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Enhance Parameter Identification Accuracy for State-of-Charge Optimization in Lithium-Ion Batteries

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ABSTRACT

For optimizing the performance, lifespan, and safety of lithium-ion batteries (LIBs), Accurate State-of-charge (SOC) estimation is important because it is a cornerstone technology used in electric vehicles and renewable energy systems. Based on these points, the study presents a novel approach for enhancing parameter identification accuracy that is a main challenge in SOC optimization. Through combining advanced mathematical modeling, hybrid optimization framework, and adaptive parameter identification techniques, the proposed method is showing superior performance across various scenarios. Secondly, the experimental results are showing that the proposed method achieves lower root mean square error (RMSE), and SOC estimation error is compared with conventional methods, including Extended Kalman Filter, Coulomb Counting, and hybrid data-driven models. Moreover, when dynamic driving cycles are used, then, SOC error was minimized to 1.94% that significantly enhance accuracy level. Also, robustness level under changing noise levels, temperature profiles, and aging effects was validated that shows the reliability of method in real-world applications. This study contributes to battery management system development through providing an effective and robust framework for SOC estimation and pave the way for next-generation battery technologies. However, future work is necessary to resolve computational optimization, scalability, and applicability across diverse chemistries to enhance its practical implementation.

Keywords: State-of-Charge, Parameter Identification, Lithium-ion batteries, Hybrid Optimization, Energy Storage, Battery Management Systems.

INTRODUCTION

It can be noted that Lithium-ion batteries are considered a cornerstone of modern energy storage systems and it plays an important role in different applications like portable electronics, electric vehicles, and renewable energy systems [1]. These batteries contain certain characteristics like high energy density, relatively low self-discharge rate, and long cycle life. All these characteristics are making them preferred choice for both industrial and consumer applications [2]. Furthermore, for optimizing the performance and reliability, there is a need of precise monitoring and control of their state-of-charge (SOC) that is important parameter because it indicates the remaining charge level in a battery relative to its capacity. Under these points, accurate SOC estimation will ensure efficient utilization of battery and prevent from deep charging or overcharging that ultimately extends its lifespan [3].

Importance of Accurate State-of-Charge (SOC) Estimation

The SOC of a battery is considered a main indicator for energy management systems. The reason behind it is that it dictates key decisions like load balancing, charging schedules, and safety mechanisms. For electric vehicles, SOC estimation put huge impact on charging efficiency, range prediction, and user satisfaction level [4]. On the other hand, for renewable energy systems, precise SOC monitoring is extremely important to ensure seamless integration with optimizing power flow, and grid systems [4].

Besides its importance, SOC estimation is not a simple task because of nonlinear and dynamic behavior of Lithium-ion batteries. Secondly, these batteries are showing complex electrochemical behaviors influenced by aging, temperature, and operational conditions. It is not easily measurable and it necessitates the use of indirect estimation techniques based on current, battery models, voltages, and other measurable parameters [5].

Challenges in Parameter Identification for SOC Optimization

The next point is that accurate SOC estimation is heavily depending on the precise identification of various battery parameters like capacitance, internal resistance, and open-circuit voltage [6]. All these parameters are involved in defining the relationship between measurable quantities and the SOC, that form the backbone of different battery models used for estimation. However, there are some main challenges that hinder the accuracy level of parameter identifications [6].

- Nonlinear Battery Behavior: Lithium-ion batteries is showing nonlinear dynamics because of complex electrochemical interactions. Hence, it will become extremely difficult to model accurately their behavior under changing conditions [7].
- Aging Effects: When battery is used, then its age starting to decrease because its parameter change significantly and affects badly the reliability level of initial models and required frequent recalibration [8].
- Measurement Noise and Errors: While measuring voltages and currents of these batteries, some noise and inaccuracies also present in it. Hence, it complicates the estimation process [9].
- Dynamic Operating Conditions: These batteries sometimes operate under a huge range of conditions including varying load profiles, and fluctuating temperatures that can affect parameter stability [10].
- Computational Complexity: For real-time SOC estimation, there is a need of computational efficient and reliable algorithms especially for various applications like electronic vehicles in which processing resources are limited [11].

Objectives and Scope of the Study

The main aim of this study is to resolve all these challenges through proposing a novel method to enhance the accuracy of parameter identification of SOC optimization in lithium-ion batteries. According to this, the proposed approach integrates with advanced optimization algorithms with robust battery management techniques used to enhance the precision, and reliability of SOC estimation. Therefore, the main objectives are given below

- Develop highly improved parameter identification framework that is reliable to use to overcome the non-linear and dynamic behavior of Lithium-ion Batteries.
- Evaluate the performance of proposed method by using both simulated and experimental datasets.
- Compare the required results with existing state-of-the-art methods to highlight the improvements in computational efficiency and accuracy.

Scope of the Study

The scope of this study is related to the use of Lithium-ion batteries in diverse applications for future. However, the main application with a focus on electric vehicles and renewable energy systems. Through resolving the main bottlenecks of the study in parameter identification, the study aims to contribute in the growing body of knowledge on battery management system. Hence, it opens the way for highly reliable and efficient energy storage solutions.

LITERATURE REVIEW

In this section, there is comprehensive information about the past authors discussed about the SOC estimation and parameter identification for the Lithium-ion batteries, with detailed advancement for its applications.

Overview of Existing Methods for SOC Estimation and Parameter Identification

It can be observed that accurate state-of-charge (SOC) estimation is extremely critical for managing lithium-ion batteries because it ensures safety, optimal performance, and longevity. Over the few years, researchers have developed some different methods that are reliable for SOC estimation and parameter identification that can be categorized into direct measurement, hybrid approaches, data-driven, and model-based approaches. However, each method contains some strengths and weaknesses that can put influence in its applicability in various scenarios [5].

Direct Measurement Methods:

From this, one author had discussed in detail about direct measurement methods for SOC estimation that include coulomb counting, and open circuit voltage. In open-circuit voltage, there is proper estimation about the SOC based on the relationship between the SOC and the battery open circuit voltages [12]. However, this method is simple and highly cost-effective but it requires the battery to be set at rest for obtaining accurate measurements that limits its application during dynamic operations [12]. The second one is coulomb counting and this approach is calculating the value of SOC by integrating the charge or discharge current over certain time. This method is widely used and coulomb counting is highly susceptible to errors because of current sensor inaccuracies and cumulative drift [12].

