consistency and comparability across the tested cells, battery performance is inherently influenced by temperature, operating conditions, and load dynamics. Variations in temperature affect discharge capacity, internal resistance, voltage response, and round-trip energy efficiency. Consequently, the classification thresholds presented in this study are most directly applicable under standardized laboratory conditions and may require adaptation for practical deployment environments.

The experimental results demonstrate substantial variability in State of Health (SoH), discharge capacity, and round-trip energy efficiency across the tested retired EV battery

population. This heterogeneity reflects differences in first-life operating conditions, including cycling history, depth of discharge, and calendar ageing. A key observation is that SoH alone does not fully characterize residual battery performance. Although SoH and discharge capacity exhibited a strong correlation, round-trip energy efficiency showed noticeably larger dispersion for a given SoH level, indicating that efficiency degradation does not necessarily evolve proportionally with capacity fade.

The correlation analysis and scatter distributions highlight several important relationships. First, the strong association between SoH and discharge capacity confirms the consistency of the experimental measurements and the expected dependence of SoH on residual capacity. Second, the weaker relationship between SoH and round-trip efficiency suggests that energy losses are influenced by additional degradation processes beyond capacity reduction alone. Furthermore, the presence of cells exhibiting relatively high residual capacity but reduced efficiency indicates that batteries with similar SoH values may still demonstrate substantially different operational behavior.

The voltage and energy time-series profiles further support these observations. Healthier cells generally sustained higher discharge voltages and exhibited lower voltage sag under load, whereas degraded cells showed larger voltage drops and reduced discharge duration [40]. These behaviors are consistent with increased internal resistance and polarization effects reported in previous lithium-ion battery degradation studies. Similarly, the capacity–time and energy–time profiles demonstrate that usable output energy decreases substantially in degraded batteries, even when residual capacity remains comparatively moderate [41].

The degradation mechanisms discussed in this work, including lithium inventory loss, active material degradation, internal resistance growth, and polarization effects, are inferred from experimentally observed electrical behavior and the existing literature reports. Since advanced diagnostic techniques such as electrochemical impedance spectroscopy (EIS), incremental capacity analysis (ICA), differential voltage analysis (DVA), or post-mortem characterization were not performed, these mechanisms should be interpreted as plausible degradation explanations rather than directly verified electrochemical conclusions.

A central aspect of this study is the integration of multiple experimentally derived health indicators into a structured screening methodology for second-life battery assessment. By combining SoH, discharge capacity, and round-trip energy efficiency, the proposed approach enables differentiation between batteries with similar capacity retention but different energy-delivery characteristics. The resulting cross-classification methodology provides an interpretable basis for preliminary reuse pathway allocation, including grid-support applications, residential energy storage, backup or low-rate applications, and recycling streams.

It should be emphasized that the proposed application mapping is intended as a preliminary screening methodology rather than a validated deployment optimization model. The classifications are based on standardized laboratory charge–discharge measurements and therefore primarily reflect comparative battery health characteristics under controlled conditions. Real second-life applications involve additional operational factors, including dynamic load profiles, temperature variation, state-of-charge windows, thermal management, and long-term cycling behavior. Consequently, application-specific validation through dynamic testing, thermal evaluation, and long-duration operational studies remains necessary before practical deployment.

Compared with many previous studies that rely on simulated ageing data or limited experimental samples, the present work provides experimental characterization of 91 heterogeneous retired EV battery cells. However, due to confidentiality constraints associated with the industrial data source, detailed information regarding originating vehicle plat-

forms, battery manufacturers, and exact chemistries could not be disclosed. Therefore, the dataset should not be interpreted as statistically representative of the global retired EV battery market, but rather as a heterogeneous experimental sample suitable for evaluating the proposed multi-metric screening methodology.

A small number of experimentally calculated efficiency values slightly exceeded the theoretical upper limit of 100%. These anomalous cases are most likely associated with cumulative measurement uncertainty, numerical integration sensitivity, or charge–discharge segmentation inconsistencies during preprocessing. Since efficiencies above 100% are not physically realizable, such values should not be interpreted as true electrochemical efficiencies. Nevertheless, these cases represented only a limited portion of the dataset and did not significantly alter the overall statistical trends observed across the battery population.

From an application perspective, the results suggest that batteries retired from automotive service may still retain sufficient functional capability for lower-demand stationary applications. Batteries exhibiting moderate residual capacity and acceptable energy efficiency may remain suitable for residential storage or backup systems, whereas severely degraded batteries with low efficiency are more appropriately directed toward recycling pathways [42]. In this context, the proposed screening methodology may support preliminary decision-making for battery repurposing and resource recovery.

