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ACCOUNTING CALENDAR AND CYCLIC AGEING FACTORS IN DIAGNOSTIC AND PROGNOSTIC MODELS OF SECOND-LIFE EV BATTERIES APPLICATION IN ENERGY STORAGE SYSTEMS

Abstract. *The rapid expansion of the electric vehicle market has significantly increased the demand for lithium-ion batteries, posing challenges for manufacturers and policymakers regarding efficient use and recycling. When these batteries reach the end of their primary lifecycle, their repurposing for secondary applications such as energy storage becomes critical to addressing environmental and resource management issues. This paper focuses on applying second-life batteries in energy storage systems, emphasizing the importance of accounting for calendar and cyclic aging factors to optimize battery performance and longevity. Calendar aging refers to the degradation that occurs over time due to chemical reactions within the battery, even when it is not in use. This type of aging is influenced by temperature, state of charge (SOC), and storage conditions. Cyclic aging, on the other hand, results from repeated charging and discharging cycles, which cause mechanical and chemical changes within the battery, leading to capacity fade and increased internal resistance. The combined effects of these aging processes necessitate the development of high-precision diagnostic and prognostic models to manage the performance and longevity of second-life batteries effectively. In Ukraine, the adoption of electric vehicles is accelerating, leading to an influx of used electric vehicles. This situation necessitates the prompt development of strategies for repurposing these batteries for energy storage applications. The complexities associated with final recycling processes make secondary use an attractive interim solution. By repurposing used EV batteries, Ukraine can mitigate immediate challenges related to battery waste and resource scarcity while supporting the transition to renewable energy sources. This paper highlights the need for an integral degradation index (DI) that combines calendar and cyclic aging factors with stochastic influences to provide a comprehensive measure of battery health. Such an index is essential for optimizing battery management practices, including the scheduling of charging and discharging cycles, to extend the operational life of secondary batteries. The study also presents practical recommendations for implementing these models in various energy storage scenarios, ranging from residential solar energy systems to industrial grid support and electric vehicle charging stations. By adopting optimized battery management strategies, the potential for extending the lifespan of secondary batteries and reducing operational costs is significant. This approach supports sustainable energy practices and aligns with global efforts to promote renewable energy sources and circular economy principles.*

Keywords: Lithium-Ion Battery, Electric Vehicle, Energy Storage, Battery Degradation, Calendar Ageing, Cyclic Ageing, Integral Degradation Index, Remaining Useful Life, State of Health.

1. Introduction

The expansion of the electric vehicle market is increasing the demand for lithium-ion batteries, which poses challenges for manufacturers and policymakers to use and recycle these resources. Once their primary life cycle is complete, depleted batteries carry environmental and social risks due to toxic emissions. It is predicted that by 2030, about 75 % of used batteries from electric vehicles can be used in energy storage systems, creating opportunities for their reuse and contributing to sustainable resource management [1–4]. The importance of using secondary electric vehicle (EV) batteries lies in the growing need for sustainable energy solutions. As the adoption of electric vehicles increases globally, a significant number of batteries will reach the end of their primary automotive life. Repurposing these batteries for energy storage systems (ESS) not only extends their lifecycle but also addresses critical issues such as resource efficiency, waste reduction, and the high costs associated with manufacturing new batteries. This practice contributes to a circular economy, where resources are reused and recycled, reducing the environmental impact of battery disposal.

In Ukraine, the development of electric transport is progressing rapidly [5–7], and the market is seeing an influx of used electric vehicles [8, 9]. Consequently, the issue of secondary use of these batteries will arise sooner than in many other countries. This urgency is compounded by the complexities associated with the final recycling of batteries. By repurposing used EV batteries for energy storage, Ukraine can address immediate challenges related to battery waste and resource scarcity while supporting the transition to renewable energy sources. Estimated forecast of secondary EV batteries availability in Ukraine is represented in Fig. 1.

To this end, global automakers are implementing initiatives to repurpose used batteries for power systems, which improves the integration of renewable energy sources and ensures efficient use of energy. In this context, special attention should be paid to the analysis of the mechanisms of battery degradation, which determine both calendar and cyclic aging. High temperatures and state of charge are critical factors contributing to the rapid decline in battery efficiency and capacity, and understanding these processes is key to developing strategies for their effective repurposing and utilization [10–13].