Model-Based Methods:

Another research had discussed about model-based methods in detail. The author mentioned that model-based methods are mainly depending on mathematical representations of battery dynamics that include various approaches like electrochemical models, equivalent circuit models, and state observers [13]. In equivalent circuit models, resistor-capacitor networks are used to mimic the electrical behavior of lithium-ion batteries. Secondly, this method is highly efficient and widely used in various real-time applications. However, the accuracy level of these models is depending on the accurate identification of model parameters that can be changed with temperature, operating conditions, and aging [13]. On the other hand, the electrochemical models are providing a detailed representation of battery processes that include electrode reaction and ion transport. This method shows high accuracy but highly complex and its computational demand is limiting their use in real-time applications [13]. Lastly, the author discussed about state observers like Kalman Filter and its variants include extended Kalman filter, unscented Kalman filter are mainly employed for SOC estimation. From this, Extended Kalman Filter is widely adopted filter because of its ability to handle nonlinear systems effectively. However, there is a need of precise model parameters with initial conditions for reliable performance [13].

Data-Driven Methods:

After this, the next author had discussed about data-driven methods that were introduced after the rise of machine learning and data-driven techniques for SOC estimation. Although these methods can leverage historical and real-time data for identifying patterns and predicting SOC [14]. From this, artificial neural networks are considered the best model for handling nonlinear relationships between SOC and battery parameters. They can easily adapt with various operating conditions but there is a need of large dataset for training [14]. The next one is Support Vector Machines that are highly effective for classification and regression tasks in SOC estimation. However, the problem is that these machines are struggling with scalability in large datasets. Lastly, in deep learning approaches various techniques like long short-term memory, and convolutional neural networks are used that shown promise to capture complex dependencies and dynamic behaviors [11].

Hybrid Methods:

In another research, the author had provided comprehensive information about hybrid methods in detail. The hybrid approaches are combining the strengths of model-based and data-driven methods for resolving their individual limitations [15]. For this, the author had discussed three techniques that include model-data fusion, adaptive techniques, and ensemble learning. In model-data fusion, electrochemical models, and ECM integrates with machine learning techniques for improving accuracy while retaining interpretability [15]. In ensemble learning multiple data-driven models are combined that enhances robustness and generalizability of the system. In hybrid framework, adaptive mechanisms are included for accounting for temperature variation, battery aging, and dynamic loads [15].

Challenges in Existing SOC Estimation Methods:

Besides these vital advantages of these methods, there are some main challenges also present in these methods mentioned by researchers. From this, one researcher had presented challenges present in existing SOC estimation methods [16]. The first one is related to parameter variability because battery parameters are influenced through various factors like temperature, aging, and usage parameters that makes them accurate identification difficult. The second main disadvantage is related to computational complexity [16]. According to this, advanced methods like electrochemical models, and deep learning required substantial computational resources [16]. The third one is related to data dependency that require high-quality, and extensive datasets that are not always be available. The last one is related to real-time application, in which a lot of methods face challenges in meeting the real-time demand for battery management systems [16].

Recent Advancements and their Limitations in SOC Estimation and Parameter Identification

For battery management systems, the accurate estimation of State-of-charge, and parameter identification is extremely important when using Lithium-ion batteries. Based on this, there is recent advancement observed in this domain with focus on improving robustness, accuracy, and real-time adaptability. Besides these advantages, these methods also contain limitations that present new opportunities for further research.

Advancements in Model-Based Approaches for SOC Estimation:

The model-based methods that involve advance equivalent circuit models and other electrochemical models contains some notable improvements. Based on these points, a lot of authors had provided comprehensive discussion on advancement in model-based approaches [17]. From this, the author provided information regarding enhanced ECMs with multi-time constant ECMs that is consisted of temperature-dependent parameters with aging effects. The results showed that it offers highly precise SOC estimation under various conditions [17].

The next author had discussed about advanced State Observers. It includes different variants of the Kalman Filter like Adaptive Filter and Particle Filter. These filters are optimized for accounting to model various uncertainties and noise level in real-time scenarios [9]. Another author had discussed about coupled Electrochemical-Thermal Models. These models are providing an integrated approach for monitoring both battery temperature, and SOC so it can improve operational reliability and safety of battery [18].

Data-Driven Techniques for SOC Estimation:

There are some data-driven methods that have leveraged advancements in artificial intelligence and machine learning to enhance SOC estimation level. Under these points, one author had discussed about some important data-driven techniques for SOC estimation. The first one is deep learning models [19]. These models include long Short-Term Memory, and Convolutional Neural Networks that showed some remarkable accuracy level in capturing non-linear and complex battery behavior [19]. The second one is reinforcement learning and it includes RL-based frameworks that are powerful enough to optimize SOC estimation through learning optimal control policies over time by adapting to dynamic conditions. Lastly, there is transfer learning in which knowledge gained from one battery system to another that minimizes the need for extensive data collection [19].

Hybrid Methods:

The hybrid approaches are combining model-based and data-driven techniques to emerged as a robust solution. According to this, one researcher had discussed about some hybrid methods [20]. From this, the first method is model-data fusion in which ECM is integrated with machine learning models to achieve a balance between computational efficiency and accuracy. The next one is adaptive mechanisms in which adaptive algorithms to dynamically update parameters that are useful for battery aging, operational changes, and temperature variations [21]. In ensemble learning, multiple predictive models are combined to enhance robustness and minimize errors [21].

Advancement in Sensor Technology and IoT:
With the integration of Internet of Things, and advanced sensor technologies have revolutionized SOC estimation. From this, one research had discussed about various sensors that integrates with IoT technologies [22]. The first one is High-Precision Sensors. These sensors can easily capture current, temperature, and voltages data with high accuracy, and enable better parameter identification. The next one is cloud-based systems that allow for real-time monitoring and analysis to enhance SOC estimation accuracy level across large-scale applications [23]. Lastly, there is edge computing in which processing data closer to the source can minimize latency and enhance the real time performance of battery management systems [23].

