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Enhanced state of charge estimation through Cluster-Based Learning Model: Impact study on degradation and profitability of second-life electric vehicle batteries

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ABSTRACT

The growing adoption of electric vehicles (EVs) presents an opportunity for repurposing end-of-life batteries for second life (SL) applications, such as energy storage systems. However, accurate estimation of the state of charge (SOC) remains critical for optimizing battery performance and extending operational life in these applications. This paper presents an in-depth investigation into the impact of advanced SOC estimation on the degradation and profitability of second-life EV batteries, utilising a Cluster-Based Learning Model (CBLM). An empirical degradation model is adapted to quantify how SOC estimation errors influence key battery health metrics, including capacity loss, State of Health (SOH), and energy retention. The study proposes the "energy advantage metric," which quantifies the usable energy retained in SL batteries based on SOC estimation accuracy. Capacity loss analysis across various SL applications demonstrates that the CBLM model significantly reduces battery degradation compared to the Standard Long Short-Term Memory (S. LSTM) model, particularly under deep discharge cycles. These improvements in capacity retention are then translated into economic impact, revealing cost savings ranging from £339 in residential PV systems to over €200,000 in grid-scale energy arbitrage. *t*-Test confirmed significant differences in degradation performance between CBLM and S. LSTM models, with Cohen's d effect size showing a small but meaningful effect size for Loss of Lithium Inventory (LLI) ($d = 0.24$).

1. Introduction

The global transition toward sustainable energy sources and the electrification of transportation are crucial in the fight against climate change. Governments worldwide, including the United Kingdom (UK), have implemented policies aimed at accelerating the adoption of electric vehicles (EVs) to reduce greenhouse gas emissions and meet climate targets [1]. To accelerate the adoption of electric vehicles (EVs) and phase out internal combustion engine (ICE) vehicles, the UK government has introduced a series of regulations and funding schemes. Notably, the UK's Zero Emission Vehicle (ZEV) mandate has set ambitious targets for the automotive industry. This initiative has led to a significant rise in EV registrations and the development of an extensive EV infrastructure.

While the surge in EV adoption is crucial for reducing carbon emissions, it presents challenges in managing the lifecycle of EV batteries [2]. Lithium-ion batteries (LIBs), the primary energy storage technology in EVs, degrade over time, limiting their effectiveness in vehicular applications [3]. To address this issue, second-life (SL) applications for EV batteries have emerged as a promising solution, extending battery utility and offering economic and environmental benefits [4–7]. SLBs can be repurposed for various energy storage applications, such as grid services, residential and commercial photovoltaic (PV) integration, and fast EV charging stations [8]. These applications help stabilise the energy grid while reducing the environmental footprint associated with battery production and disposal.

A key challenge in utilising SL batteries effectively is accurate State of Charge (SOC) estimation, which is critical for maximising performance and extending battery life. SOC estimation provides crucial information on the available capacity of a battery, ensuring its safe and efficient operation by preventing overcharging and deep discharging. Poor SOC estimation can lead to premature battery degradation, negatively affecting both battery health and economic viability. Although extensive research has focused on improving SOC estimation, there remains a significant gap in understanding the direct impact of SOC

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estimation errors on SL batteries.

Our previous work addressed the challenge of SOC estimation under diverse working conditions by introducing the Cluster-Based Learning Model (CBLM) [9]. The CBLM integrates clustering techniques with Long Short-Term Memory (LSTM) networks to improve the accuracy and adaptability of SOC estimation across various operational scenarios. However, while SOC estimation accuracy has been enhanced, there is still a lack of comprehensive framework that allows to quantify the tangible benefits of improved SOC estimation for second-life battery applications, particularly concerning long-term degradation and profitability.

By addressing the gaps identified in the literature, this study aims to provide a comprehensive assessment of how improved SOC estimation influences battery health and economic viability in SL applications.

The main contributions of this paper are that we:

1. Adapted an empirical SL battery degradation model to incorporate SOC estimation errors, providing a novel framework for assessing the impact of estimation accuracy on battery health.
2. Proposed an "energy advantage metric" to quantify the impact of SOC estimation errors on battery performance. This metric enables a clear comparison of the usable energy retained across different SOC estimation methods, offering insights into their influence on long-term battery degradation in various SL applications.
3. Conducted a comprehensive economic impact assessment of enhanced SOC estimation accuracy in second-life battery scenarios, demonstrating substantial cost savings and improved profitability across various energy storage use cases.
4. Implemented a simulation-based investigation of the effect of estimation errors on battery degradation mechanisms under the Multi-Stage Constant Current (MSCC) charging protocol using the Python Battery Mathematical Modelling (PyBaMM) tool, providing insights into the electrochemical processes affected by SOC estimation inaccuracies.

2. Literature review

The repurposing of EV batteries for second-life applications has emerged as a promising strategy to enhance resource efficiency and promote environmental sustainability. SL batteries, derived LIBs that have reached the end of their automotive use, can still retain up to 80 % of their original capacity, making them suitable for less demanding energy storage applications [6]. These applications include grid services, renewable energy integration, residential and commercial Systems, and fast EV charging stations [8,10,11].

Despite the potential benefits, several challenges hinder the widespread adoption of SLBs. Key among these are concerns regarding the lifespan, reliability, and profitability of SLBs in secondary applications [12,13]. Stakeholders are particularly apprehensive about the uncertainties associated with battery performance after varied first-life usage patterns, which can affect the predictability of SLBs in terms of degradation and economic returns.

Accurate SOC estimation is critical for both first-life and second-life batteries to ensure safe and efficient operation. However, in second-life applications, SOC estimation becomes an absolute necessity due to the increased variability in battery performance resulting from diverse usage histories and degradation states and reduced lifespan compared to first-life batteries [14]. This variability poses significant challenges to traditional SOC estimation methods, necessitating the development of techniques tailored to handle the complexities of SLBs.

Stakeholders' concerns about the lifespan and profitability of SLBs are closely linked to SOC estimation accuracy. Inaccurate SOC estimates can lead to suboptimal battery utilization, increased degradation rates, and reduced overall efficiency. These issues can diminish the economic viability of SLBs, as premature battery failure or reduced performance can result in higher operational costs and lower returns on investment [15].

2.1. Importance of accurate SOC estimation

SOC estimation is vital for BMS as it provides real-time information on the available capacity, ensuring safe and efficient operation by preventing overcharging and deep discharging. While BMS systems traditionally rely on voltage-based methods to estimate SOC to prevent overcharging or deep discharging, these methods have limitations. Voltage-based SOC estimation does not account for varying operational conditions or temperature fluctuations, both of which significantly influence battery performance. This often results in inaccurate SOC predictions, leading to suboptimal management decisions by the BMS to manage overcharging or excessive discharging, which can lead to accelerated degradation, reduced lifespan, and safety hazards [16].

Unlike battery parameters like voltage, current and temperature, measuring the current charge of the battery while its operating is challenging, which necessitates utilising estimation methods instead [17]. Measurable battery parameters are of great help in terms of estimating SOC; yet understanding the relationship among battery parameters, including current, voltage, temperature, and SOC becomes a complex task due to the uncertainties in electrochemical and thermodynamic reactions lithium-ion batteries and their nonlinear dynamics [18]. M. A. Hannan et al. have discussed the challenges of SOC estimation in terms of operational conditions and states that since batteries in various applications are not always performing in the same charge/discharge rate which significantly affects SOC estimation [19]. Batteries are significantly influenced by varying operational conditions such as charge/discharge rates (C-rates) and ambient temperature. As previously reported in [20], at lower discharge rates, the impact of environmental temperature on battery performance is relatively minor. However, as discharge rates increase, the effects of temperature become more pronounced, with lower temperatures leading to diminished performance and higher temperatures enhancing it. This interplay between operational conditions and environmental factors drastically varies battery behaviour adding further complexity to SOC estimation. Such variability highlights the need for adaptive SOC estimation methods capable of handling these dynamic conditions.

A wide range of SOC estimation methodologies have been explored, including Coulomb counting, model-based approaches, and data-driven models. Coulomb counting is the most straightforward method, integrating the current flow to estimate SOC [21]. Despite its simplicity, it accumulates substantial errors due to inaccuracies in sensor readings and initial SOC misestimations, particularly in long-term or varied operational conditions [22]. Model-based approaches, such as equivalent circuit models (ECMs) and the Extended Kalman Filter (EKF), leverage detailed mathematical models to simulate battery behaviour [16,23]. However, these methods depend heavily on accurate parameter identification and tend to falter under real-world conditions, where noise, non-linearities, and temperature variations undermine their performance. For example, EKF-based approaches assume Gaussian noise, which oversimplifies the complexity of real-world environments, leading to estimation errors [24].

Data-driven models have earned significant attention for their adaptability and ability to capture non-linear battery behaviour [25]. Among these, neural networks, particularly Long Short-Term Memory (LSTM) networks, have emerged as highly effective for SOC estimation [25,26]. LSTM networks can model long-term dependencies and dynamic battery behaviours without the need for complex feature engineering. Cui et al. [18,27] have emphasised the limitations of existing approaches that often rely on fixed charging and discharging currents, which do not accurately reflect actual battery usage. These observations suggest the need for models that can account for time-varying currents to enhance the applicability and accuracy of neural network methods in SOC estimation.