Several limitations should be acknowledged. The experiments were conducted using a single testing protocol under controlled environmental conditions, and long-term second-life cycling performance was not evaluated. In addition, advanced electrochemical diagnostics and application-specific operational testing were beyond the scope of the present study. Future work should incorporate dynamic load profiles, temperature-dependent testing, impedance-based diagnostics, and long-duration second-life cycling studies to further improve battery health characterization and reuse pathway assessment.

Overall, the results demonstrate that multi-metric characterization provides a more informative representation of second-life battery condition than capacity-based SoH evaluation alone. The proposed methodology offers a practical and experimentally grounded approach for preliminary screening of retired EV batteries and may support safer and more effective second-life battery utilization strategies.

A limitation of the present study is the lack of access to detailed first-life operational information, including vehicle model, driving profile, charging history, environmental exposure, and cumulative cycling records. Consequently, a direct correlation between prior usage conditions and the observed battery health indicators could not be established. The proposed framework therefore focuses on experimentally measured residual performance characteristics rather than degradation pathways associated with specific usage histories. Future studies incorporating battery passport information or detailed lifecycle records could provide deeper insight into the relationship between first-life operating conditions and second-life suitability.

It should be noted that the present assessment was performed at the individual cell level rather than at the battery pack level. Consequently, practical second-life deployment would require additional processes including cell matching, balancing, module or pack reassembly, battery management system (BMS) integration, and safety validation. The proposed classification framework is therefore intended to support the preliminary screening and selection of candidate cells for second-life applications rather than direct deployment. Future work should extend the methodology to module- and pack-level assessment to evaluate the influence of cell heterogeneity, balancing requirements, and system-level operational constraints on second-life battery performance.

6. Conclusions

This study presented an experimental multi-metric assessment of 91 retired electric vehicle (EV) battery cells for second-life battery screening and application-oriented classification. In addition to conventional capacity-based State of Health (SoH), the proposed framework incorporated discharge capacity, round-trip energy efficiency, and voltage–current time-series characteristics to evaluate residual battery performance under standardized laboratory conditions.

The experimental results demonstrated substantial variability in degradation characteristics across the evaluated battery population. Although SoH and discharge capacity exhibited the expected strong correlation, the relationship between SoH and round-trip energy efficiency was considerably weaker and more dispersed. These findings indicate that capacity retention alone does not fully characterize residual battery performance and that batteries with comparable SoH values may still exhibit significantly different energy-delivery capability and operational efficiency. Consequently, the results highlight the importance of integrating complementary health indicators when assessing second-life battery suitability.

Building upon these observations, the proposed multi-metric classification framework combines capacity-related and energy-related performance indicators to support application-oriented battery screening. Based on experimentally measured battery characteristics, cells exhibiting relatively high residual capacity and energy efficiency were identified as potentially suitable for demanding stationary energy storage applications, whereas more degraded batteries were directed toward lower-demand applications or recycling pathways. Rather than relying exclusively on a single degradation metric, the proposed framework provides a systematic and interpretable approach for relating experimentally measured battery health characteristics to practical second-life deployment decisions.

It should be emphasized that the proposed methodology is intended as a practical decision-support framework for preliminary battery screening rather than a fully validated deployment optimization model. The classifications presented in this study are derived from standardized laboratory charge–discharge measurements and therefore represent comparative assessments of battery condition under controlled operating conditions. Additional validation under application-specific environments, including dynamic load profiles, thermal operating conditions, and long-term cycling, remains necessary before large-scale practical deployment.

Several limitations should also be acknowledged. The experimental dataset represents a heterogeneous but non-universal sample of retired EV batteries, and advanced electrochemical diagnostic techniques, such as electrochemical impedance spectroscopy, incremental capacity analysis, and post-mortem characterization, were beyond the scope of the present study. Furthermore, all experiments were conducted using a single testing protocol under controlled laboratory conditions. Future work should therefore incorporate impedance-based diagnostics, temperature-dependent evaluation, dynamic operating profiles, long-duration cycling experiments, and application-specific validation to further strengthen battery health assessment and second-life deployment methodologies.

Overall, this study demonstrates that multi-metric battery health assessment provides a more comprehensive evaluation of retired EV batteries than capacity-based State of Health alone. By integrating experimentally derived health indicators within a transparent and application-oriented classification framework, the study establishes a practical connection between laboratory battery characterization and structured second-life reuse pathway determination. Although the proposed framework is not intended to replace detailed electrochemical diagnostics or predictive degradation models, it provides an experimentally

grounded methodology that can support scalable battery screening, battery repurposing, and more informed second-life deployment decisions.