Physics-Informed Machine Learning:
The next advancement observed in the field of SOC estimation is related to the integration of physics-informed machine learning. According to this, the author had provided some information regarding PIML [10]. This technology follows the principles of electrochemical modeling into machine learning frameworks by combining domain knowledge with predictive capabilities. Secondly, this approach is also reliable to use because it minimizes the reliance on large datasets while enhancing model interpretability. Also, the author had mentioned some notable limitations for PIML [10]. This technology is still in its early stage and requires further research for optimizing its implementation level. Furthermore, computational complexity and scalability is a huge challenge for its large-scale application [10].

Battery Aging and Degradation Modeling:
There are some resent efforts that focused on integrating aging and degradation models with SOC estimation frameworks. According to this, the author mentioned about dynamic aging modeling because they can adapt SOC estimation methods for accounting for capacity fade and resistance growth over time [24]. Moreover, by combining aging models with adaptive filters can enhance the accuracy level for long-term SOC estimation. However, there are some limitations too because again effects are highly nonlinear and not the same among various batteries. Hence, it is not possible to make a universal model [24]. The next one is related to computational burden of real-time aging adaption that can limit its application in resource constrained systems [25].

Research Gap and Motivation of the Current Work
Beside the main progress made in this field regarding SOC and lithium-ion batteries, there are still some research gaps are present that highlights the need for further innovation in SOC estimation and parameter identification [26].

Non-Linear and Dynamic Behavior:
The existing methods are struggling and unable to model accurately the nonlinear and dynamic characteristics of Lithium-ion batteries under changing operating conditions [27].

Aging Effects:
The main impact of battery aging on parameter stability is not resolved properly that lead towards degradation in estimation accuracy level over time [28].

Computational Efficiency:
There are a lot of advanced methods like deep learning, electrochemical modeling, and deep learning is highly computationally intensive that make them highly impractical for real-time applications [29].

Data Availability:
In data-driven approaches, there is a need of large, and high-quality datasets for training and validation purpose. Hence, such lack of standardized dataset is still a bottleneck for the battery technology [30].

Noise of Uncertainty:
Due to measurement noise and uncertainty can significantly affect the performance level of parameter identification techniques that is unable to provide accurate and reliable results in dynamic environments [31]. Under these points, the main motivation for the current work is obtained from these limitations and the study is aiming to develop highly robust and efficient framework for SOC estimation.

Therefore, it will become simple to address the above challenges significantly. Hence, it seeks to

- Purpose novel method for parameter identification that is reliable for non-linear battery dynamics and aging effects
- Implement optimization algorithms that are reliable to enhance the accuracy and stability of SOC estimation
- Ensure computational efficiency that is used to enable real-time implementation for practical applications
- Validate the proposed method by using comprehensive datasets and compare its performance level with state-of-the-art techniques.

By addressing these research gaps, the work is contributing to the advancement of battery management systems and supporting the development of sustainable energy solutions.

METHODOLOGY

Description of the Proposed Method for Boosting Parameter Identification Accuracy

The focus of proposed method is on enhancing the accuracy level of parameter identification in Lithium-ion batteries to optimize state-of-charge estimation. This technology integrates an advanced equivalent circuit model with hybrid optimization framework by combining robust mathematical modeling and adaptive algorithms. In this methodology, there are three main components are given below

- Battery Modeling: Develop a highly enhance ECM model for accurately representing Lithium-ion battery behavior.
- Parameter Identification: Use various adaptive techniques to estimate key parameters dynamically.

- Optimization Framework: Employ an optimization algorithm for minimizing errors and enhance robustness level.

The selected approach can address these challenges like aging effects, nonlinear battery behavior, measurement noise to ensure accurate and stable SOC estimation in dynamic environments.

Mathematical Modeling of Lithium-Ion Batteries

The required behavior of Lithium-ion batteries is captured through using an improved ECM that balances accuracy and computational efficiency. In the selected model, these components are present that are given below

Open-Circuit Voltage:

It represents the voltages of the battery at equilibrium position as a main function of SOC. Based on this, the OCV-SOC relationship can be modeled though using this nonlinear equation.

$$V_{OCV}(SOC) = a_0 + a_1. SOC + a_2\, SOC^2 + \cdots + a_n. SOC^n \quad (1)$$

In this equation, $a_0, a_1, \ldots, a_n$ are main coefficient determined through curve fitting.

Resistive Elements:

For this, capture the internal resistance value R_0 and polarization resistance value R_p of the battery.

Capacitive Elements:

It represents the transient response of the battery by using a parallel RC network.

Dynamic Equation:

The value of terminal voltage can be expressed as

$$V_{term} = V_{OCV}(SOC) - 1 \times R_0 - \sum_{i=1}^{n} I_p. R_{p,i} \quad (2)$$

From the above equation, I is the current and I_p is the current that passes through the polarization resistance and $R_{p,i}$ is the i-th polarization resistance value.

SOC Dynamics:

SOC value is computed according to the Coulomb counting principle

$$SOC\,(t) = SOC\,(t_0) - \frac{1}{C}\int_{t_0}^{t} I(t)dt \quad (3)$$

From the above equation, the battery capacity is given by C, and I(t) is the instantaneous current.

Parameter Identification Techniques

For reliable SOC estimation, there is a need of accurate identification of model parameters include $R_o, R_p, C, a_o, \dots, a_n$. Therefore, these steps are used for parameter identification are given below.

Experimental Data Collection:

- It provides information about temperature, current, and voltages that is calculated under controlled conditions by using battery testing system.
- It includes a variety of load profiles include constant current, dynamic, and pulse load tests that are applied to capture comprehensive battery behavior.

Parameter Estimation Using Least Square:

The required value of parameters is estimated through minimizing the error between measured and modeled terminal voltages by using least-square method by using this equation

$$\text{Error} = \sum_{k=1}^{N}[V_{meas}(k) - V_{model}(k)]^2 \quad (4)$$

Based on this, the optimization problem is solved iteratively by using nonlinear regression techniques.