In response to the limitations of traditional SOC estimation models, clustering-based learning approaches have emerged as a promising alternative. Our previous work introduced the Cluster-Based Learning Model (CBLM) [9], which leverages the strengths of LSTM networks and clustering techniques to enhance SOC estimation accuracy under diverse operational conditions. CBLM addresses the limitations of conventional models by segmenting the battery's operational states into clusters, allowing for more targeted learning and improved prediction accuracy. However, while clustering-based models have demonstrated superior performance in reducing SOC estimation errors, their impact on battery degradation and economic outcomes in second-life applications has yet to be thoroughly explored.

2.2. Impact of SOC estimation errors

The relationship between SOC estimation accuracy and battery health, particularly capacity loss and degradation, is underrepresented in existing research. Many studies have suggested that accurate SOC estimation can significantly prolong battery life. For instance, [28] compares various ML algorithms for SOC estimation and mentions that accurate SOC estimation is essential for maximising the lifespan of LIB; however, the study does not show the impact of enhanced SOC on battery life. Similarly, [29] states that SOC is an important indicator for evaluating a battery management system (BMS), which is crucial for the reliability, performance, and life management of a battery; however the paper solely explores the estimation errors reduction for the proposed Suboptimal Multiple Fading Factor Extended Kalman Filter (SMFEKF) algorithm without assessing the effect of enhanced SOC estimation on the performance and life management of the battery. Many of these studies often emphasise the potential benefits of enhanced SOC estimation techniques, including optimised charge cycles and reduced overcharging or deep discharging events [30–35]. However, despite the recognised importance of SOC estimation accuracy, there is a notable gap in the literature regarding the evaluation of SOC estimation errors on battery degradation. No study has comprehensively assessed how SOC estimation inaccuracies directly impact the lifespan of batteries.

Existing degradation models for LIBs typically focus on stress factors such as cycle depth, temperature, and charging rate, but they do not account for the role of SOC estimation errors in accelerating degradation [11,36–38]. To date, no comprehensive model integrates SOC estimation errors into degradation predictions, leaving a critical gap in understanding how inaccuracies in SOC estimation contribute to capacity loss and other degradation mechanisms over extended cycles. This study addresses this gap by modifying an existing empirical degradation model to incorporate the effects of SOC estimation errors, providing a novel framework for evaluating their impact on SL health and performance.

While much of the existing research on SLB focuses on technical challenges like battery degradation and performance, there has been little attention paid to the economic implications of SOC estimation errors. Accurate SOC estimation plays a pivotal role in ensuring the economic viability of second-life applications, particularly in cost-sensitive sectors such as grid storage and residential PV integration. Inaccurate SOC predictions can lead to increased degradation, higher replacement costs, and reduced operational efficiency, all of which negatively impact profitability. However, no studies to date have thoroughly explored the financial consequences of SOC estimation errors, a gap that this research aims to fill by conducting a comprehensive economic analysis alongside technical assessments.

3. Methodology

This section outlines the approach taken to assess the impact of SOC estimation errors on the degradation and profitability of SL EV batteries. The methodology comprises two primary sub-sections. In Section 3.1, we describe the adaptation of an empirical degradation model to incorporate SOC estimation errors and evaluate their influence on battery health and profitability. Section 3.2 investigates the degradation mechanisms associated with SOC estimation errors using PyBaMM [39].

3.1. Impact of SOC estimation on SL battery health and profitability

The empirical degradation model employed in this study is based on the work of [40] which models cyclic aging in SL batteries using three primary stress factors: cycle depth ΔSOC, mean charge level (SOC_m) and charging rate (C_{rate}). In this study, the model is further modified to incorporate the effects of SOC estimation errors. The modifications enable us to quantify the impacts of SOC inaccuracies on both battery health and economic viability. The following sections detail the model's modifications and the simulation setup for various second-life battery applications.

3.1.1. Empirical degradation model

The cells used for the experiments are second life Li-NMC 18650 format cells, with specifications listed in Table 1. The experimental setup involved cycling these cells under controlled conditions, measuring capacity loss over time to gather comprehensive aging data.

The derived empirical model is defined by the following equations:

$$Q_{loss} = a e^{\sigma b Q_c} \tag{1}$$

where, Q_{loss} represents the capacity loss, a and b are empirically derived parameters from experimental data, Q_c is the cumulative charge throughput and σ is aging effect due to stress factors and calculated as:

$$\sigma = \gamma \bullet \delta \tag{2}$$

where, γ is a function of cycle depth and mean SOC and δ is a function of charging rate; these terms are calculated using Eq. (3) and Eq. (4) respectively:

$$\gamma = \left(r_1 (SOC_m)^2 + r_2 SOC_m + r_3 + \frac{\Delta SOC}{100} \right) \tag{3}$$

$$\delta = \alpha \, e^{\beta |C_{rate}|} \tag{4}$$

where, r_1, r_2, r_3, α and β are obtained by fitting the function to the experimental battery data.

The values of the derived parameters from data fitting are listed in Table 2.

3.1.2. Incorporation of SOC estimation errors

In real-world applications, SOC estimation errors have varying effects on different operational aspects of LIBs. Therefore, the above-mentioned empirical model is modified to allow the assessment of impact of estimation models on battery degradation under varied operational conditions.

This study builds upon our two prior works that developed and evaluated the Cluster-Based Learning Model (CBLM) for enhanced SOC estimation. The first study introduced the CBLM, which combines k-means clustering with LSTM networks to enhance SOC estimation accuracy [9]. The clustering process groups battery operational data including current, voltage, temperature, and C-rate into clusters with homogeneous characteristics. Each cluster is assigned a dedicated LSTM model to capture the non-linear relationships among battery parameters

Table 1
SL battery cell specifications [41].

Battery specification	Value
Cell format	18,650
Chemistry	NMC/LMO
Nominal capacity (Q_{nom})	2.1 Ah
Maximum C_{rate}	4.8
Cell nominal voltage (V_{nom})	3.65 V

Table 2
Degradation model parameters [40].

Model parameter	Setting
a	0.0190
b	0.0090
r_1	1.5365×10^{-4}
r_2	-1.5365×10^{-2}
r_3	0.3841
α	0.8277
β	0.3904

more effectively. A real-time cluster assignment mechanism was introduced using the cluster proximity technique to assign the most appropriate model in real time. Results demonstrated the superior performance of the CBLM compared to S. LSTM models in reducing SOC estimation errors [9]. To ensure a fair evaluation, we previously compared the CBLM with other clustering-integrated neural network methods, such as fuzzy c-means (FCM) clustering combined with LSTM networks. The results showed that the k-means CBLM provided more stable and accurate SOC estimation across various conditions, justifying its selection for this study. Specifically, when evaluating SOC estimation errors at 0 °C across different cluster sizes, k-means CBLM exhibited consistent performance with RMSE values remaining below 1 %, even at a higher cluster count (k = 6). In contrast, FCM CBLM demonstrated significant instability as cluster size increased, with RMSE increasing from approximately 0.66 % at k = 2 to over 4.7 % at k = 6. The second paper extended this evaluation by comparing the performance of the CBLM and S. LSTM model under varied ambient temperature conditions, providing insights into their robustness across diverse thermal environments [42]. Based on the previously demonstrated superiority of k-means CBLM over FCM CBLM, this study adopts k-means clustering for SOC estimation at 10 °C and 40 °C to evaluate its impact on degradation and profitability in second-life battery applications. In developing the CBLM, the dataset was partitioned into training (80 %) and testing (20 %) sets, ensuring the 20 % test data includes varied operational battery conditions. We conducted ablation study to evaluate the importance of the features by removing one feature at a time to highlight the critical importance of each feature in the estimation outcome. Additionally, we conducted hyperparameters tuning and revealed the optimal configuration for the CBLM model are learning rate of 0.001, Adam optimiser, 20 epochs, 1 LSTM layer and 50 neurons. Further details on the development of CBLM model can be found in [9,42].

The focus of this paper is different from these earlier studies [9,42]. Here, we quantify the impact of improved SOC estimation, achieved by the CBLM, on SLB degradation and lifespan. Specifically, we investigate how reducing SOC estimation errors affects battery health, performance, and economic feasibility.

For the current analysis, we utilise the root mean square error (RMSE) values of the models derived from this earlier research for 10 °C and 40 °C which are optimal ambient operating temperatures for LIBs. The RMSE values for the CBLM and the S. LSTM models are as presented in Table 3:

These RMSE values are incorporated into the degradation model to simulate the impact of SOC estimation errors on battery health and performance as follows:

Table 3
RMSE for CBLM and S. LSTM models at different ambient temperatures.