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Data Availability Statement: The experimental battery datasets analyzed in this study were obtained from laboratory testing of retired electric vehicle cells provided through an academic-industry collaboration. Due to confidentiality agreements with the data provider, raw data cannot be made publicly available. However, processed summary data, including State of Health, discharge capacity, and round-trip energy efficiency, can be provided by the corresponding author upon reasonable request for academic research purposes. All analysis procedures used in this study are fully described in the manuscript to ensure transparency and reproducibility.

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References

1. Ralls, A.M.; Leong, K.; Clayton, J.; Fuelling, P.; Mercer, C.; Navarro, V.; Menezes, P.L. The Role of Lithium-Ion Batteries in the Growing Trend of Electric Vehicles. *Materials* **2023**, *16*, 6063. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Gao, W.; Thoo, A.C.; Sarker, M.; Lee, N.; Deng, X.; Yang, Y. Secondary Use of Retired Lithium-Ion Traction Batteries: A Review of Health Assessment, Interface Technology, and Supply Chain Management. *Batteries* **2026**, *12*, 1. [\[CrossRef\]](#)
3. Cintra, R.S.; Avila, L.V.; Schvartz, M.A.; Filho, W.L.; Anholon, R.; Moraes, G.H.S.M.d.; Siluk, J.C.M.; Lisboa, G.d.S.; Khaled, N.N.D. Analysis of the Life Cycle and Circular Economy Strategies for Batteries Adopted by the Main Electric Vehicle Manufacturers. *Sustainability* **2025**, *17*, 3428. [\[CrossRef\]](#)
4. Hossen, M.S.; Sarker, M.T.; Ramasamy, G.; Eng Eng, N. Physics-Informed and Explainable Machine Learning for State-of-Health Estimation of Second-Life Lithium-Ion Batteries Under Sparse Cycling. *Batteries* **2026**, *12*, 149. [\[CrossRef\]](#)
5. Sinha, S.S.; Lehman, B.; Bharadwaj, P. Life Extension of Lithium-Ion Battery: Degradation Comprehension, Modeling, Characterization, and Mitigation Strategies. *IEEE Open J. Power Electron.* **2025**, *7*, 1–27. [\[CrossRef\]](#)
6. Eleftheriadis, P.; Leva, S.; Gangi, M.; Rey, A.V.; Borgo, A.; Coslop, G.; Groppo, E.; Grande, L.; Sedzik, M. Second Life Batteries: Current Regulatory Framework, Evaluation Methods, and Economic Assessment: Reuse, refurbish, or recycle. *IEEE Ind. Appl. Mag.* **2023**, *30*, 46–58. [\[CrossRef\]](#)
7. Shaker, L.M.; Al-Amiery, A.A.; Hanoon, M.M.; Al-Azzawi, W.K.; Kadhum, A.A.H. Examining the influence of thermal effects on solar cells: A comprehensive review. *Sustain. Energy Res.* **2024**, *11*, 6. [\[CrossRef\]](#)
8. Xue, Y.; Zhou, H.; Luo, Y.; Lam, J. Battery Degradation Modelling and Prediction with Combination of Machine Learning and Semi-empirical Methods. In Proceedings of the 2022 12th International Conference on Power, Energy and Electrical Engineering (CPEEE), Shiga, Japan, 25–27 February 2022; pp. 78–85. [\[CrossRef\]](#)
9. Li, J.; He, S.; Yang, Q.; Wei, Z.; Li, Y.; He, H. A Comprehensive Review of Second Life Batteries Toward Sustainable Mechanisms: Potential, Challenges, and Future Prospects. *IEEE Trans. Transp. Electr.* **2023**, *9*, 4824–4845. [\[CrossRef\]](#)
10. Dini, P.; Colicelli, A.; Saponara, S. Review on Modeling and SOC/SOH Estimation of Batteries for Automotive Applications. *Batteries* **2024**, *10*, 34. [\[CrossRef\]](#)