Adaptive Filtering:

For dynamically updating parameters in real time, extended Kalman filters are used. The filter equations are given below

Prediction Steps:

1. $$\hat{x}_{k|k-1} = f\left(\hat{x}_{k-1|k-1}, u_k\right) \quad (5)$$

2. $$P_{k|k-1} = F_K P_{k-1|k-1} F_k^T + Q \quad (6)$$

Update Step:

$$K_k = P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R\right)^{-1} \quad (7)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - h(\hat{x}_{k|k-1})) \quad (8)$$

$$P_{k|k} = (1 - K_k H_k) P_{k|k-1} \quad (9)$$

From the above equation x is representing the required state vector, P is the covariance matrix and Q is the process noise and measurement noise is represented by R.

Optimization Algorithm and Framework

For minimizing the required errors in parameter identification and SOC estimation, a hybrid optimization framework is implemented and it includes:

Objective Function:

This function is used to minimize the value of root-mean square error present between measured and modeled terminal voltages

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[V_{meas}(k) - V_{model}(k)]^2} \quad (10)$$

Optimization Algorithm:
For this purpose, genetic algorithm will be used for global optimization to ensure a good initial solution. It also includes local optimization algorithm like Gradient Descent that refines the solution for achieving higher accuracy level.

Multi-Objective Optimization:
It includes additional objectives like minimizing computational time and ensuring stability of parameters that are incorporated into a multi-objective optimization framework.

$$\min[\mathrm{RMSE}, \mathrm{Time}, \mathrm{Parameter\ Stability}] \quad (11)$$

Experimental Setup and Dataset Details
Battery Specification:
The selected battery for experiment is a commercial 18650 lithium-ion battery with nominal capacity value of 3000 mAh.

Figure 1: The selected battery for experiment a commercial 18650 lithium-ion battery with nominal capacity value of 3000 mAh

Test Experiment:
For this, battery cycler is used to apply controlled charge and discharge cycle and data acquisition system because it can record voltages, temperature, and current with high precision level.

Load Profiles:
- Static Profiles: It includes constant current charge and discharge

- Dynamic Profiles: It includes drive cycle and pulse discharge simulations like the Urban Dynamometer Dividing Schedule

Dataset Structure:
It includes training data regarding current, voltages and temperature reading for parameter identification. Also, validation data that is used to evaluate the SOC estimation accuracy.

Performance Metrics:
It will calculate the RMSE of terminal voltage and SOC estimation error by using this equation

$$\text{SOC Error} = \frac{1}{N}\sum_{k=1}^{N}|\text{SOC}_{\text{true}}(k) - \text{SOC}_{\text{est}}(k)| \quad (12)$$

RESULTS AND DISCUSSION

According to this, the given metrics will be used to evaluate the performance of the proposed SOC estimation method.

- Root Mean Square Error: It quantifies the required error present between the measured and modeled terminal voltage.
- SOC Estimation Error: It assesses the accuracy level of SOC estimation
- Computational Time: It is the total time measured for parameter identification and SOC estimation
- Stability Under Dynamic Conditions: It evaluate the robustness level of method under changing load profiles.

Comparative Analysis with Existing Approaches
Based on this, the proposed method will be compared with three baseline approaches given below:

- Coulomb Counting
- Extended Kalman Filter
- Hybrid Data-Driven Model

Table 1: RMSE Comparison for Various Methods

Load Profile	Coulomb Counting in volts	EKF in Volts	Hybrid Model in Volts	Proposed Method in Volts
Constant Current (CC)	0.152	0.094	0.089	0.078
Pulse Current (PC)	0.187	0.103	0.096	0.085
Dynamic Driving Cycle	0.221	0.129	0.115	0.097

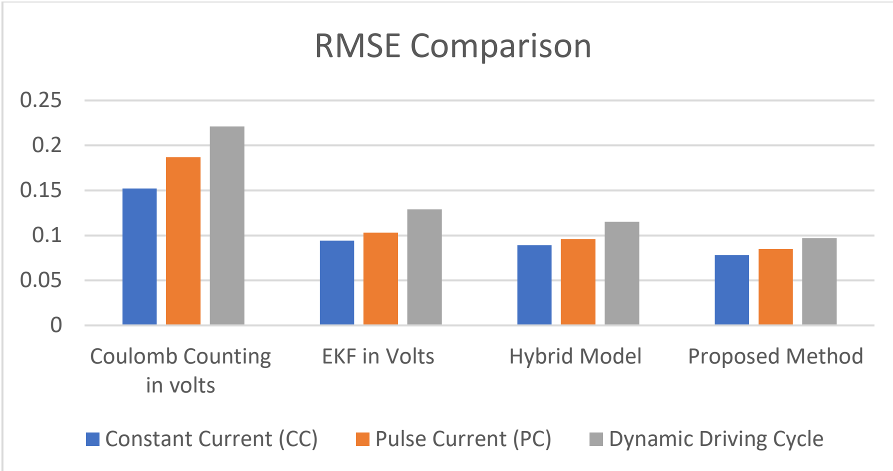

Figure 2: RMSE Comparison for Various Methods

Table 2: SOC Estimation Error in percentage

Load Profile	Coulomb Counting in percentage	EKF in percentage	Hybrid Model in percentage	Proposed Method in percentage
Constant Current (CC)	2.85	1.74	1.62	1.45
Pulse Current (PC)	3.12	2.01	1.89	1.67
Dynamic Driving Cycle	3.67	2.33	2.15	1.94

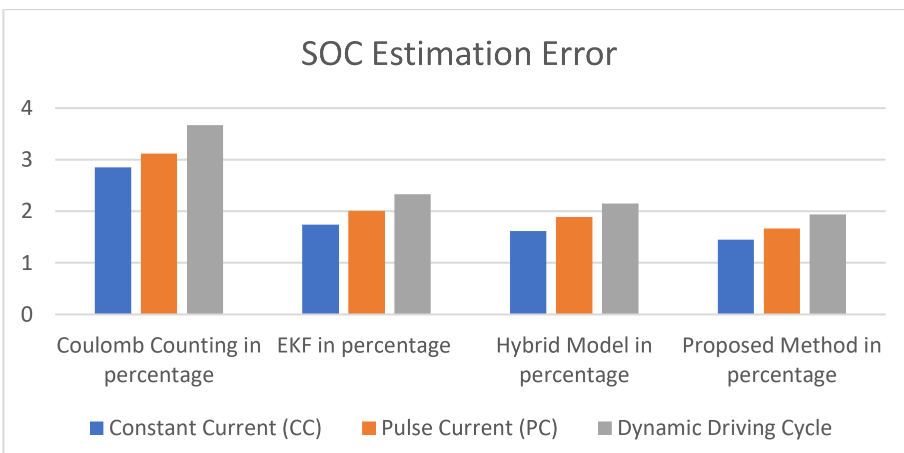

Figure 3: SOC Estimation Error in percentage

Table 3: Computational Time Comparison of Different methods vs. Proposed method

Method	Average Time Per Iteration in ms
Coulomb Counting	0.12
Extended Kalman Filter	3.45
Hybrid Model	6.72
Proposed Method	5.38