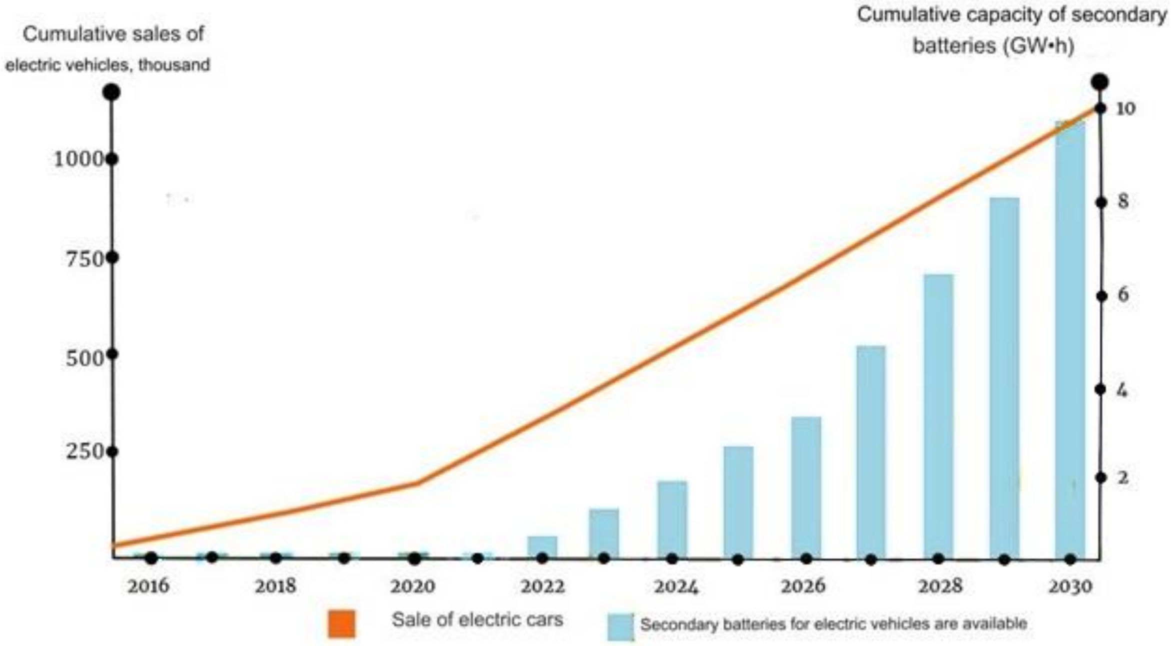

Figure 1. Estimated forecast of secondary EV batteries availability in Ukraine

Accurate diagnostic and prognostic models for secondary energy storage systems are essential to maximize the performance and lifespan of repurposed EV batteries [14–16]. These models must account for factors such as calendar aging and cyclic aging, which significantly impact battery degradation. By considering these factors, the models can provide a more precise prediction of the battery's remaining useful life (RUL) and state of health (SOH). Such detailed modeling is vital for various applications, from residential and commercial energy storage to grid stability and electric vehicle charging infrastructure. Developing and implementing these advanced models is key to unlocking the full potential of secondary EV batteries, thereby supporting both global and national energy sustainability goals.

The purpose of this article is to formalize an integral degradation index, which combines the effects of both calendar and cyclic aging, is crucial for a comprehensive assessment. This index helps in optimizing usage patterns and maintenance schedules, ensuring that the secondary batteries perform reliably and efficiently over their extended lifecycle. develop diagnostic and prognostic models for optimizing the use of second-life EV batteries in energy storage systems. The article focuses on considering factors such as calendar aging, cyclic aging, and the introduction of an integral degradation index, which allows for more accurate assessments of the RUL and SOH of lithium-ion batteries.

2. Methods and Materials

There is a wealth of research dedicated to various aspects of lithium-ion batteries, both in EVs and stationary energy storage systems. These studies cover a wide range of topics, including but not limited to, the following:

Battery Chemistry and Materials: Research in this area focuses on the development and optimization of electrode materials, electrolytes, and other components to enhance the performance, safety, and longevity of lithium-ion batteries [17–21]. Innovations in battery chemistry, such as the use of advanced materials like silicon anodes and solid-state electrolytes, aim to increase energy density and reduce degradation rates.

Battery Management Systems (BMS): Effective battery management systems are crucial for monitoring and controlling the performance of lithium-ion batteries [18, 22–24]. Studies explore advanced BMS algorithms that optimize charging and discharging cycles, balance cell performance, and extend battery lifespan. These systems play a key role in ensuring the safety and reliability of batteries in both EVs and stationary applications [25, 26].

Aging and Degradation Mechanisms: Understanding the aging and degradation processes in lithium-ion batteries is critical for predicting their lifespan and performance [10, 27–30]. Research in this area investigates the effects of cyclic and calendar aging, temperature, state of charge (SOC), depth of discharge (DOD), and other operational factors on battery health. These studies provide insights into the physical and chemical changes that occur over time, helping to develop better models for predicting battery life.

Thermal Management: Efficient thermal management is essential for maintaining the performance and safety of lithium-ion batteries [10, 25, 26]. Studies examine various cooling and heating strategies, thermal management materials, and system designs to prevent overheating, reduce thermal gradients, and improve overall battery efficiency. Thermal management is particularly important in high-power applications like EVs and large-scale energy storage systems.

Safety and Reliability: Ensuring the safety and reliability of lithium-ion batteries is a major focus of research [13, 14, 27]. This includes studying the causes and prevention of thermal runaway, developing safer battery designs, and implementing robust safety protocols. Research also explores diagnostic tools and techniques for early detection of potential failures and anomalies in battery systems.

Recycling and Second-Life Applications: With the growing adoption of lithium-ion batteries, there is increasing interest in sustainable end-of-life solutions. Studies on battery recycling aim to recover valuable materials and reduce environmental impact [31, 32]. Additionally, research on second-life applications explores the repurposing of used EV batteries for stationary energy storage, examining their performance, economic viability, and environmental benefits [33–38].