11. Bokstaller, J.; Schneider, J.; Brocke, J.v. Estimating SoC, SoH, or RuL of Rechargeable Batteries via IoT: A Review. *IEEE Internet Things J.* **2024**, *11*, 7559–7582. [\[CrossRef\]](#)
12. Rahman, A.; Sun, W. Bridging Market Efficiency and System Resilience: Unified Multi-Service Operation of Long-Duration Energy Storage in Decarbonized Power Systems. *IEEE Trans. Sustain. Energy* **2026**, *17*, 2759–2772. [\[CrossRef\]](#)
13. Cheng, M.; Zhang, X.; Ran, A.; Wei, G.; Sun, H. Optimal dispatch approach for second-life batteries considering degradation with online SoH estimation. *Renew. Sustain. Energy Rev.* **2023**, *173*, 113053. [\[CrossRef\]](#)
14. Hossen, M.S.; Sarker, M.T.; Al Qwaid, M.; Ramasamy, G.; Eng Eng, N. AI-Driven Framework for Secure and Efficient Load Management in Multi-Station EV Charging Networks. *World Electr. Veh. J.* **2025**, *16*, 370. [\[CrossRef\]](#)
15. Hossen, M.S.; Sarker, M.T.; Nabi, M.S.; Bannah, H.; Ramasamy, G.; Eng Eng, N. Federated AI-OCPP Framework for Secure and Scalable EV Charging in Smart Cities. *Urban Sci.* **2025**, *9*, 363. [\[CrossRef\]](#)
16. Azizighalehsari, S.; Breazu, B.; Soeiro, T.B.; Rietveld, G.; Venugopal, P. Li-Ion Battery Prognostics Using Statistical Models and RNN Trained on EIS-Based Features. *IEEE Trans. Ind. Electron.* **2026**, *73*, 10084–10096. [\[CrossRef\]](#)
17. Ahmad, H.; Prabakaran, R.; Kim, S.C. Electrochemical–thermal coupled modeling of lithium-ion batteries: A comprehensive review of mechanisms, methods, and applications. *J. Therm. Anal. Calorim.* **2026**, *151*, 5889–5928. [\[CrossRef\]](#)
18. Fan, C.; Tian, X.; Gu, C. Perturbation-Based Battery Impedance Characterization Methods: From the Laboratory to Practical Implementation. *Batteries* **2024**, *10*, 414. [\[CrossRef\]](#)
19. Renold, A.P.; Kathayat, N.S. Comprehensive Review of Machine Learning, Deep Learning, and Digital Twin Data-Driven Approaches in Battery Health Prediction of Electric Vehicles. *IEEE Access* **2024**, *12*, 43984–43999. [\[CrossRef\]](#)
20. Zhang, Y.; Wang, A.; Zhang, C.; He, P.; Shao, K.; Cheng, K.; Zhou, Y. State-of-Health Estimation for Lithium-Ion Batteries via Incremental Energy Analysis and Hybrid Deep Learning Model. *Batteries* **2025**, *11*, 217. [\[CrossRef\]](#)
21. Tiane, A.; Okar, C.; Alzayed, M.; Chaoui, H. Comparing Hybrid Approaches of Deep Learning for Remaining Useful Life Prognostic of Lithium-Ion Batteries. *IEEE Access* **2024**, *12*, 70334–70344. [\[CrossRef\]](#)
22. Li, T.; Wang, E.; Yang, J. Lifelong Learning-Enabled Fractional Order-Convolutional Encoder Model for Open-Circuit Fault Diagnosis of Power Converters Under Multi-Conditions. *Sensors* **2025**, *25*, 1884. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Xiao, H.; Fu, L.; Shang, C.; Fan, Y.; Bao, X.; Xu, X. A Lithium-Ion Battery State-of-Health Prediction Model Combining Convolutional Neural Network and Masked Multi-Head Attention Mechanism. *IEEE Trans. Energy Convers.* **2025**, *40*, 218–232. [\[CrossRef\]](#)
24. Aghmadi, A.; Mohammed, O.A. Energy Storage Systems: Technologies and High-Power Applications. *Batteries* **2024**, *10*, 141. [\[CrossRef\]](#)
25. Patrizi, G.; Canzanella, F.; Nikiforova, N.D.; Berni, R.; Vining, G.G.; Ciani, L. A Novel Framework for Estimating Battery Health Indicator Under Different Operating Conditions. *IEEE Trans. Instrum. Meas.* **2026**, *75*, 9003814. [\[CrossRef\]](#)
26. Rahman, T.; Alharbi, T. Exploring Lithium-Ion Battery Degradation: A Concise Review of Critical Factors, Impacts, Data-Driven Degradation Estimation Techniques, and Sustainable Directions for Energy Storage Systems. *Batteries* **2024**, *10*, 220. [\[CrossRef\]](#)
27. Madani, S.S.; Shabeer, Y.; Allard, F.; Fowler, M.; Ziebert, C.; Wang, Z.; Panchal, S.; Chaoui, H.; Mekhilef, S.; Dou, S.X.; et al. A Comprehensive Review on Lithium-Ion Battery Lifetime Prediction and Aging Mechanism Analysis. *Batteries* **2025**, *11*, 127. [\[CrossRef\]](#)
28. Wei, Y.; Yao, Y.; Pang, K.; Xu, C.; Han, X.; Lu, L.; Li, Y.; Qin, Y.; Zheng, Y.; Wang, H.; et al. A Comprehensive Study of Degradation Characteristics and Mechanisms of Commercial Li(NiMnCo)O₂ EV Batteries under Vehicle-To-Grid (V2G) Services. *Batteries* **2022**, *8*, 188. [\[CrossRef\]](#)
29. Yu, Z.; Liu, N.; Zhang, Y.; Qi, L.; Li, R. Battery SOH Prediction Based on Multi-Dimensional Health Indicators. *Batteries* **2023**, *9*, 80. [\[CrossRef\]](#)
30. Saldana, G.; San Martín, J.I.; Zamora, I.; Asensio, F.J.; Onederra, O.; Gonzalez-Perez, M. Empirical calendar ageing model for electric vehicles and energy storage systems batteries. *J. Energy Storage* **2022**, *55*, 105676. [\[CrossRef\]](#)
31. Su, X.; Sun, B.; Wang, J.; Ruan, H.; Zhang, W.; Bao, Y. Experimental study on charging energy efficiency of lithium-ion battery under different charging stress. *J. Energy Storage* **2023**, *68*, 107793. [\[CrossRef\]](#)
32. Strange, C.; Allerhand, M.; Dechent, P.; Dos Reis, G. Automatic method for the estimation of li-ion degradation test sample sizes required to understand cell-to-cell variability. *Energy AI* **2022**, *9*, 100174. [\[CrossRef\]](#)
33. Terkes, M.; Demirci, A.; Gokalp, E.; Cali, U. Battery Passport for Second-Life Batteries: Potential Applications and Challenges. *IEEE Access* **2024**, *12*, 128424–128467. [\[CrossRef\]](#)
34. Haraz, A.; Abualsaud, K.; Massoud, A. State-of-Health and State-of-Charge Estimation in Electric Vehicles Batteries: A Survey on Machine Learning Approaches. *IEEE Access* **2024**, *12*, 158110–158139. [\[CrossRef\]](#)
35. Kweon, S.-J.; Rafi, A.K.; Cheon, S.-I.; Je, M.; Ha, S. On-Chip Sinusoidal Signal Generators for Electrical Impedance Spectroscopy: Methodological Review. *IEEE Trans. Biomed. Circuits Syst.* **2022**, *16*, 337–360. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Paudel, S.; Zhang, J.; Ayalew, B.; Griddaluru, V.Y.; Singh, R. Design, Prototyping, and Integration of Battery Modules for Electric Vehicles and Energy Storage Systems. *Electricity* **2025**, *6*, 63. [\[CrossRef\]](#)