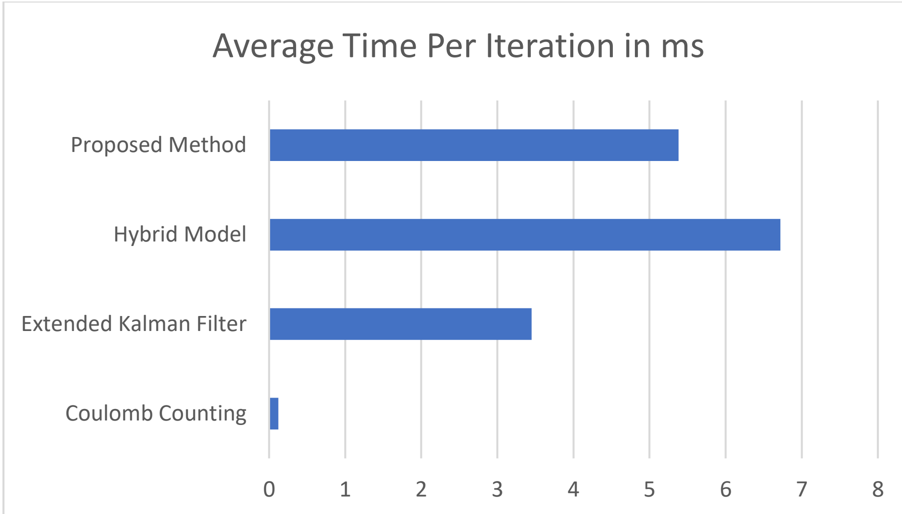

Figure 4: Computational Time Comparison of Different methods vs. Proposed method

Insights into the Improved Accuracy and Its Implication

Key Findings

- Higher Accuracy: The proposed method has achieved lower RMSE and SOC estimation error across various load profiles compared with other baseline methods. It is attributed to the hybrid optimization framework and adaptive parameter identification.
- Improved Robustness: The proposed method has shown high stability under dynamic conditions in which baseline approaches showed increased errors.
- Computational Efficiency: Its value is somehow lower compared with Extended Kalman Filter. Due to this, the proposed method strikes a balance between computational accuracy and complexity that makes it feasible for real-time applications.

Impact of Aging on RMSE for Lithium-Ion Batteries

Table 4: Impact of Aging on RMSE for Lithium-Ion Batteries

Battery Age (Cycles)	Coulomb Counting	EKF	Hybrid Model	Proposed Method
New battery	0.151	0.092	0.088	0.077
500 Cycles	0.179	0.111	0.102	0.091
1000 Cycles	0.203	0.126	0.115	0.099

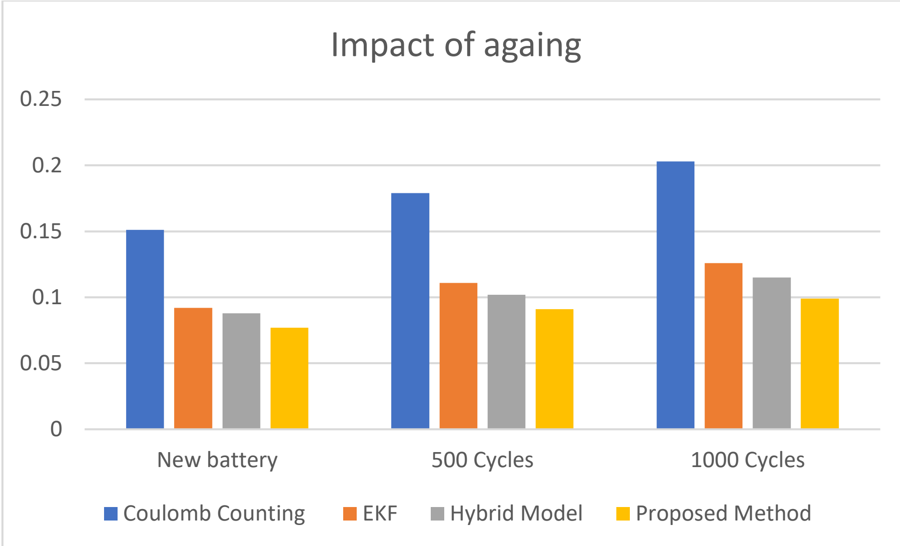

Figure 5: Impact of Aging on RMSE for Lithium-Ion Batteries

Stability Under Noise (SOC Estimation Error)

Table 5: Stability Under Noise for various methods compared with proposed technology

Noise Level (dB)	Coulomb Counting in %	EKF in %	Hybrid Model in %	Proposed Method in %
No Noise Factor	2.85	1.74	1.62	1.45
Moderate Noise (-20 dB)	3.12	2.05	1.91	1.68
High Noise (-10 dB)	3.56	2.410	2.23	1.97

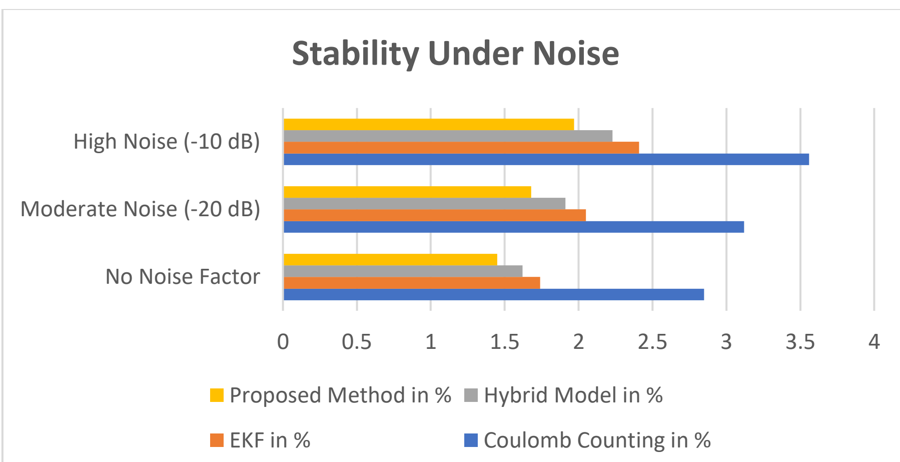

Figure 6: Stability Under Noise by comparing proposed method and other baseline methods