Electrochemical Modeling and Simulation: Advanced modeling and simulation techniques are used to predict the behavior of lithium-ion batteries under various conditions [39–45]. These models help in understanding complex electrochemical processes, optimizing battery design, and improving performance. Research includes both empirical and physics-based models, which are essential for developing accurate battery management systems and diagnostic tools.

Energy Storage System Integration: Integrating lithium-ion batteries into broader energy systems, such as renewable energy grids and microgrids, is a significant area of research [32–37]. Studies focus on optimizing the performance of battery storage systems in combination with solar, wind, and other renewable energy sources. This includes investigating energy management strategies, grid stability, and economic implications of battery storage integration.

These diverse research efforts collectively contribute to advancing the technology and application of lithium-ion batteries, ensuring their effective use in both electric vehicles and stationary energy storage systems. In secondary applications, such as stationary energy storage systems, the ability to accurately assess and predict battery life allows for efficient management of battery life, ensuring the stability of power supply and optimizing the efficiency of systems.

Understanding the operating modes and stressors that influence the acceleration of degradation (as shown in Fig. 2) is critical for implementing tools to assess battery health and predict remaining useful life.

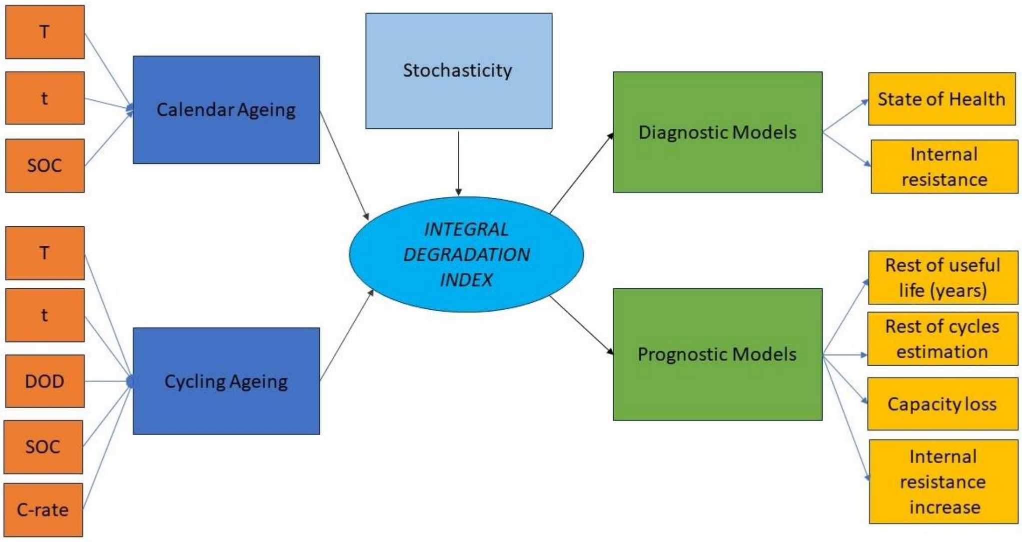

Figure 2. Framework for Predicting State of Health and Remaining Useful Life of Repurposed EV Batteries

A widely accepted classification divides the main modes of degradation operating in lithium-ion batteries into three: loss of lithium supply; loss of active material in the electrodes and an increase in the internal resistance of the element [10, 14, 17]. It is mostly associated with the consumption of lithium ions due to adverse reactions such as the formation of a solid electrolyte layer on the surface of the graphite negative electrode, electrolyte decomposition reactions, or lithium degradation reactions [36, 37]. Such adverse reactions irreversibly consume lithium ions, making them unavailable for subsequent charge/discharge cycles. The loss of active material in the electrodes usually arises from a combination of factors. One of them is the structural degradation of electrodes due to volumetric changes in active materials during cycling. This causes mechanical stress, which leads to cracks in the particles and a decrease in the density of lithium storage sites. Other factors include the chemical decomposition and dissolution of transition metals in the electrolyte and the modification of the solid electrolyte layer [38, 39]. An increase in resistance can be caused by the formation of parasitic phases, such as a layer of solid electrolyte on the surface of the electrode, as well as a loss of electrical contact within the porous electrode.

Several failure mechanisms have been identified as leading to second-stage degradation, including lithium plating, electrode saturation, resistance increase, and mechanical deformation. Neural networks have been employed to forecast this degradation phase, generally assuming that capacity loss determines battery lifespan and that aging models hold true until the battery's SOH drops to 70 %.

Calendar Aging depends on time and storage conditions (temperature, SOC) [10, 49]. The calendar aging model can be described by the following equation:

$$Q_{calendar}(t) = k_{calendar} \cdot e^{\frac{E_a}{RT}} \cdot t \cdot f(SOC), \tag{1}$$

where:

$Q_{calendar}(t)$ – loss of capacity due to calendar aging; $k_{calendar}$– reaction rate constant; E_a – activation energy; R – universal gas constant; T is the temperature; t is the time; *f(SOC)* is a function that describes the dependence on the SOC.

In summary, both temperature and SOC directly impact battery calendar aging. The resulting capacity fade and resistance increase are non-linear over time, indicating a strong interaction between these factors and the aging behavior.