37. Huang, H.; Xue, S.; Zhao, L.; Wang, W.; Wu, H. Privacy-Preserving Smart Energy Management by Consumer-Electronic Chips and Federated Learning. *IEEE Trans. Consum. Electron.* **2024**, *70*, 2200–2209. [[CrossRef](#)]
38. Fallah, N.; Fitzpatrick, C. How will retired electric vehicle batteries perform in grid-based second-life applications? A comparative techno-economic evaluation of used batteries in different scenarios. *J. Clean. Prod.* **2022**, *361*, 132281. [[CrossRef](#)]
39. Olivero-Ortiz, V.; Pantoja, I.O.; Robles-Algarín, C. Data-Driven Capacity Modeling of 18650 Lithium-Ion Cells from Experimental Electrical Measurements. *Sustainability* **2025**, *17*, 4718. [[CrossRef](#)]
40. Kumar, R.R.; Bharatiraja, C.; Udhayakumar, K.; Devakirubakaran, S.; Sekar, K.S.; Mihet-Popa, L. Advances in Batteries, Battery Modeling, Battery Management System, Battery Thermal Management, SOC, SOH, and Charge/Discharge Characteristics in EV Applications. *IEEE Access* **2023**, *11*, 105761–105809. [[CrossRef](#)]
41. Khan, A.; Naqvi, I.H.; Hassan, N.U. A Comprehensive Analysis of Battery EV (BEV) Performance Under Conflicting Metrics Through Strategic State of Charge Management. *IEEE Trans. Transp. Electr.* **2025**, *11*, 9613–9629. [[CrossRef](#)]
42. Coccato, S.; Barhmi, K.; Lampropoulos, I.; Golroodbari, S.; van Sark, W. A Review of Battery Energy Storage Optimization in the Built Environment. *Batteries* **2025**, *11*, 179. [[CrossRef](#)]

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