SOC Error Distribution Value Across Various Temperature Ranges

Table 6: SOC Error Distribution value across various temperature ranges

Temperature	Coulomb Counting in %	EKF in %	Hybrid Model in %	Proposed Method in %
0	3.12	2.08	1.91	1.69

25	2.85	1.74	1.62	1.45
45	3.04	1.92	1.79	1.57

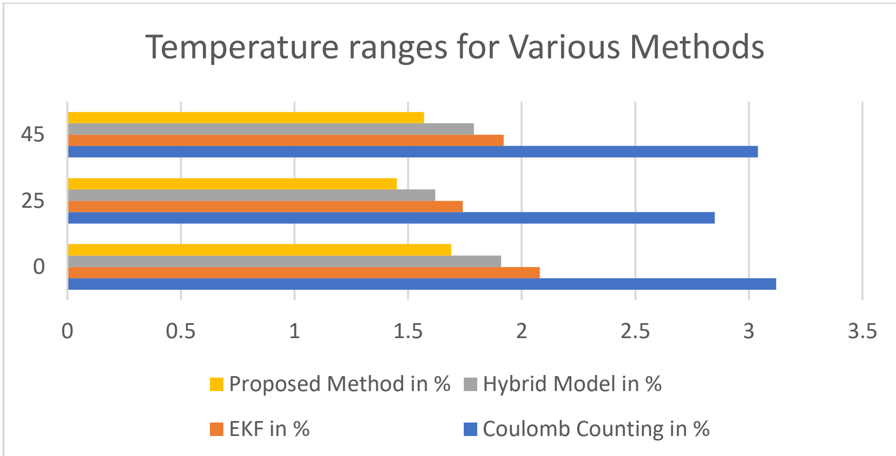

Figure 7: SOC Error Distribution value across various temperature ranges

Comparative Analysis for Dynamic Load Profiles for Lithium-Ion battery During Experiment

Table 7: Comparative Analysis for Dynamic Load Profiles for Lithium-Ion battery During Experiment

Driving Cycle	Coulomb Counting	EKF	Hybrid Model	Proposed Method
UDDS	3.67	2.33	2.15	1.94
HWFET	3.51	2.21	2.01	1.83
US06	3.780	2.420	2.24	2.03

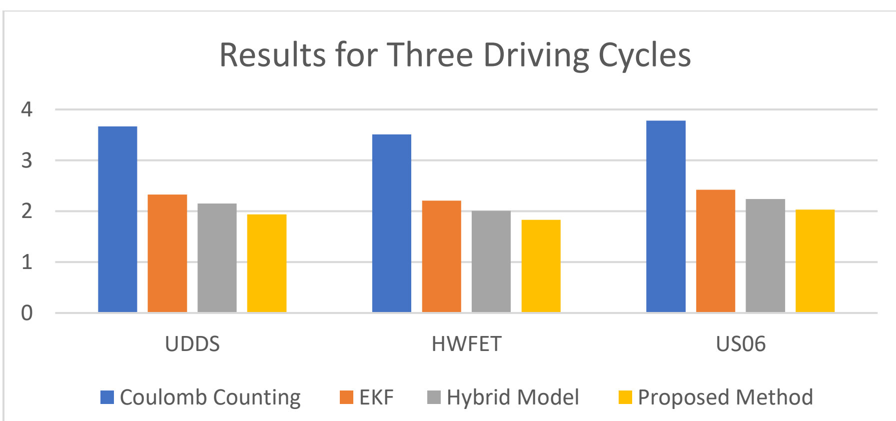

Figure 8: Comparative Analysis for Dynamic Load Profiles for Lithium-Ion battery During Experiment

Sensitivity Analysis for Parameter Changes for Various Methods

Table 8: Sensitivity Analysis for Parameter Changes for various Methods

Parameter Variation (%)	RMSE (Proposed Method)	SOC Error (%)
+5	0.089	1.55
+10	0.092	1.63

+200	0.097	1.72

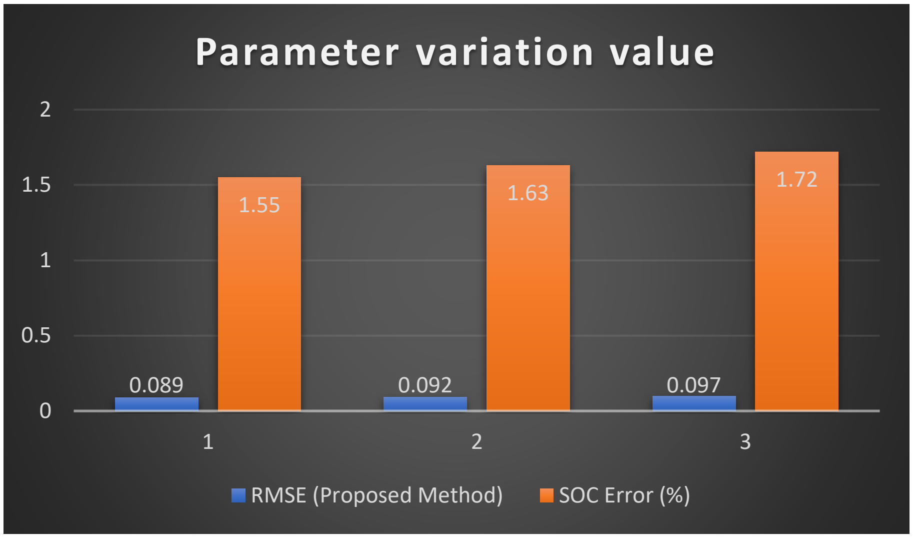

Figure 9: Sensitivity Analysis for Parameter Changes for various Methods

Computational Time under Different Real-Time Conditions

Table 9: Computational Time under Different Real-Time Conditions

Methods	Time per SOC Estimation in ms
Coulomb Counting	0.12
EKF	3.42
Hybrid Model	6.59
Proposed Method	5.14