Cycling Aging depends on the number of charge/discharge cycles, depth of discharge (DOD), charging rate (C-rate), and temperature [49]. The cyclic aging model can be described by the following equation:

$$Q_{cycle}(t) = k_{cycle} \cdot (DOD)^{\alpha} \cdot (C_{rate})^{\beta} \cdot e^{\frac{E_a}{RT}} \cdot N_{cycle}(t), \tag{2}$$

where: $Q_{cycle}(t)$ – loss of capacity due to cyclic aging; k_{cycle} – reaction rate constant for cyclic aging; *DOD* – depth of discharge; *Crate* – charging/discharging speed; α and β – model parameters; $N_{cycle}(t)$ – the number of charge/discharge cycles.

Additionally, high current peaks during charging or discharging can induce significant energy transfer, which accelerates aging. These peaks can cause thermal and mechanical stress, leading to further degradation.

The proposed ***Integral Degradation Index (DI)*** takes into account not only calendar and cyclic aging, but also random variables that simulate component in operating conditions, such as temperature, depth of discharge, and others, and allows to obtain a more accurate estimate of the overall degradation of the battery, taking into account various operational factors [46]. The inclusion of a stochastic component in the degradation index for secondary batteries is crucial due to the unique characteristics and usage history of these batteries. Secondary EV batteries have experienced diverse and often unpredictable usage patterns. This variability makes their degradation behavior more complex and less predictable than that of new batteries. Unlike new batteries that typically start their life under controlled and consistent conditions, secondary batteries have been subjected to varied driving conditions, charging habits, and environmental exposures. These inconsistent operational environments, including different temperatures, SOC, DOD, and charge/discharge rates, significantly impact the degradation process. A stochastic component can account for these random and variable factors, providing a more accurate and individualized assessment of the battery's current state.

Secondary batteries may exhibit unpredictable aging effects due to their complex history of cyclic and calendar aging. The rate of degradation can vary significantly over time and may not follow a simple linear pattern. Incorporating a stochastic element allows the degradation index to reflect these random aging effects, improving the accuracy of RUL and SOH predictions. Moreover, the remaining capacity of secondary batteries can vary widely due to the heterogeneous nature of their prior usage. Batteries with similar initial capacities may degrade differently based on their usage history. The stochastic component helps address this variability, providing a more realistic measure of the remaining capacity and the battery's ability to meet future energy demands. This enhanced predictive accuracy is critical for optimizing battery management strategies, scheduling maintenance, and planning for replacements. By reflecting the actual performance more closely, the stochastic approach ensures that the degradation index is robust and applicable to real-world scenarios, thereby supporting the efficient and reliable use of secondary batteries in energy storage systems.

Incorporating factors such as inconsistent operational environments, diverse usage histories, and unpredictable aging effects, our integral degradation index is designed to provide an accurate and individualized assessment of secondary batteries. This index reflects the random and variable factors impacting battery health, enabling improved RUL and SOH predictions.

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

where: $Q_{total}(t)$ – total loss of battery capacity, taking into account the factors of calendar and cyclic aging; *ΔQ(t)* – taking into account the uncertainty of the state/behaviour of secondary batteries under operating conditions; ΔT, $\Delta SOC, \Delta DOD, \Delta C_{rate}$ are random variables, respectively, temperature, state of charge, depth of discharge, charge/discharge rate with a certain distribution (e.g., normal), derivatives represent $\frac{\partial Q}{\partial T}\frac{\partial Q}{\partial SOC}, \frac{\partial Q}{\partial DOD}, \frac{\partial Q}{\partial C_{rate}}$ the sensitivity of the battery capacity to changes in each of these parameters.

By integrating a stochastic component, we account for the complexities and variability inherent in the prior usage of secondary batteries, ensuring a realistic measure of their remaining capacity and performance capabilities. This approach enhances predictive accuracy, optimizes battery management strategies, and supports the efficient and reliable application of secondary batteries in energy storage systems.

This indicator can be used to develop and adjust optimal battery charging and discharging modes, minimizing the impact of adverse factors and extending the life cycle of the battery. In empirical battery aging studies, data is usually collected under constant storage or cycling conditions. However, real-world applications often involve variable conditions. Historical charging and discharging patterns, known as path dependency, significantly impact battery performance and characteristics. Considering path dependency makes testing more complex, requiring dynamic cyclic aging tests with fluctuating SOC, Depth of Discharge (DOD), temperature, and discharge rates. Previous research indicates that path dependency is particularly relevant for lithium-ion batteries under high C-rate conditions.

The ***Remaining Useful Life (RUL)*** of a battery is a critical metric that indicates how long a battery can continue to operate effectively before it reaches a specified critical state of health (SOH). Knowing the initial SOH and the critical SOH value, we can calculate the RUL using the following formula:

$$RUL = \frac{SOH_0 - SOH_{critical}}{DI} \tag{4}$$

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

The equation 4 helps to determine the number of years or cycles the battery can still be useful before reaching the critical SOH.

Capacity Loss is an essential measure that shows the decrease in the battery's capacity over time due to degradation. It can be calculated using the following formula:

$$Loss = SOH_0 - (SOH_0 \times (1 - DI \times t)) \tag{5}$$

The equation 5 calculates the difference between the initial capacity and the reduced capacity after a certain period or number of cycles, indicating the extent of capacity loss due to degradation over time.