Ambient temperature.	Model	RMSE (%)
40 °C	CBLM	3.22
	S. LSTM	6.21
10 °C	CBLM	0.95
	S. LSTM	3.62

1. Adjusted cycle depth $\left(\Delta SOC_{adj}\right)$ (direct impact): SOC estimation errors directly influence the cycle depth, potentially leading to deeper charge-discharge cycles in practice. We account for this effect by adjusting the cycle depth with the root mean square error (RMSE) of the SOC estimation model

$$\Delta SOC_{adj} = \Delta SOC + \left(\Delta SOC \bullet \frac{RMSE}{100}\right) \tag{5}$$

This adjustment simulates the direct impact of SOC estimation inaccuracies on the battery's charging protocol.

2. Fluctuated mean SOC ($SOC_{\{f,m\}}$) (indirect impact): In this empirical model, SOC_m represents the battery's charge level during operation. This metric indicates whether the battery is operating near the top, bottom, or middle range of its charge capacity. The charge level is important because degradation rates vary depending on the SOC, with higher degradation typically occurring at the extreme high or low ends of the charge spectrum. Model the real-world implications of SOC estimation errors: The SOC estimation errors are modelled as a stochastic process, capturing the randomness and variability of real-time SOC estimation inaccuracies

$$SOC_{\{f,m\}} = SOC_m + \left(\frac{RMSE}{100}\right) \bullet N(0,1) \tag{6}$$

Based on the integrated SOC estimation errors, the final aging effect equation is updated as shown below:

$$\sigma = \left(r_1 \left(SOC_{\{f,m\}}\right)^2 + r_2 SOC_{\{f,m\}} + r_3 + \frac{\Delta SOC_{adj}}{100}\right) \bullet \left(\alpha\, e^{\beta |C_{rate}|}\right) \tag{7}$$

This modified model captures the long-term impact of SOC estimation errors on battery degradation and lifetime performance.

3.1.3. Case study: simulation setup

To evaluate the effects of SOC estimation errors, we simulate four different second-life application scenarios under specific operational conditions. These scenarios are detailed in Table 4 and include:

- S0: This scenario simulates the second life battery cell providing ancillary services to the electrical grid, such as frequency regulation and load balancing. Batteries need to respond quickly to changes in grid demand, which requires high power output and frequent, shallow discharge cycles. These services help maintain grid stability.

Table 4
Scenarios of SL applications under investigation.

Scenario	Application	C_{rate}	ΔSOC (%)	Daily operation/ years	Description
S0	Grid services	4	30	20/1.5	
S1	Commercial and residential PV integration	2	60	3/7	
S2	Fast EV charging stations	4	80	2/3	
S3	Grid scale energy arbitrage	2	80	2/7	

* is representative of power demand, is representative of depth of cycle.

- S1: This scenario represents the integration of second-life EV batteries with PV systems in commercial and residential settings. The batteries store excess solar energy generated during the day and discharge it during peak demand periods. This scenario involves moderate power output and relatively deep discharge cycles to maximise the use of stored solar energy.
- S2: This scenario focuses on the use of second-life batteries in fast charging stations for EVs. The batteries provide high power output to charge EVs quickly, supporting rapid charging protocols. This involves high C-rates and deep discharge cycles to meet the fast-changing requirements, which are essential for reducing EV charging times and improving user convenience.
- S3: This scenario simulates using second-life EV batteries for grid-scale energy arbitrage, where batteries charge during periods of low electricity prices (off-peak) and discharge during periods of high electricity prices (peak) in the wholesale market. This involves moderate power output and deep discharge cycles to maximise economic returns by leveraging price differentials in the electricity market.

An algorithm was developed to simulate the effect of SOC estimation errors on battery degradation over a long term under different operational scenarios with the steps involved in the simulation are presented in the pseudocode as Algorithm 1. The algorithm begins by initialising the model parameters, including those derived from experimental data, as outlined in Section 3.1.1. It then iterates over various models (CBLM and S. LSTM in this case) and application scenarios (described in Table 4) to simulate the battery's operational life. The analysis considers two ambient temperature conditions: 40 °C and 10 °C, as these fall within the optimal performance range for lithium-ion batteries. For each scenario, the algorithm adjusts the SOC and other stress factors based on SOC estimation errors, following the modified equations introduced earlier (Eqs. 5–7). The simulation proceeds by calculating the degradation effects over the battery's lifespan, updating the SOH and Qc accordingly.

Algorithm 1. Pseudocode for the simulation of battery degradation in the context of SOC estimation models.

Algorithm 1 Simulation of Battery Degradation for SOC Estimation Models

function SOCEstimationImpactOnDegradation(M, dt, S)
    Initialise model parameters:
    Set model parameters a, b
    Set γ function parameters $r1$, $r2$, $r3$
    Set δ function parameters α, β
    Set Nominal capacity in Ah Q_{nom}
    Set SOH_{init}
    $\mathbf{R} \leftarrow \{\}$
    for all $m \in M$ **do**
        for all $S_i \in S$ **do**
            Set $SOC_m \leftarrow S_i$-specific
            Set $\Delta SOC \leftarrow S_i$-specific
            Set $C_{\text{rate}} \leftarrow S_i$-specific
            Calculate $T_{\text{sim}} \leftarrow$ operations per day $\times 365 \times$ years
            Initialise $Q_{\text{current}} \leftarrow Q_{\text{nom}} \times SOH_{\text{init}}$
            $Q_c \leftarrow 0$
            for $t \leftarrow 0$ to T_{sim} by dt **do**
                Calculate ΔSOC_{adj} using EQ. (5)
                Calculate $SOC_{f,m}$ using EQ. (6)
                Calculate σ using EQ. (7)
                Calculate Q_{loss} using EQ. (1)
                Update Q_c
                Update $Q_{\text{current}} \leftarrow Q_{\text{current}} - Q_{\text{loss}}$
                Calculate $SOH \leftarrow Q_{\text{current}}/Q_{\text{nom}}$
            end for
            Store results in $\mathbf{R}[m][S_i]$
        end for
    end for
    return R
end function

3.1.4. Energy advantage metric and economic analysis

The energy advantage represents the additional usable energy preserved by the CBLM model compared to the S. LSTM model over the battery's lifetime. It is calculated by first converting the advantage in ampere-hours (Ah) to kilowatt-hours (kWh) as follows:

$$\text{Energy}_{\text{adv}}\ (\text{kWh}) = \text{Energy}_{\text{adv}}\ (\text{Ah}) \times \text{V}_{\text{nom}} \times 10^{-3} \tag{8}$$

This conversion allows the energy advantage to be expressed in practical terms, suitable for evaluating its economic impact across battery energy storage systems (BESS) applications.

For the economic analysis, the energy advantage is scaled to represent realistic BESS capacities for each application scenario, ranging from residential PV systems (30 kWh) to grid-scale energy arbitrage (20 MWh). The number of battery cells required to meet the target BESS capacity is determined by:

$$\text{Cells}_{\text{count}} = \frac{\text{BESS}_{\text{target}}\ (\text{kWh})}{\text{Energy}_{\text{adv}}\ (\text{kWh})} \tag{9}$$

This scaling approach allows us to estimate the total energy savings and the subsequent economic impact across different BESS configurations in various applications.

The economic analysis was conducted specifically for scenarios S1 to S3, where the market dynamics are well-defined. S0, which involves grid services, was excluded from the economic simulation due to the complexity of modelling the economic returns, which heavily depend on contractual agreements between BESS owners and the grid operators.

3.2. Impact of SOC estimation on degradation mechanisms

This section details the methodology used to simulate the effects of SOC estimation errors on key degradation mechanisms in lithium-ion batteries. The simulation was carried out using the Python PyBaMM tool, employing the Doyle-Fuller-Newman (DFN) model, which is widely accepted for simulating detailed electrochemical processes in batteries [43–45]. The degradation model parameters were drawn from [37] to ensure accurate representation of electrochemical dynamics in lithium-ion batteries. The simulation investigates three primary degradation metrics: Loss of Lithium Inventory (LLI), Negative Electrode Porosity (NEP), and Loss of Active Material (LAM). These degradation mechanisms were chosen because they are critical to understanding long-term battery health and performance. LLI and LAM directly affect capacity fade and performance decline, as highlighted in [38]. Additionally, according to [46] NEP plays a major role in aging processes at electrode interfaces, significantly influencing ion transport and internal resistance which is often overlooked in traditional aging models but essential for a comprehensive understanding of degradation.

3.2.1. Incorporating SOC estimation errors into the DFN model

To evaluate the impact of SOC estimation errors on battery degradation, the DFN model was modified to account for deviations in SOC caused by estimation inaccuracies. These deviations influence the battery's charge-discharge voltage cutoffs, leading to either overcharging or deeper discharging, both of which accelerate battery degradation. SOC errors were incorporated into the model by adjusting the voltage thresholds which define the transitions between different SOC levels during charging and discharging cycles:

$$V_{adj} = V_{threshold} \pm \left(\Delta V \bullet \frac{\text{RMSE}}{100} \right) \tag{10}$$

Where, V_{adj} is the adjusted voltage cutoff for SOC transitions, $V_{threshold}$ is the voltage associated with a specific SOC transition (e.g., moving from 25 % SOC to 50 % SOC), ΔV is the nominal voltage range for the battery under study — 1.7 V and RMSE is the SOC estimation error of the models. The voltage adjustment reflects the magnitude of SOC estimation errors, leading to deviations in the charging or discharging cycles. For instance, if the SOC is inaccurately estimated, the battery might discharge to a lower SOC than intended or overcharge beyond its optimal SOC, which accelerates degradation.