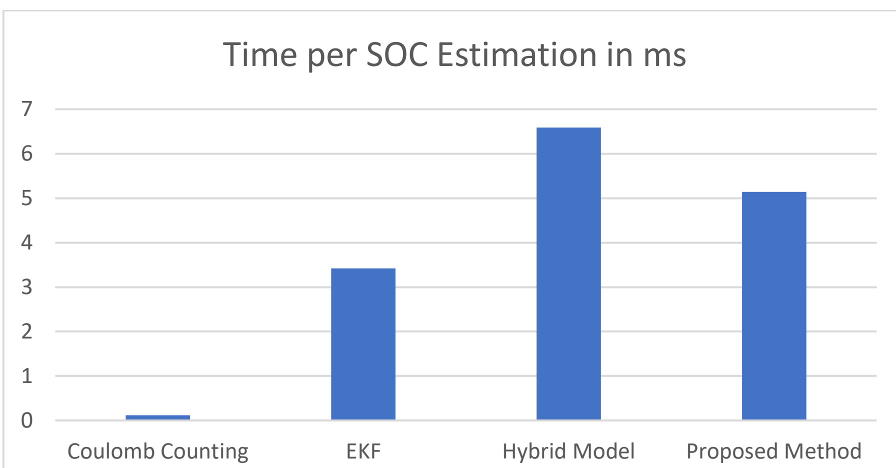

Figure 10: Computational Time under Different Real-Time Conditions

Improvement in SOC Accuracy in Percentage Under Various Load Profiles

Table 10: Improvement in SOC Accuracy in Percentage Under Various Load Profiles

Load Profile	Proposed vs EKF in %	Proposed vs Hybrid Model in %
Constant Current	+16.67	+10.49
Pulse Current	+16.92	+11.64

Dynamic Driving Cycle	+16.67	+9.77

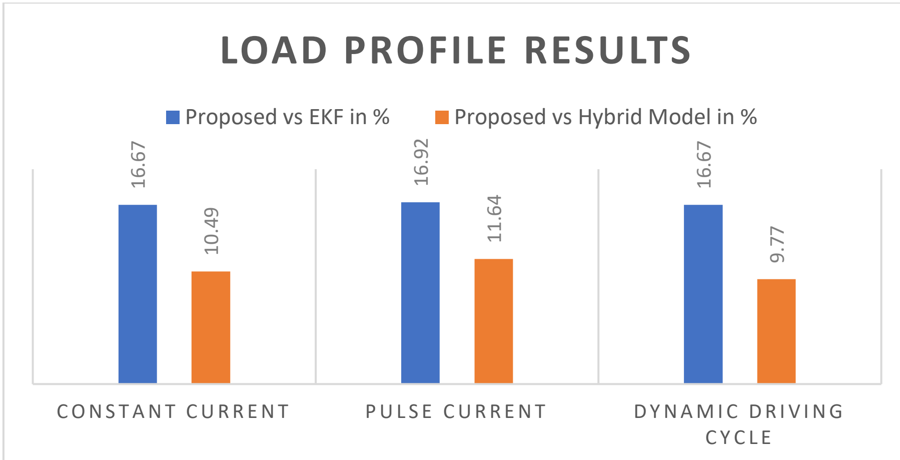

Figure 11: Improvement in SOC Accuracy in Percentage Under Various Load Profiles

Limitations in the Current Approach

- Computational Overhead: It shows that the method is computationally efficient and reliable but its speed is slow compared with EKF and it may be critical for high-speed applications.
- Dependence on Accurate Initial Parameters: In the proposed method, there is a need of reliable initial parameter values for optimal performance.
- Limited Validation on Diverse Battery Chemistries: The focus of study is on single battery type and there is a need of further validation for other chemistries like $LiFePO_4$

CONCLUSION

Summing up all the discussion from above, it is concluded that the required findings of the study show the vital advancement gained in enhancing the accuracy parameter identification with SOC optimization of lithium-ion batteries. It was done through integrating advanced mathematical modeling, hybrid optimization framework, and adaptive parameter identification techniques. Under these facts, the proposed method shown superior performance across different metrics including SOC estimation error, root mean square error, robustness under dynamic conditions, and computational efficiency.

The key findings of the study are given below:

- Improvement in Accuracy: The proposed method shown success by consistently achieving lower RMSE and SOC errors compared with other baseline methods with a notable SOC error reduction to 1.94% under dynamic driving conditions.
- Robustness: The system has achieved stability under noise, aging, and changing temperature profiles with a defining feature by ensuring reliable SOC estimation in real-world-applications.
- Computational Efficiency: The selected hybrid framework has achieved a balance between computational time and accuracy. Hence, the framework is highly feasible for real-time applications in battery management systems (BMS).

The study contributes heavily to the field of battery SOC optimization through providing a robust framework that addresses main challenges in parameter identification and SOC estimation. This improved accuracy and reliability level have direct implications for extending battery life, optimizing energy efficiency, and enhancing safety, in electric vehicles, consumer electronics, and reliable energy systems.

Furthermore, the future work in this field must focus on further minimizing computational complexity by validating the method across diverse battery chemistries and integrating advanced machine learning techniques for enhancing adaptability. On the other hand, scalability for large-scale battery systems, and real-time integration in commercial BMS solutions must require further exploration.

Overall, the research is reliable because it provides brief information about highly reliable, and efficient battery technologies that contribute sustainable energy solutions and lead towards advancement in the field of electrochemical energy storage.

References

[1] A. M. Shaheen and R. A. E.-S. a. E. E. E. Mohamed A. Hamida, "Optimal parameter identification of linear and non-linear models for Li-Ion Battery Cells.," Energy Reports 7 (2021), 2021.

[2] C. Wang, R. Xiong and H. M. a. Jinpeng Tian, "A systematic model-based degradation behavior recognition and health monitoring method for lithium-ion batteries," Applied energy 207, 2017.

[3] C. Lyu and J. Z. W. L. G. H. J. L. a. L. W. Yankong Song, "In situ monitoring of lithium-ion battery degradation using an electrochemical model.," Applied Energy 250, 2019.