Remaining Cycles Estimation refers to the total number of full charge-discharge cycles a battery can undergo before it reaches the end of its useful life. It can be determined using the degradation index:

$$Cycles = \frac{SOH_0 - SOH_{critical}}{DI \times DOD} \tag{6}$$

In essence, the equation 6 can be understood as the remaining useful life (RUL) of the battery, determined by the difference between the initial and critical SOH, divided by the product of the degradation index (DI) and the depth of discharge (DOD). This approach allows for a more precise estimation of battery cycles by factoring in how deeply the battery is discharged in each cycle and the overall rate of degradation.

These formulas are essential for evaluating the performance and longevity of secondary batteries in various scenarios. They allow for precise calculations and predictions about the battery's useful life, capacity loss over time, and the expected number of cycles, facilitating effective planning and management of battery storage systems.

3. Results and discussions

The scenario approach in this work allows for a detailed study of the various operating conditions of secondary batteries and the development of optimal strategies for their use. Each scenario is characterized by unique technical and economic features that affect the battery's operating mode, aging, and residual capacity. Taking these differences into account enables the creation of more accurate forecasting and management models, which contribute to maximizing the efficiency of battery use in specific conditions.

In Table 1, the scenarios for the use of secondary electric vehicle (EV) batteries in various energy storage applications are presented. Each scenario is characterized by specific calendar and cyclic aging factors, typical battery capacities, and unique charging/discharging features. The scenarios range from residential self-consumption to commercial and industrial energy storage, island installations, electric vehicle fast charging, hybrid power systems for power and frequency regulation, and hybrid systems for local communities. This detailed categorization helps to understand the different operational demands and aging characteristics that secondary EV batteries must withstand, ensuring their optimal utilization and extended lifecycle in diverse energy storage applications.

Table 1. General Characteristics of Calendar and Cyclic Aging for Different Scenarios

Scenario		Calendar Aging	Cyclic Aging	Typical Battery Capacity (kWh)	Charging/Discharging Features
Scenario 1	Residential consumers with rooftop PV	Low	High	20-50	High cycle frequency due to daily charging/discharging cycles
Scenario 2	Commercial storage systems with distributed generation	Medium	High	50-100	Regular charging/discharging dependent on generation and consumption
Scenario 3	Grid storage with solar generation	Medium	High	500	Intensive use during the daytime solar generation cycle
Scenario 4	Grid storage with wind generation	Medium	Medium	500	Variable cycles depending on unpredictable wind generation
Scenario 5	Fast charging stations for electric vehicles	Low	Very high	200	Very fast charging/discharging to provide high power
Scenario 6	Storage for frequency regulation	High	Low	100	Mostly maintaining grid stability with rare charging/discharging cycles
Scenario 7	Storage for power regulation	High	Medium	150	More frequent charging/discharging cycles for power regulation
Scenario 8	Storage for self-sufficiency of local communities	Medium	High	200-300	Combination of charging/discharging depending on consumer needs and generation

In Table 2, the specific parameters for each scenario are outlined, including initial and final state of health, initial depth of discharge, charge/discharge rate, and average state of charge. These parameters provide a detailed view of the operational conditions and performance expectations for secondary EV batteries in various energy storage applications. By understanding these parameters, it becomes possible to tailor the management and maintenance strategies for each scenario, ensuring the effective and prolonged use of repurposed EV batteries in different contexts.

Table 2. Scenario-Specific Parameters for Secondary EV Battery Application

Scenario	Initial SOH (%)	Final SOH (%)	Initial DOD (%)	C-rate	Average SOC (%)
Scenario 1	80	40	85	C/20	50
Scenario 2	80	60	85	C/10	60
Scenario 3	80	60	70	C/5	70
Scenario 4	80	60	70	C/5	70
Scenario 5	80	60	90	1.5C	85
Scenario 6	80	60	50	C/2	40
Scenario 7	80	60	60	C	50
Scenario 8	80	40	80	C/3	60

Each scenario describes a specific application of secondary EV batteries, highlighting the corresponding strategy, detailed description, and expected impact. By implementing these tailored strategies, operators can optimize the performance and longevity of repurposed EV batteries, ensuring their efficient utilization in various energy storage contexts. The table provides a comprehensive overview of the practical measures that can be taken to address the unique demands and aging characteristics of batteries in different scenarios.

Table 3 compares the regular operating parameters with optimized parameters to demonstrate how effective management can significantly extend the lifespan of secondary batteries.

Table 3. Comparative Analyses of Regular and Enhanced (Optimized) Operating Modes Efficiency

Scenario	Regular operating mode				Enhanced (optimized) operating mode			
	DI	**RUL (years)**	**Capacity Loss (%/year)**	**Cycle Count (cycles/year)**	**DI**	**RUL (years)**	**Capacity Loss (%/year)**	**Cycle Count (cycles/year)**
Scenario 1	0.020	5.0	1.60	365	0.010	10.0	0.80	200
Scenario 2	0.018	6.7	1.20	300	0.010	10.0	0.80	150
Scenario 3	0.019	5.3	1.40	250	0.011	9.1	0.90	150
Scenario 4	0.017	7.1	1.00	200	0.010	10.0	0.80	150
Scenario 5	0.021	4.8	1.70	400	0.012	8.3	1.00	200
Scenario 6	0.015	8.0	0.80	100	0.008	12.5	0.60	100
Scenario 7	0.016	7.5	0.90	150	0.009	11.1	0.72	120
Scenario 8	0.018	6.7	1.20	250	0.010	10.0	0.80	150

The Table 4 outlines strategies for extending the remaining useful life and reducing capacity loss of secondary EV batteries through effective operational management.