3.2.2. MSCC protocol

The charging process was simulated using an SOC-based MSCC protocol, designed to represent advanced charging patterns that has shorter charging time than traditional charging methods. The MSCC protocol divides the charging process into stages with different C-rates and SOC thresholds. To incorporate SOC estimation errors, the SOC transition points were adjusted based on the SOC errors from the CBLM and S. LSTM. The c-rate for each stage and the respective SOC transition is based on [47] and described in Table 5.

This protocol was executed for 800 cycles to observe the impact of SOC estimation errors on battery degradation over an extended period.

Table 5
SOC-based MSCC charging protocol implemented for simulation.

Stage.	Protocol
Charge Stage 1	Charge at 1.4 C until 25 % + SOC error
Charge Stage 2	Charge at 1 C until 50 % + SOC error
Charge Stage 3	Charge at 0.7 C until 75 % + SOC error
Charge Stage 4	Charge at 0.4 C until 100 % + SOC error
Rest 1	Rest for 1 h
Discharge	Discharge at 1 C until 0 % − SOC error
Rest 2	Rest for 1 h

3.2.3. Degradation metrics and statistical analysis

To capture the effects of SOC estimation errors on battery health, we tracked three key degradation metrics LLI, NEP and LAM.

LLI: This metric quantifies the percentage of lithium lost relative to the initial lithium inventory. Higher lithium loss indicates increased degradation, leading to reduced capacity and efficiency of the battery.

NEP: This metric measures the porosity of the negative electrode, indicating the fraction of the electrode volume occupied by pores. Porosity affects ion transport within the battery. Lower porosity values suggest higher degradation, resulting in poorer ion transport.

LAM: This metric represents the percentage loss of active material in the electrode, which participates in electrochemical reactions during charging and discharging. Loss of active material is a direct indicator of degradation, reducing the battery's capacity and lifespan.

To further analyse the effect of SOC estimation errors on battery degradation, detailed statistical analysis was conducted to confirm the significance of differences observed across the degradation metrics and quantify the practical implications of these findings. The following were the steps taken to conduct the statistical analysis:

1. We resampled the degradation data 1000 times to generate distributions of the means for both CBLM and S. LSTM models. This was conducted due to the complex, non-linear nature of physics-based PyBaMM models, which involve stochastic processes and sensitive parameters, making the underlying data distribution difficult to predict. Bootstrapping allows robust statistical inferences without assuming a known distribution, ensuring reliability in this context.
2. To determine the appropriate statistical test to use for this analysis, the Shapiro-Wilk (SW) test was used to assess the normality of the bootstrap distributions for each metric. The Null Hypothesis (H0): The data follows a normal distribution. If the *p*-value of computed SW test is <0.01, the null hypothesis is rejected, meaning that the data does not follow a normal distribution and hence *t*-test cannot be used.
3. For metrics where the Shapiro-Wilk test indicated normal distribution (p-value ≥ 0.01) for both CBLM and S. LSTM models, the independent two-sample *t*-test was employed. The *t*-test is a parametric test used to compare the means of two independent groups, assuming that the data is normally distributed. It assesses whether the means of two groups are statistically significantly different from each other. The Null Hypothesis (H0): There is no significant difference between the means of the degradation metric for CBLM and S. LSTM models.
4. To quantify the magnitude of the differences between the models, Cohen's d effect size was calculated for each metric. This provides practical significance of the differences between the models [48], complementing the statistical significance determined by the hypothesis tests. According to [49], a commonly used interpretation of Cohen's d values is 0.2 is small effect, 0.5 has medium effect and 0.8 has large effect.

4. Results and discussion

This section presents the results of the simulations and analyses conducted to assess the impact of SOC estimation errors on the degradation and profitability of SL LIBs. The findings are organised into two main subsections: (Section 4.1) the impact of SOC estimation on SL battery health and profitability, and (Section 4.2) the impact of SOC estimation on degradation mechanisms.

Table 6
Energy advantage and final SOH difference between CBLM and S. LSTM models across various scenarios.

Scenario	Temperature (°C)	Energy advantage of CBLM over S. LSTM (Ah – cycles)	SOH difference (CBLM − S. LSTM) (%)
S0	40 °C	39.74	5.41
	10 °C	31.66	3.66
S1	40 °C	47.60	3.53
	10 °C	37.68	3.22
S2	40 °C	21.66	4.35
	10 °C	17.04	3.38
S3	40 °C	65.20	5.66
	10 °C	50.87	4.50

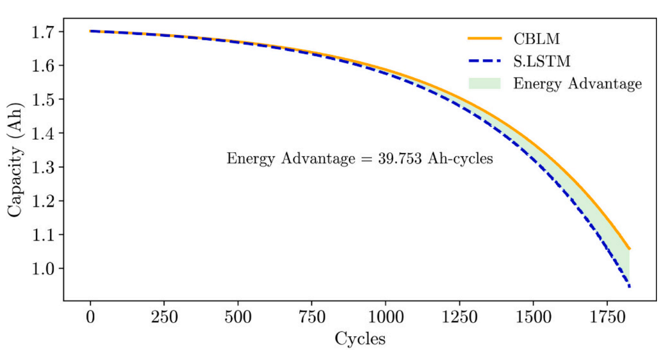
4.1. *Impact of SOC estimation on SL battery health and profitability*

4.1.1. *Capacity loss across scenarios*

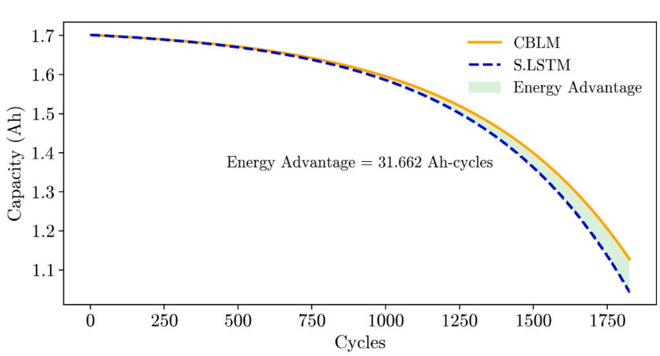
The simulation results demonstrate that the CBLM consistently results in lower capacity loss and higher final SOH compared to the S. LSTM model across all scenarios and temperatures. Table 6 summarises the energy advantage of the CBLM over the S. LSTM model in terms of additional ampere-hours (Ah) preserved and the corresponding SOH differences.

In Scenario S0, which simulates providing ancillary services to the electrical grid through frequent shallow cycling, the CBLM model demonstrated a significant reduction in capacity loss compared to the S. LSTM model as evident in Fig. 1. Specifically, the energy advantage, the additional capacity preserved by the CBLM model is:

- At RMSE difference of 2.99 % (from 6.21 % to 3.22 % at 40 °C): energy advantage of 39.74 Ah, resulting in a final SOH difference of 5.41 %.



(a) 40°C



(b) 10°C

Fig. 1. Comparison of CBLM and S. LSTM estimation impact on second-life battery degradation under S0.

- At RMSE difference of 2.67 % (from 3.62 % to 0.95 % at 10 °C): energy advantage of 31.66 Ah, with a final SOH difference of 3.66 %.

The SOH difference represents the percentage point difference in the final SOH between the CBLM and S. LSTM models at the end of the simulation. The results indicate that even modest improvements in SOC estimation accuracy (reflected by the RMSE differences) can lead to substantial reductions in capacity loss in applications involving frequent shallow cycles.

In Scenario S1, involving moderate power output and deeper discharge cycles typical of PV integration, the energy advantage of the CBLM model is shown in Fig. 2:

- At RMSE difference of 2.99 % (40 °C): 47.60 Ah, with an SOH difference of 3.53 %.
- At RMSE difference of 2.67 % (10 °C): 37.68 Ah, with an SOH difference of 3.22 %.

As shown in Fig. 2, the deeper discharge cycles amplified the effects of SOC estimation errors emphasised by the larger green area. The deeper discharge cycles amplify the effects of SOC estimation errors. Inaccurate SOC estimates can lead to over-discharge or overcharge, accelerating degradation. The CBLM model's enhanced accuracy mitigates these risks, preserving battery health more effectively than the S. LSTM model.

Fig. 3 demonstrates the performance of the battery under S2, characterised by high C-rates and deep discharge cycles associated with fast EV charging, the CBLM model achieves:

- At RMSE difference of 2.99 % (40 °C): Energy advantage of 21.66 Ah, with an SOH difference of 4.35 %.
- At RMSE difference of 2.67 % (10 °C): Energy advantage of 17.04 Ah, with an SOH difference of 3.38 %.

Fast charging imposes significant stress on batteries. SOC estimation errors in this context can lead to operating the battery outside safe voltage limits, increasing the risk of thermal runaway and accelerated degradation. The CBLM model's superior accuracy reduces these errors, enhancing safety and battery longevity.