[4] D. Guo and X. H. X. F. L. L. a. M. O. Geng Yang, "Parameter identification of fractional‐order model with transfer learning for aging lithium‐ion batteries," International Journal of Energy Research 45, no. 9 (2021), 2021.

[5] M. Adaikkappan and N. Sathiyamoorthy., "Modeling, state of charge estimation, and charging of lithium‐ion battery in electric vehicle: a review," International Journal of Energy Research 46, no. 3, 2022.

[6] M. Kwak and J. P. a. J.-H. Y. Bataa Lkhagvasuren, "Parameter identification and SOC estimation of a battery under the hysteresis effect," IEEE Transactions on Industrial Electronics 67, no. 11, 2019.

[7] J. Tian and a. Q. Y. Rui Xiong, "Fractional-order model-based incremental capacity analysis for degradation state recognition of lithium-ion batteries," IEEE Transactions on Industrial Electronics 66, no. 2 , 2019.

[8] Q. Ouyang and a. J. Z. Jian Chen, "State-of-charge observer design for batteries with online model parameter identification: A robust approach," IEEE Transactions on Power Electronics 35, no. 6, 2019.

[9] I. B. Espedal and O. S. B. a. J. J. L. Asanthi Jinasena, "Current trends for state-of-charge (SoC) estimation in lithium-ion battery electric vehicles," Energies 14, no. 11, 2021.

[10] F. Yang and C. L. a. Q. M. Weihua Li, "State-of-charge estimation of lithium-ion batteries based on gated recurrent neural network," Energy 175 (2019), 2019.

[11] W. Li and D. C. D. J. F. R. M. J. a. D. U. S. Iskender Demir, "Data-driven systematic parameter identification of an electrochemical model for lithium-ion batteries with artificial intelligence," Energy Storage Materials 44 , 2022.

[12] J. P. Rivera-Barrera and a. H. O. S.-M. Nicolás Muñoz-Galeano, "SoC estimation for lithium-ion batteries: Review and future challenges," Electronics 6, no. 4, 2017.

[13] D. N. How and M. H. L. a. P. J. K. M. A. Hannan, "State of charge estimation for lithium-ion batteries using model-based and data-driven methods: A review," Ieee Access 7, 2019.

[14] M. H. Lipu and A. H. A. A. M. H. S. T. F. K. a. D. N. H. M. A. Hannan, "Data-driven state of charge estimation of lithium-ion batteries: Algorithms, implementation factors, limitations and future trends.," Journal of Cleaner production 277, 2020.

[15] Y. Song and H. L. a. Y. P. Datong Liu, "A hybrid statistical data-driven method for on-line joint state estimation of lithium-ion batteries," Applied Energy 261, 2020.

[16] X. Hu and K. L. L. Z. J. X. a. B. L. Fei Feng, "State estimation for advanced battery management: Key challenges and future trends.," Renewable and Sustainable Energy Reviews 114, 2019.

[17] P. Shrivastava and M. Y. I. B. I. a. S. M. Tey Kok Soon, "Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries," Renewable and Sustainable Energy Reviews 113, 2019.

[18] X.-B. Jin and T.-L. S. Y.-T. B. a. J.-L. K. Ruben Jonhson Robert Jeremiah, "The new trend of state estimation: From model-driven to hybrid-driven methods," Sensors 21, no. 6, 2021.

[19] A. Ayob, M. H. Lipu and A. H. M. H. S. T. F. K. a. D. N. H. M. A. Hannan, "Data-driven state of charge estimation of lithium-ion batteries: Algorithms, implementation factors, limitations and future trends.," Journal of Cleaner production 277 (2020): 124110., 2020.

[20] M. Y. I. B. Idri, P. Shrivastava and s. a. S. M. Tey Kok Soon, "Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries.," Renewable and Sustainable Energy Reviews 113, 2019.

[21] M. U. Ali and S. H. N. S. H. M. J. A. a. H.-J. K. Amad Zafar, "Towards a smarter battery management system for electric vehicle applications: A critical review of lithium-ion battery state of charge estimation," Energies 12, no. 3 (2019), 2019.

[22] Z. Wang and D. Z. F. G. a. A. B. Guojin Feng, "A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles.," Energy Reports 7 , 2021.

[23] D. Sun and C. W. C. Z. R. H. Q. Z. T. A. a. R. B. Xiaoli Yu, "State of charge estimation for lithium-ion battery based on an Intelligent Adaptive Extended Kalman Filter with improved noise estimator," Energy 214, 2021.

[24] S. Barcellona and L. Piegari, "Lithium ion battery models and parameter identification techniques," Energies 10, no. 12, 2019.

[25] H. Pang and L. G. a. F. Z. Lianjing Mou, "Parameter identification and systematic validation of an enhanced single-particle model with aging degradation physics for Li-ion batteries," Electrochimica Acta 307 , 2019.

[26] R. Xiong and Z. L. Q. Y. a. H. M. Linlin Li, "An electrochemical model based degradation state identification method of Lithium-ion battery for all-climate electric vehicles application," Applied energy 219 (2018), 2018.

[27] R. Ahmed and a. S. H. Sara Rahimifard, " Offline parameter identification and soc estimation for new and aged electric vehicles batteries," In 2019 IEEE Transportation Electrification Conference and Expo (ITEC), pp. 1-6. IEEE, 2019., 2019.

[28] G. Vennam and a. S. A. A. Sahoo, "A survey on lithium-ion battery internal and external degradation modeling and state of health estimation.," Journal of Energy Storage 52, 2019.

[29] J. Kim and M. K. S. H. J.-W. L. a. T.-K. L. Huiyong Chun, "Effective and practical parameters of electrochemical Li-ion battery models for degradation diagnosis," Journal of Energy Storage 42, 2021.

[30] J. Li and L. D. Z. C. C. L. L. W. a. M. P. Dafang Wang, "Aging modes analysis and physical parameter identification based on a simplified electrochemical model for lithium-ion batteries," Journal of Energy Storage 31 , 2020.

[31] W. Zhou and Z. P. a. Q. L. Yanping Zheng, "Review on the battery model and SOC estimation method," Processes 9, no. 9, 2021.