Table 4. Strategies for Extending RUL and Reducing Capacity Loss through Operational Management

Scenario	Strategy	Description	Expected Impact
Scenario 1	Time-of-use optimization	Align battery charging/discharging with peak PV generation and household demand, limit DOD to 70–80 %	Extends RUL by reducing full cycles per year and lowers capacity loss with moderate DOD levels
Scenario 2	Peak shaving and load shifting	Charge during off-peak hours, discharge during peak times, maintain DOD at 70–80 %, controlled charging rate (C/10)	Extends RUL by preventing excessive DOD and high current rates, reduces capacity loss
Scenario 3	Daytime cycling with SOC stabilization	Charge during high solar generation, discharge during peak usage, maintain SOC range 40–80 %, avoid deep discharges	Enhances RUL by preventing deep discharges, reduces capacity loss by maintaining stable SOC
Scenario 4	Variable load management with controlled cycling	Predict wind patterns, manage charging/discharging, limit DOD to 60–70 %, avoid high-rate discharges	Prolongs RUL by adapting to variable wind patterns, reduces capacity loss through moderate DOD and rate limits
Scenario 5	High-power buffering and managed charging	Use battery as buffer for peak loads, manage charging to avoid overloading, reduce DOD to 80 %, use active cooling	Extends RUL by reducing thermal and cyclic stress, lowers capacity loss with controlled high-power management
Scenario 6	Minimal cycling with responsive power management	Keep battery at high SOC (50–70 %), minimize full charge/discharge cycles, implement low-rate discharges	Increases RUL by minimizing full cycles, reduces capacity loss through strategic SOC management
Scenario 7	Frequent but controlled cycling with SOC balancing	Regular but controlled power regulation, maintain SOC range 40–80 %, limit charge/discharge rates (C/2 or C)	Prolongs RUL by preventing deep discharges, reduces capacity loss through balanced SOC and controlled cycling
Scenario 8	Community-based energy management with hybrid generation support	Integrate battery storage with solar and wind sources, maintain SOC range 40–80%, control DOD	Enhances battery performance, extends RUL, reduces capacity loss by maintaining stable SOC and controlled DOD

These strategies focus on optimizing the operational parameters of secondary batteries, such as SOC range, DOD, and charge/discharge rates, tailored to the specific requirements of each scenario. By implementing these measures, the RUL can be extended, and capacity loss minimized, ensuring more efficient and sustainable battery use.

The table presents various strategies for optimizing battery operation modes across eight energy storage scenarios. Implementing these strategies can significantly extend battery life (RUL) and reduce capacity loss by controlling DOD, stabilizing SOC, and managing thermal conditions. Some strategies are suitable for multiple scenarios. For example, the peak shaving and load shifting strategy with controlled charging (Scenario 2) is similar to the strategy for power regulation storage systems (Scenario 7), where regular but controlled cycling with SOC balancing is utilized. Individual strategies are required for scenarios with specific operating conditions. For instance, the high-power buffering and managed charging strategy (Scenario 5) is specifically designed for fast charging stations for electric vehicles, where batteries are subjected to high thermal and cyclic stresses. Additionally, scenarios for energy independence of local communities (Scenario 8) require integration with hybrid generation sources and a corresponding management strategy to maintain stable SOC and controlled DOD.

Fig. 3 illustrates the state of health degradation of batteries over time across eight different scenarios. Each scenario represents a unique application of battery storage. The SOH is plotted against time, showing two degradation strategies: a regular operating mode and an enhanced operating mode.

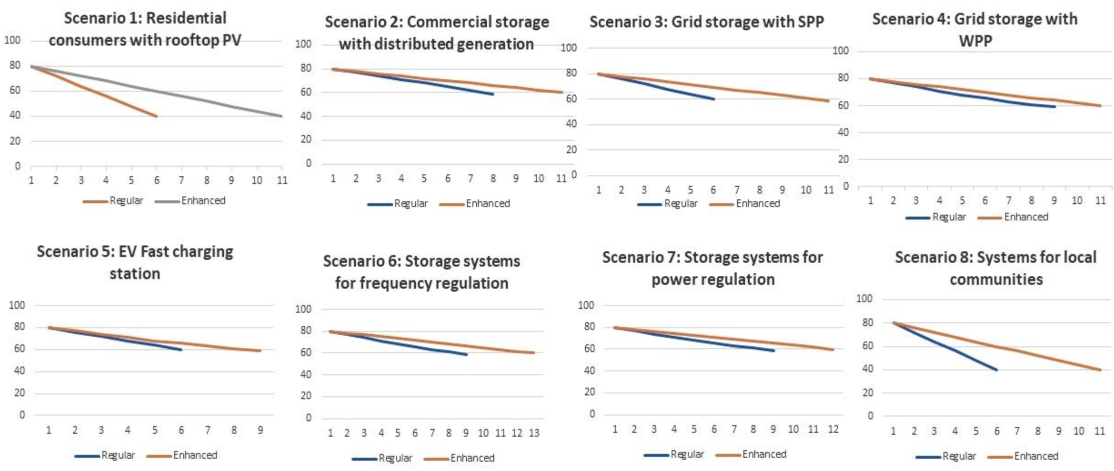

Figure 3. Second-Life Battery Health Degradation Over Time for Different Usage Scenarios with Regular and Enhanced Strategies

In the regular operating mode, batteries are managed with standard charging and discharging practices. In the enhanced operating mode, advanced strategies are employed to minimize degradation, such as limiting DOD, maintaining optimal SOC ranges, and controlling charge/discharge rates. Each graph compares the SOH trends for the regular and enhanced strategies over a specified period, highlighting the impact of these strategies on extending battery life.