In Scenario S3, involving extensive cycling to exploit electricity price differentials, the CBLM model exhibits the largest energy advantages across all scenarios as illustrated in Fig. 4:

- At RMSE difference of 2.99 % (40 °C): 65.20 Ah, with an SOH difference of 5.66 %.
- At RMSE difference of 2.67 % (10 °C): 50.87 Ah, with an SOH difference of 4.50 %.

The results consistently demonstrate that the CBLM model outperforms the S. LSTM model in preserving battery capacity and SOH across all scenarios. The energy advantages and SOH differences correlate with the RMSE differences between the models, highlighting the impact of SOC estimation accuracy on battery degradation.

The findings suggest that:

- Higher RMSE differences lead to greater energy advantages: The larger the disparity in SOC estimation errors between the models, the more pronounced the benefits of the CBLM model.
- Applications involving deep discharge cycles are more sensitive to SOC estimation errors: Scenarios S1 and S3 show larger energy advantages and SOH differences, emphasizing the importance of accurate SOC estimation in these contexts.

4.1.2. *Impact of SOC estimation on SL profitability*

The energy advantages obtained through improved SOC estimation were converted to kilowatt-hours (kWh) using Eq. (8) to assess the

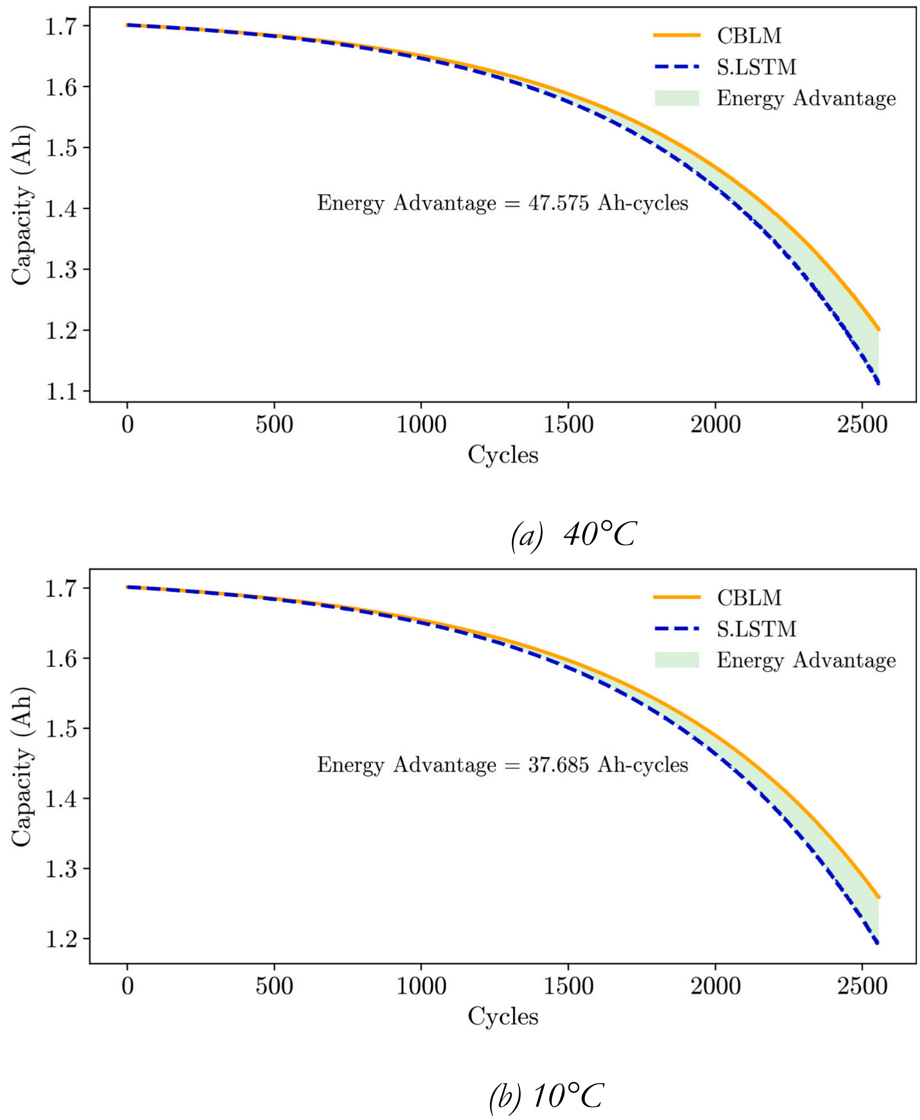


Fig. 2. Comparison of CBLM and S. LSTM estimation impact on second-life battery degradation under S1.

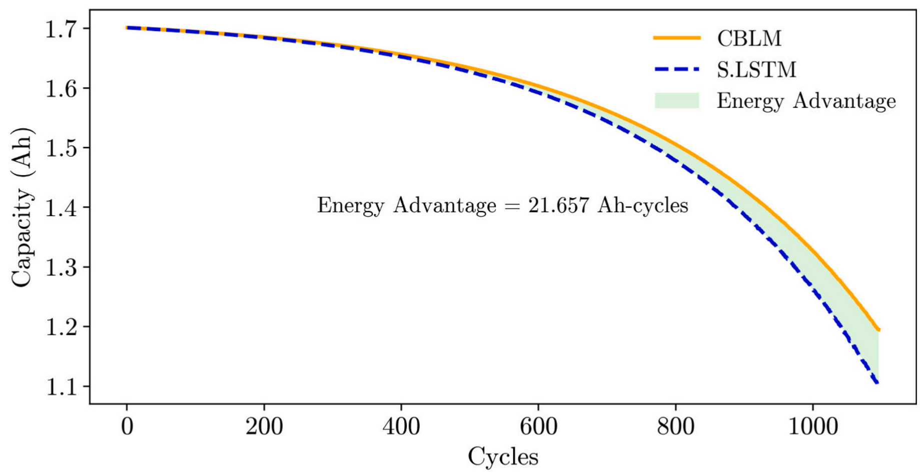
economic implications across different application scenarios. The analysis focuses on scenarios S1 to S3, where market dynamics allow for quantifiable financial impacts. The economic savings achieved by using the CBLM model over the S. LSTM model are summarised in Table 7 for scenarios S1 and S2, and in Table 8 for S3 across different countries.

In scenario S1, second-life batteries are integrated with residential and commercial photovoltaic (PV) systems to store excess solar energy generated during periods of high irradiance. This stored energy is used during low or no sunlight periods, reducing reliance on grid electricity and avoiding purchases during peak pricing periods. The economic analysis employs a differential pricing model with peak and off-peak electricity rates set at £0.35/kWh and £0.20/kWh [50], respectively. For residential applications with a BESS capacity of 30 kWh, the CBLM model yields additional savings of £378 at 40 °C and £299 at 10 °C, averaging £339 over the battery's lifetime. These savings are directly attributed to the improved SOC estimation accuracy of the CBLM model, which enhances battery health preservation and allows for greater utilization of stored solar energy. In commercial applications with a BESS capacity of 1000 kWh, the economic impact is more pronounced. The CBLM model results in savings of £12,586 at 40 °C and £9969 at 10 °C, averaging £11,278. The substantial cost reduction is due to the model's ability to maintain battery health more effectively over time, enabling increased energy storage capacity and reducing peak-period grid electricity purchases.

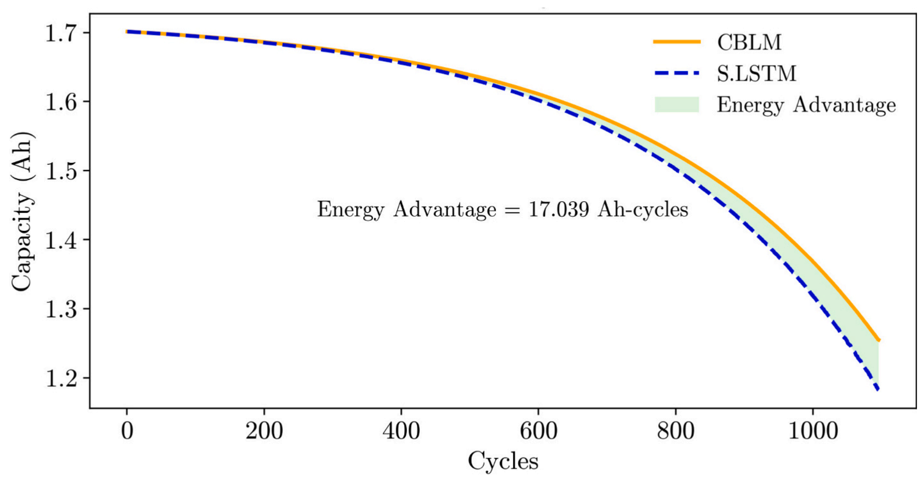
Scenario S2 examines the economic impact of advanced SOC estimation in fast EV public charging services, comparing rapid charging stations (50 kW) and ultra-fast charging stations (150 kW). The pricing model is based on current market tariffs, with rates set at £0.77/kWh for rapid charging and £0.83/kWh for ultra-fast charging [51].

