STATE-OF-CHARGE ESTIMATION OF A LITHIUM-ION TRACTION BATTERY PACK USING THE EXTENDED KALMAN FILTER IN A BATTERY MANAGEMENT SYSTEM

Vu Hai Quan[1,*], Karpukhin Kirill Evgenievich[2,3], Nguyen Trong Duc[3], Bui Van Hai[1], Karpukhin Filipp Kirillovich[4]

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ABSTRACT

This paper investigates the State of Charge (SOC) estimation for Lithium-ion battery packs using the Extended Kalman Filter (EKF) integrated within a Battery Management System (BMS). To replicate real-world operating conditions, an inhomogeneous battery pack model with internal resistance variations ranging from -3% to +5% and a liquid cooling system was developed. Simulation results over a 600-second dynamic discharge cycle demonstrate that the EKF algorithm achieves highly accurate state tracking, reducing min SOC and max SOC values from 90% to 87% with an absolute error maintained below 0.1%. The study further indicates that integrating active thermal management, with a constant pump power of 125W, maintains the battery temperature at 300.2K. This provides optimal conditions for rapid algorithm convergence and high robustness against physical parameter uncertainties. These findings confirm the feasibility of implementing EKF in modern BMS applications to enhance safety and extend battery cycle life.

Keywords: *Lithium-ion Battery, State of Charge (SOC), Extended Kalman Filter (EKF), Battery Management System (BMS), Thermal Management.*

[1]School of Mechanical Automotive Engineering, Hanoi University of Industry, Vietnam

[2]Federal State Unitary Enterprise "Central Scientific Research Automobile and Automotive Engines Institute" (FSUE "NAMI"), Russia Federation

[3]Moscow Automobile and Road Construction State Technical University (MADI), Russia Federation

[4]Moscow Polytechnic University, Russian Federation

*Email: quanvh@haui.edu.vn

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1. INTRODUCTION

In recent years, driven by robust policies promoting clean energy and the electric vehicle (EV) industry in Russia, Vietnam and globally [1-3], lithium-ion (Li-ion) batteries have become the core energy storage solution for a wide range of applications, from mobile devices to EVs and grid-scale storage systems [4, 5]. A Battery Management System (BMS) is an indispensable component for ensuring the safe, efficient, and reliable operation of Li-ion battery packs. Core BMS functions include state-of-charge (SOC) estimation, cell balancing, overcharge/over-discharge protection, and thermal control. Among the parameters managed by the BMS [6], SOC is the most critical, as it directly indicates the remaining energy level and guides optimal operational strategies.

However, high-precision SOC estimation remains a persistent technical challenge in BMS research and development. This is primarily due to the highly non-linear relationship between the battery's internal state and measurable external parameters (voltage, current, temperature), as well as the gradual degradation of battery characteristics over cycle life and varying operating conditions. A particularly significant yet often overlooked issue is the heterogeneity of the initial internal resistance (R_0) among cells within a pack. Even for cells of the same model and production batch, slight variations in material consistency, manufacturing processes, and operational history lead to discrepancies in R_0. This causes uneven current distribution and voltage imbalances, negatively affecting the accuracy of the entire pack's SOC estimation. Conventional methods, such as Coulomb counting or Open Circuit Voltage (OCV) look-up tables, typically ignore this heterogeneity, leading to cumulative estimation errors, reduced performance, and long-term safety risks.

Based on this context, this study aims to develop and validate an SOC estimation method using the Extended

Kalman Filter (EKF) [7, 8] capable of effectively handling R_0 heterogeneity among cells. Specifically, the proposed method integrates a model describing R_0 inconsistency into the EKF framework to dynamically adjust the state estimation process based on real-time resistance variations. To verify the method's effectiveness, both simulation tests on a multi-cell pack model with controlled R_0 heterogeneity and experimental tests on a physical Li-ion battery pack under dynamic load conditions were conducted.