The graphs demonstrate a clear distinction between the regular and enhanced operating modes across all scenarios. In Scenario 1 (residential consumers with rooftop PV), the regular mode shows a steep decline in SOH, reaching the critical threshold much sooner than the enhanced mode. This pattern is consistent across all scenarios, indicating the effectiveness of enhanced strategies in slowing down the degradation process.

For instance, in Scenario 5 (fast charging stations for electric vehicles), the regular mode results in a rapid decrease in SOH due to high stress from frequent fast charging cycles. However, the enhanced mode significantly extends the battery's useful life by mitigating these stresses. Similarly, in Scenarios 6 and 7, which involve frequency and power regulation, the enhanced strategies maintain higher SOH levels over time compared to the regular modes.

Overall, the enhanced strategies consistently improve battery longevity, making them essential for applications requiring prolonged battery use. The comparative analysis underscores the importance of adopting optimized battery management practices to enhance the performance and lifespan of energy storage systems.

Optimizing operational parameters such as DOD, SOC, C-rate, and maintaining a controlled temperature environment can significantly extend the lifespan of secondary batteries from the regular 5–6 years to 10–15 years. This highlights the importance of effective battery management strategies to enhance both performance and longevity.

Diagnostic models are essential for real-time monitoring and evaluation of the state of health (SOH) and performance of secondary batteries. Applying optimized parameters is particularly important for secondary batteries, which have already experienced significant use and therefore require precise management to maximize their remaining lifespan and utility. Prognostic models predict the future state of secondary batteries, including their RUL and capacity loss, based on historical and real-time data. The use of optimized parameters improves the reliability of these predictions and is particularly important for secondary batteries to ensure their continued viability.

4. Future Researches in Optimization of Operating Modes

Numerous studies in Ukraine have looked into various aspects of electric transportation, power generation, energy usage, and energy storage systems [47–52]. These studies also consider factors like system resilience, operational modes, and the roles of consumers and regulators. But there still is a significant gap in the exploration of electric vehicle batteries and their potential for secondary applications as well as modes of their use. Implementing the optimized parameters for secondary batteries (such as controlled DOD, SOC, C-rate, and temperature) enables significant improvements in the management of these batteries. This approach allows for the optimization of operating modes, ensuring that secondary batteries are used in the most efficient and effective manner possible. Here's how this optimization is achieved:

Improved Performance and Longevity: By maintaining DOD between 20–60 %, SOC within 40–80 %, and C-rate in the range of C/10 to C/5, the stress on the battery is minimized. This results in a reduction of degradation rates and prolongs the battery's useful life. Proper temperature control (15–25 °C) further ensures that the batteries operate within an optimal thermal range, reducing thermal stress and chemical degradation.

Enhanced Reliability: Real-time monitoring and adjustment of the battery's operating conditions ensure that any deviations from the optimal parameters are promptly addressed. This enhances the reliability of the battery system, preventing unexpected failures and maintaining consistent performance.

Cost Efficiency: Optimizing the operating modes reduces the frequency of battery replacements and maintenance interventions. This leads to significant cost savings over the battery's lifecycle. By extending the lifespan of secondary batteries from 5–8 years to potentially 10–15 years, the overall cost efficiency of the energy storage system is greatly improved.

Environmental Benefits: Extending the lifespan of secondary batteries reduces the need for new battery production, thereby decreasing the environmental impact associated with battery manufacturing and disposal. This contributes to more sustainable energy practices and aligns with global efforts to reduce carbon footprints.

Adaptability to Various Applications: Enhanced operating modes allow secondary batteries to be effectively utilized in a range of applications, from residential solar energy storage to industrial grid support and electric vehicle charging stations. This flexibility ensures that secondary batteries can meet the specific demands of different energy storage scenarios.

By continuously monitoring the performance and degradation patterns of the batteries, operators can make informed decisions about when to replace or repurpose the batteries, thereby maximizing their lifespan and efficiency. By adopting these practices, energy storage systems can achieve greater reliability, reduce operational costs, and contribute to a more sustainable energy infrastructure.

5. Conclusions

This study underscores the critical importance of diagnostic and prognostic models in managing the operational regimes of secondary EV batteries used in energy storage systems. By incorporating factors such as calendar and cyclic aging, these models provide a comprehensive framework for predicting the remaining useful life and state of health of secondary batteries, which have already undergone significant usage.