For rapid charging stations, the CBLM model achieves additional savings of £880 at 40 °C and £692 at 10 °C, averaging £786. In ultra-fast charging stations, the savings increase to £2869 at 40 °C and £2257 at 10 °C, averaging £2563.

In S3, a 20 MWh BESS was used for grid-scale energy arbitrage across various European countries, utilising historical hourly wholesale electricity price data from European Network of Transmission System Operators for Electricity (ENTSO-e) and applying a commercial dynamic day-ahead pricing model [52]. The calculation of economic savings was based on factoring in daily minimum and maximum electricity prices to assess the profitability of using the CBLM over the S. LSTM model. The CBLM model's energy advantage was first determined by calculating the difference in daily retained usable energy between the two SOC estimation models. This energy advantage was then scaled to represent the target BESS capacity (20 MWh) and factored into the daily electricity price variations to compute the additional revenue generated by the price differentials. The pricing model considered the BESS to



(a) 40°C



(b) 10°C

Fig. 3. Comparison of CBLM and S. LSTM estimation impact on second-life battery degradation under S2.

charge during lowest hourly price (off-peak) and discharge during the highest (peak), maximising the profit from energy arbitrage.

The economic savings from using the CBLM model over the S. LSTM model were significant as shown in Table 8. The table highlights the savings at the two temperature points, reflecting the differences in SOC estimation errors:

At RMSE difference of 2.99 % (40 °C), Germany saw the highest additional savings of EUR 231,172, while Austria followed with EUR 216,519.

At RMSE difference of 2.67 % (10 °C), savings remained substantial but slightly lower, with Germany at EUR 178,132 and Austria at EUR 166,705.

These small RMSE differences, between 2.67 % and 2.99 %, led to noticeable changes in the savings. Even modest improvements in SOC estimation accuracy resulted in significant economic benefits, underlining the importance of reducing SOC errors for maximising profitability in SL battery applications.

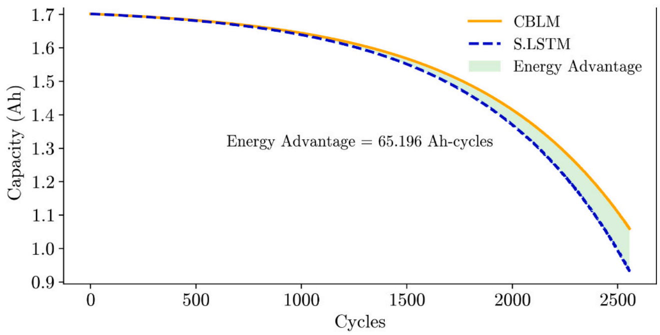
The substantial savings achieved with the CBLM model enhance the economic viability of grid-scale energy storage systems. Operators can maximise revenue by efficiently exploiting price differentials without incurring excessive degradation costs. The variation in average savings between countries shown in Fig. 5 reflects the differences in electricity market dynamics, price fluctuation and overall energy demand patterns. Germany and Austria show the highest potential for savings, likely due to their more volatile electricity markets and higher price differentials between peak and off-peak periods.

These results emphasise the potential for advanced SOC estimation models like CBLM to significantly enhance the economic viability of grid-scale energy storage systems, potentially improving the integration of renewable energy sources and contributing to more stable and efficient electricity grids across Europe.

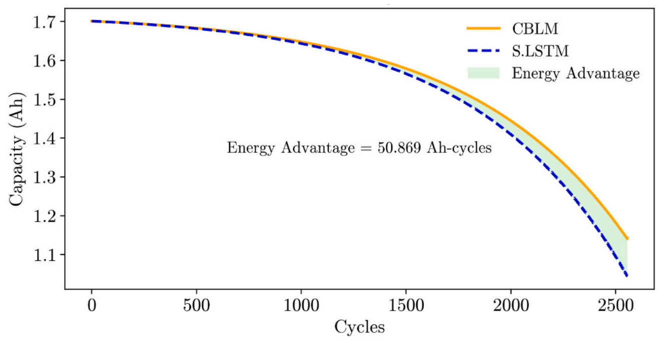
4.1.3. *Discussion on battery health and economic implications*

The results highlight the critical relationship between SOC estimation accuracy and both battery health and economic performance in SL applications. Key observations include:

- Even small improvements in SOC estimation accuracy (as indicated by RMSE differences of approximately 2.67 % to 2.99 %) can lead to substantial reductions in capacity loss and significant economic benefits.
- Applications involving deeper discharge cycles (S1 and S3) and high C-rates (S2) are more sensitive to SOC estimation errors, resulting in greater benefits from improved SOC estimation accuracy.
- The financial savings across scenarios justify the investment in advanced SOC estimation techniques like the CBLM model.



(a) 40°C



(b) 10°C

Fig. 4. Comparison of CBLM and S. LSTM estimation impact on second-life battery degradation under S3.

Table 7
Economic savings achieved by CBLM over S. LSTM across S1 and S2.

Scenario.	Service	40 °C	10 °C	Average saving
S1	Residential PV BESS (30 kWh)	£378	£299	£339
	Commercial PV BESS (1000 kWh)	£12,586	£9969	£11,278
S2	Rapid (50 kW)	£880	£692	£786
	Ultra-fast (150 kW)	£2869	£2257	£2563

Table 8
Economic savings achieved by CBLM over S. LSTM across S3.

Scenario.	Country	40 °C	10 °C	Average Saving
S3 (20 MWh BESS)	Austria	EUR 216,519	EUR 166,705	EUR 191,612.32
	Italy	EUR 169,555	EUR 130,750	EUR 150,152.71
	Germany	EUR 231,172	EUR 178,132	EUR 204,652.31
	Portugal	EUR 102,039	EUR 78,821	EUR 90,430
	Spain	EUR 103,847	EUR 80,225	EUR 92,036

4.2. Impact of SOC estimation on degradation mechanisms

4.2.1. Degradation metrics analysis

The simulation results highlight the impact of SOC estimation errors on key battery degradation metrics over 800 cycles. Fig. 6 presents a comparison of key degradation metrics, LLI, NEP, and LAM between the CBLM and S. LSTM models, focusing on the final portion of the simulation. The comparison between CBLM and S. LSTM models provides insights into the extent of degradation caused by different SOC estimation accuracies.

The LLI plot (a) shows a clear divergence between the CBLM and S. LSTM models in the later stages of the simulation. The CBLM model consistently results in lower LLI than the S. LSTM model. This suggests that the CBLM model's superior SOC estimation significantly reduces the stress on the battery during charge-discharge cycles, thereby minimising lithium inventory loss,. The regular cycling pattern seen in both models reflects repeated charge-discharge cycles, but the S. LSTM model experiences deeper LLI peaks, indicating more severe degradation due to SOC estimation errors.

NEP follows a similar cyclic pattern as LLI, with the CBLM model again showing less degradation. Although NEP is less sensitive to SOC estimation errors compared to LLI, the periodic fluctuations suggest that SOC inaccuracies lead to increased electrode stress over time, particularly in the S. LSTM model. By the end of the simulation, the S. LSTM model exhibits more pronounced electrode porosity reduction, while the CBLM model manages to mitigate this effect. This could have long-term implications for battery efficiency, as electrode porosity affects ion transport and overall performance.

The LAM plot displays a gradual but steady increase in material loss, with the S. LSTM model exhibiting higher degradation levels. The widening gap between the two models in this late phase of the simulation indicates that active material loss is directly impacted by SOC estimation accuracy. The CBLM model preserves more active material, which is critical for maintaining battery capacity and electrochemical performance over time. This is particularly relevant for second-life applications, where active material preservation can extend the battery's usable life.

The cumulative LLI plot underscores the importance of SOC estimation accuracy in the final stages of battery life. Both models exhibit a steep increase in cumulative LLI, but the CBLM model consistently accumulates less lithium loss than the S. LSTM model. This trend becomes especially pronounced as cycling progresses, emphasizing that SOC estimation errors compound over time. As second-life batteries are typically used in these later cycles, this difference highlights the critical role of advanced SOC estimation (such as that employed by the CBLM model) in extending battery lifespan.

4.2.2. Statistical analysis of degradation metrics

The Shapiro-Wilk (SW) test confirmed that the data for LLI, NEP, and LAM followed a normal distribution, allowing for parametric statistical analysis as shown in Table 9.

Fig. 7 shows the *t*-test results for three degradation metrics LLI, NEP, and LAM, comparing the CBLM and S. LSTM models. All metrics exhibit statistically significant differences, with particularly strong deviations observed in LLI and LAM, as indicated by the large magnitude of their *t*-statistics. This suggests that the choice between these models can have a considerable impact on degradation predictions, especially for these two metrics.

To further quantify the magnitude of these differences, Cohen's d was calculated and presented in Fig. 8, showing that:

- LLI had a small effect size above 0.2, suggesting a meaningful difference between the two models in terms of lithium inventory loss.
- In contrast, NEP and LAM showed trivial effects, indicating that the practical significance of SOC estimation on these metrics is less pronounced.

The cumulative sum analysis, depicted in Fig. 9, demonstrates a comparison of the rate at which LLI, NEP, and LAM accumulate over time. The steeper gradient observed in the cumulative sum of LLI, particularly in the later cycles, clearly demonstrates that LLI is the fastest-accumulating degradation factor among the three metrics. While all metrics initially exhibit similar rates of increase, LLI rapidly diverges as cycling progresses, suggesting that Loss of Lithium Inventory is the dominant degradation mechanism over time.

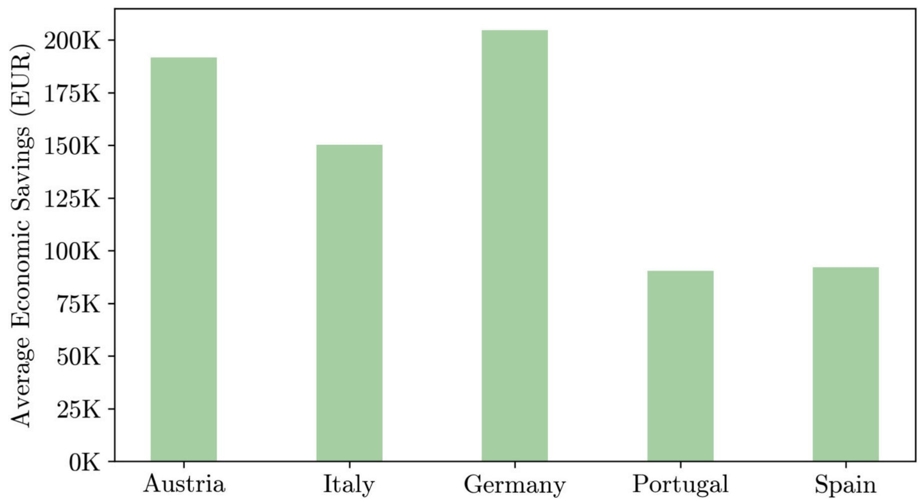


Fig. 5. Additional economic savings for SL batteries under S3 for using CBLM over S. LSTM.

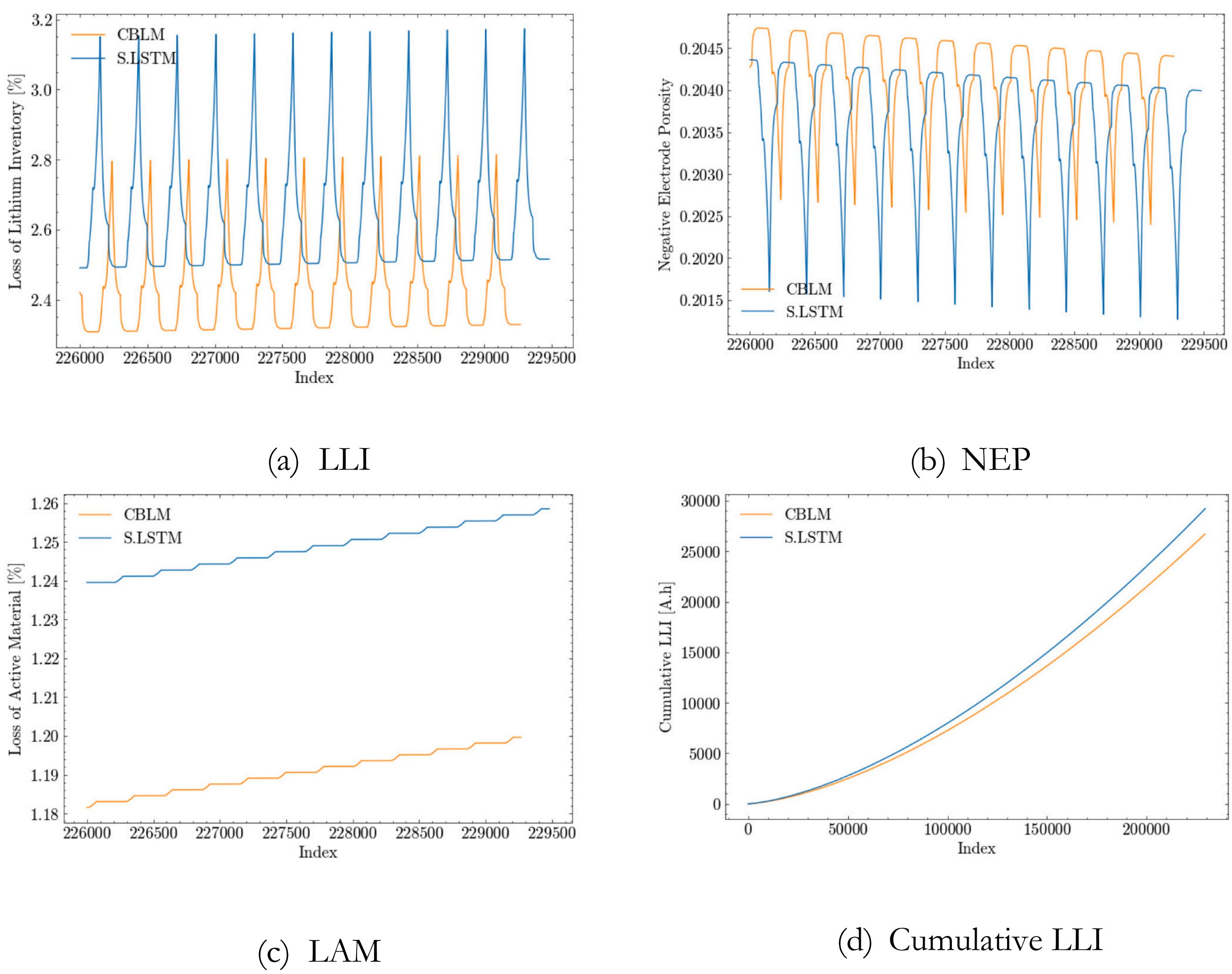


Fig. 6. Comparison of degradation metrics between CBLM and S. LSTM models.

This is particularly critical when considering the operational lifespan of SL batteries, which are employed in the later stages of a battery's life. As second-life batteries are exposed to additional cycling, the degradation mechanism shifts more heavily toward LLI accumulation. The faster rate of LLI loss suggests that advanced SOC estimation methods, such as those employed by the CBLM model, become increasingly important in these later cycles.

Table 9
SW normality test.

Degradation meric	CBLM *p*-value	S. LSTM *p*-value	H0	Follow normal distribution?
LLI	0.7059	0.9228	Fail to reject	Yes
NEP	0.7306	0.4620	Fail to reject	Yes
LAM	0.4137	0.9574	Fail to reject	Yes

5. Wider implications for the energy ecosystem

The findings of this study have significant implications for the energy ecosystem, particularly in optimizing the use of SL EV batteries. By demonstrating that improved SOC estimation through CBLM reduces battery degradation and enhances economic viability, this research provides actionable insights for stakeholders in energy storage, grid management, and renewable energy integration.

The study proves that accurate SOC estimation directly affects the longevity and performance of SL batteries. With the CBLM reducing capacity loss and maintaining higher SOH across various applications, operators can extend the service life of SL batteries. This prolongation maximises the return on investment for battery assets and also delays the environmental impact associated with battery disposal and manufacturing of new units.

The study demonstrates that advanced SOC estimation leads to significant economic benefits by reducing operational costs and extending battery life. This improved economic viability makes SL battery

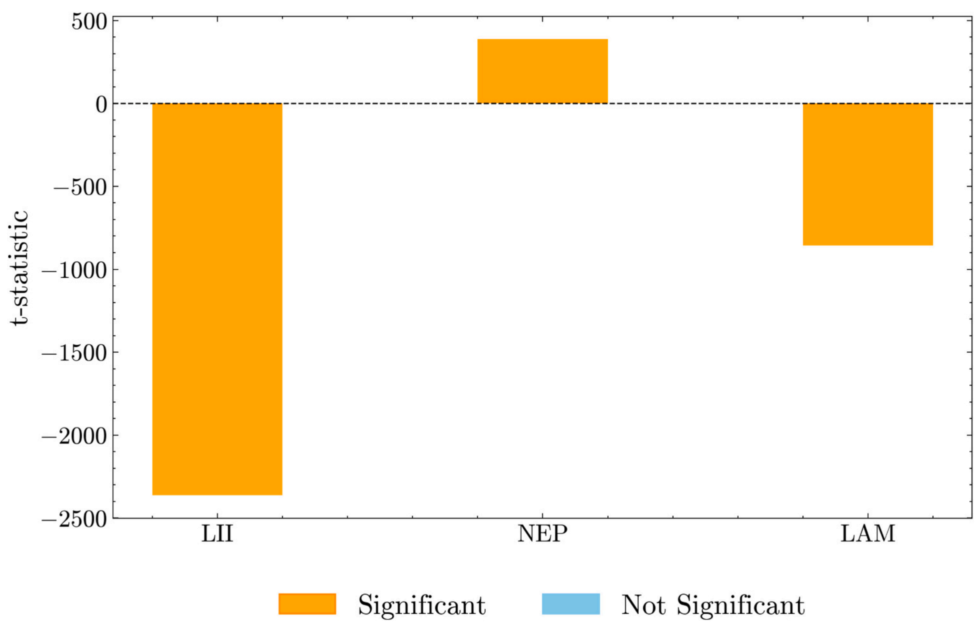


Fig. 7. *t*-Statistics of degradation metrics (LLI, NEP, and LAM) comparing the CBLM and S. LSTM models.