The introduction of the integral degradation index (DI) is a key element in these models. By considering multiple factors like Depth of Discharge, State of Charge, C-rate, and temperature, the DI offers a holistic measure of battery degradation. This index helps in maintaining optimized parameters, which is crucial for secondary batteries to ensure precise management and to maximize their remaining lifespan and utility. The integral degradation index allows us to combine all aspects of battery aging, such as calendar and cyclic aging, into one generalized parameter. This simplifies the analysis of the battery's health and allows you to adequately assess its remaining lifespan. As a result, users and energy storage operators can get a holistic picture of battery health without having to analyze many individual parameters. Taking into account stochastic factors in degradation models will allow you to more accurately simulate the real operating conditions of batteries and assess the impact of random changes on their condition.

Through real-time monitoring of DOD, SOC, C-rate, and temperature, diagnostic models ensure precise insights into battery conditions, enabling timely interventions and optimal maintenance strategies. This is particularly crucial for secondary batteries, which are more susceptible to accelerated degradation if not managed properly. Integrating temperature sensors and employing machine learning algorithms for anomaly detection further enhances the accuracy and reliability of these models. Prognostic models, on the other hand, offer predictive analytics for RUL and capacity loss, utilizing historical and real-time data to forecast future battery performance. By applying the integral degradation index (DI) and optimized parameters, these models can simulate various usage scenarios, providing valuable insights for optimizing battery usage across different applications. This approach not only extends the lifespan of secondary batteries but also reduces operational costs and enhances overall system efficiency.

The strategies outlined for different scenarios demonstrate how tailored operational management can significantly extend RUL and reduce capacity loss of secondary EV batteries. From residential self-consumption with rooftop PV systems to industrial storage with solar and wind generation, each strategy emphasizes the importance of maintaining optimal operational parameters to maximize battery utility and longevity.

In conclusion, the integration of advanced diagnostic and prognostic models, along with the use of the integral degradation index (DI), is essential for the effective utilization of secondary EV batteries in energy storage systems. These models ensure that secondary batteries operate under the most favorable conditions, enhancing their performance and extending their useful life. As the demand for sustainable energy solutions grows, the optimization of secondary battery usage through these models will play a pivotal role in achieving energy resilience and sustainability.

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УРАХУВАННЯ ФАКТОРІВ КАЛЕНДАРНОГО ТА ЦИКЛІЧНОГО СТАРІННЯ В ДІАГНОСТИЧНИХ І ПРОГНОСТИЧНИХ МОДЕЛЯХ ЗАСТОСУВАННЯ ВТОРИННИХ БАТАРЕЙ ЕЛЕКТРОМОБІЛІВ В СИСТЕМАХ ЗБЕРІГАННЯ ЕНЕРГІЇ

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Анотація. *Швидке розширення ринку електромобілів значно збільшило попит на літій-іонні акумулятори, що створює виклики для виробників та політиків щодо ефективного використання та утилізації. Коли ці акумулятори досягають кінця свого первинного використання, їх повторне застосування для зберігання енергії стає критично важливим для вирішення багатьох екологічних та ресурсних проблем. Ця стаття зосереджена на вторинному застосуванні акумуляторів електромобілів у системах зберігання енергії з урахуванням факторів календарного та циклічного старіння для оптимізації продуктивності та довговічності акумуляторів. Календарне старіння стосується деградації, що відбувається з часом через хімічні реакції в акумуляторі, навіть коли він не використовується. На цей тип старіння впливають: температура, стан заряду та умови зберігання. Циклічне старіння, з іншого боку, є результатом повторних циклів заряджання та розряджання, що спричиняє механічні та хімічні зміни в акумуляторі, призводячи до зменшення ємності та збільшення внутрішнього опору. Комбінований вплив цих процесів старіння вимагає розробки високоточних діагностичних та прогнозних моделей для ефективного управління продуктивністю та довговічністю вторинних акумуляторів. Розвиток ринку вживаних електромобілів в Україні викликає необхідність швидкого розроблення стратегій для повторного використання цих акумуляторів у системах зберігання енергії. Складнощі, пов'язані з остаточними процесами утилізації, роблять повторне використання привабливим проміжним рішенням. Повторне використання акумуляторів електромобілів дозволяє Україні пом'якшити наявні проблеми, пов'язані з токсичними відходами при остаточній переробці, водночас підтримуючи перехід до відновлюваних джерел енергії. У даній статті підкреслюється необхідність створення інтегрального індексу деградації DI, що поєднує фактори календарного та циклічного старіння зі стохастичними впливами для надання комплексної оцінки стану акумулятора. Такий показник є важливим для оптимізації практик управління акумуляторами, включаючи планування циклів заряджання та розряджання для продовження експлуатаційного терміну вторинних акумуляторів. Дослідження містить практичні рекомендації щодо впровадження цих моделей у різних сценаріях зберігання енергії, від побутових сонячних енергосистем до промислової підтримки мережі та станцій заряджання електромобілів. Прийняття оптимізованих стратегій управління акумуляторами має значний потенціал для продовження терміну служби вторинних акумуляторів та зниження операційних витрат. Такий підхід підтримує сталу енергетику і відповідає глобальним зусиллям щодо сприяння відновлюваним джерелам енергії та принципам циркулярної економіки.*

Ключові слова: літій-іонні батареї, електромобіль, зберігання енергії, деградація батареї, календарне старіння, циклічне старіння, інтегральний індекс деградації, залишковий термін корисного використання, стан здоров'я батареї.

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