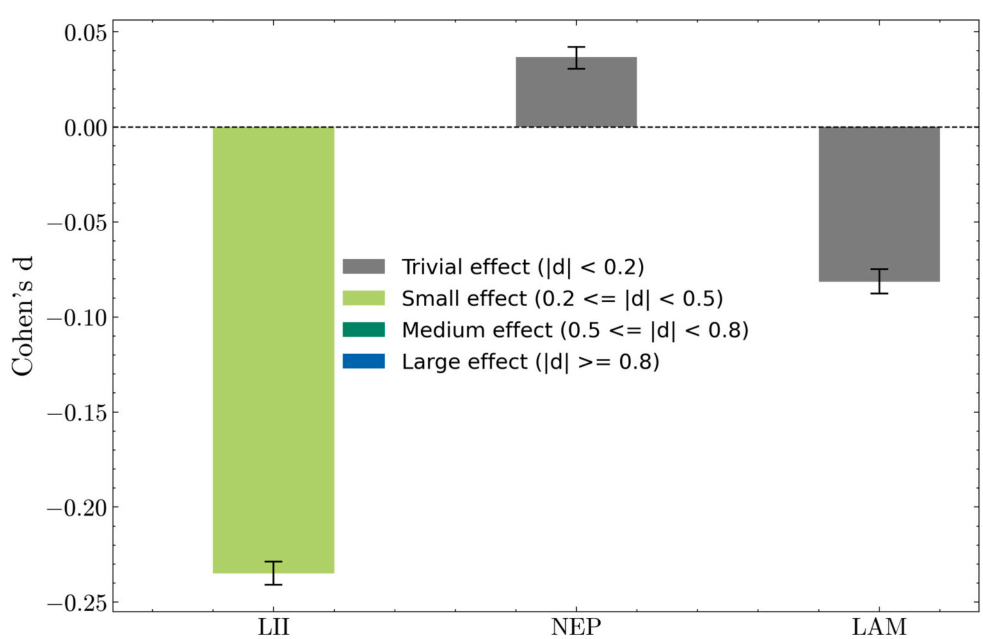


Fig. 8. Cohen's d effect size for LLI, NEP, and LAM comparing CBLM and S. LSTM models.

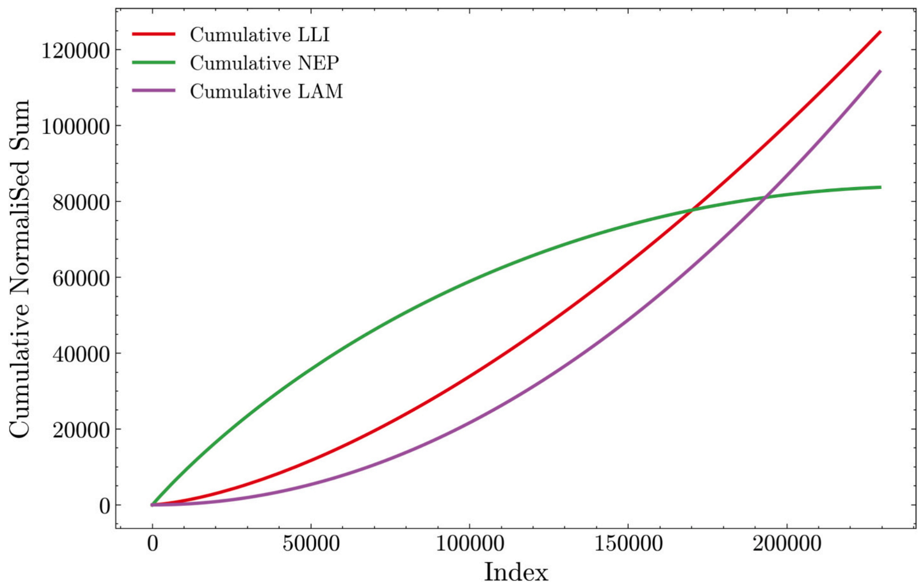


Fig. 9. Cumulative normalised sum of LLI, NEP and LAM for the CBLM model over 800 cycles.

solutions more attractive to stakeholders, encouraging investment and adoption in various sectors. Furthermore, as SLBs become more economically viable through advanced SOC management, the scalability of SLB solutions in different sectors becomes more attractive. This scalability can accelerate the deployment of energy storage systems, promoting wider use of SL batteries in applications ranging from residential energy storage to grid-scale systems.

In applications like grid services (Scenario S0), where batteries perform frequent shallow cycles for ancillary services, the reduced degradation offered by the CBLM means that batteries can operate reliably over longer periods. This reliability is crucial for maintaining grid stability, especially as the grid incorporates more intermittent renewable energy sources.

For residential and commercial PV systems (Scenario S1), the enhanced SOC estimation enables better energy management, allowing users to store excess solar energy more efficiently and use it during peak demand times. The study quantified significant economic savings, which can incentivise more consumers and businesses to adopt solar plus storage solutions. This, in turn, supports broader renewable energy adoption by making it more economically attractive.

In the context of fast EV charging stations (Scenario S2), accurate SOC estimation reduces the risk of battery overuse and overheating, which are critical concerns at high C-rates. By mitigating these risks, charging station operators can offer more reliable and safer services, encouraging EV adoption by alleviating range anxiety and reducing charging times. This improvement supports the expansion of EV infrastructure, a key component in reducing transportation-related emissions.

The research showed that in grid-scale energy arbitrage (Scenario S3), the CBLM leads to substantial financial gains by preserving more usable energy and reducing degradation-related losses. Energy storage operators can capitalize on electricity price differentials more effectively, enhancing the profitability of energy trading activities. This economic incentive can drive further investment in large-scale battery storage systems, contributing to grid flexibility and stability.

By extending the effective lifespan of SL batteries, the study's findings contribute to resource conservation. Less frequent battery replacements mean reduced demand for raw materials like lithium and cobalt, lowering the environmental footprint of battery production. Additionally, prolonged battery life reduces waste and the burden on recycling systems, aligning with circular economy principles and sustainability goals.

The demonstrated benefits of advanced SOC estimation suggest a need for supportive policies and regulations. Policymakers could consider setting standards for SOC estimation accuracy in battery management systems or providing incentives for adopting technologies like the CBLM. Such measures could accelerate the integration of efficient SL batteries into the energy ecosystem, amplifying the positive impacts identified in this study.

6. Conclusion

This study critically examined the impact of advanced SOC estimation methods on the degradation and profitability of second-life electric vehicle batteries, specifically focusing on the performance of CBLM compared to S. LSTM model. The research demonstrated that more accurate SOC estimation can substantially mitigate battery degradation and offer financial benefits across various SL applications including grid services, residential and commercial PV integration, fast EV charging stations, and grid-scale energy arbitrage. We adapted an empirical degradation model for SL batteries, integrating SOC estimation errors into the degradation metrics. The modified degradation model accurately captured the electrochemical stress induced by SOC estimation inaccuracies, thus allowing for a more precise prediction of battery degradation over time. The results from the four operational SL scenarios clearly showed that SOC estimation errors lead to significant deviations in battery degradation rates, especially under deep discharge cycles. Additionally, we introduced the "energy advantage metric," which provides a quantitative comparison of the usable energy retained across different SOC estimation models. The CBLM consistently demonstrated higher energy advantage, with advantages ranging from 21.66 to 65.20 Ah-cycles depending on the application. Furthermore, the economic impact investigation using the energy advantage comparison across the SOC estimation models, showed that improved SOC estimation led to significant cost savings, with mean savings ranging from £339 in residential PV systems to over EUR 200,000 in grid-scale energy arbitrage. Which underscores the economic viability of integrating advanced SOC estimation models in SL battery applications, where even small improvements in SOC accuracy translate into significant financial benefits over time. Results of PyBaMM simulations on the effects of SOC estimation errors on key degradation mechanisms such as LLI, NEP and LAM demonstrated that the CBLM model significantly reduced LLI and LAM compared to the S. LSTM model, with statistical tests confirming the magnitude of these improvements. The findings emphasise that SOC estimation errors compound over time, accelerating battery degradation. Future research work could focus on implementing the proposed framework under varied real-world charging and discharging duty cycles, as this study used static predefined charging scenarios. Additionally, future research could expand on this work by assessing the degradation impact of various SOC estimation models using the proposed framework developed in this study. This includes investigating the performance of other deep learning-based models and hybrid architectures, as well as exploring the potential of alternative clustering-based SOC estimation models.

CRediT authorship contribution statement

Mohammed Khalifa Al-Alawi: Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Ali Jaddoa:** Writing – review & editing, Supervision. **James Cugley:** Writing – review & editing, Supervision. **Hany Hassanin:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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