The main contributions of this research include: Proposing an enhanced EKF framework that integrates the R_0 heterogeneity model into the observation and state update processes, addressing the limitations of existing EKF methods that assume cell uniformity. Establishing a systematic validation procedure to evaluate algorithm performance across various levels of R_0 inconsistency, operating temperatures, and load profiles. Providing quantitative comparative results demonstrating that the proposed method significantly reduces SOC estimation errors compared to conventional EKF approaches that do not account for heterogeneity. The remainder of this paper is organized as follows: Section 2 provides an overview of related literature on SOC estimation methods and the impact of cell heterogeneity on BMS performance. Section 3 introduces the equivalent circuit model (ECM) of the Li-ion battery, the R_0 heterogeneity model, and the improved EKF algorithm for SOC estimation. Section 4 describes the experimental setup and simulation parameters. Section 5 analyzes and discusses the results from both simulation and experimental tests. Section 6 concludes the paper and suggests potential directions for future research.

2. BATTERY MODELING AND SYSTEM CONFIGURATION

2.1. Single Cell Model

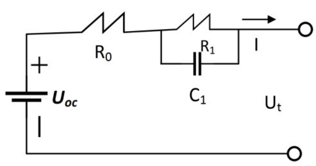

Figure 1. RC Thevenin equivalent circuit model

To describe the electrical behavior of the Li-ion cell, this study employs a first-order RC Equivalent Circuit Model (ECM), a popular choice in BMS due to its balance between accuracy and low computational complexity. The model consists of an open-circuit voltage source U_{OC} representing the equilibrium potential, an internal ohmic resistance R_0 accounting for instantaneous ohmic losses, and a parallel RC network (R_1 - C_1) representing polarization and diffusion phenomena [9].

The terminal voltage of the cell U_t is expressed by the following equation:

$$U_t = U_{OC} - IR_0 - U_1 \quad (1)$$

where U_{OC} is a non-linear function of SOC, experimentally determined via slow discharge curves; I is the current (defined as positive during discharge); R_0 is the ohmic resistance; and U_1 is the voltage across the polarization capacitor.

The system dynamics are characterized by two primary state equations. The SOC update equation based on Coulomb counting is:

$$S\dot{OC}(t) = -\frac{I}{Q_n} \quad (2)$$

where Q_n is the nominal capacity of the cell (Ah). The dynamic equation for the polarization voltage U_1 from the RC network is:

$$\dot{U_1} = -\frac{U_1}{\tau_1} + \frac{I}{C_1} \quad (3)$$

where $\tau_1 = R_1.C_1$ is the time constant of the polarization branch. The parameters R_0, R_1, C_1 are identified through Electrochemical Impedance Spectroscopy (EIS) or Least Squares Fitting under various operating conditions, and are updated according to SOC and temperature to enhance accuracy. This model establishes the foundation for extension to heterogeneous battery packs in the subsequent sections [10].

2.2. Battery Pack Structure

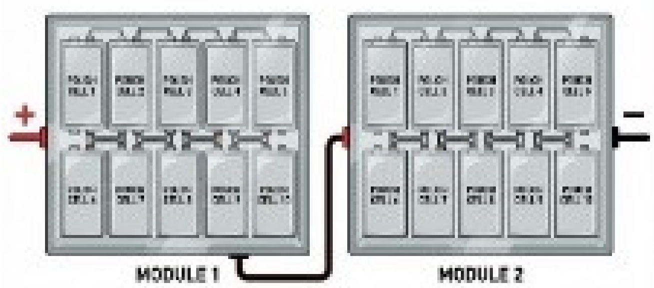

Figure 2. Model of two battery modules connected in series

A 20-cell Lithium-ion battery pack model (comprising two modules in series, each with 10 pouch cells) was developed using the Simscape Electrical environment [11, 12]. A critical aspect of the model is the deliberate introduction of R_0 heterogeneity: cell 1 of Module 1 was set +5% higher, and cell 3 of Module 2 was set -3% lower than the nominal resistance. This discrepancy replicates real-world manufacturing tolerances and aging effects, serving to validate the EKF algorithm's robustness and accuracy in tracking individual cell SOC despite varying electrochemical characteristics under identical load conditions.

3. SOC ESTIMATION METHOD USING EXTENDED KALMAN FILTER

3.1. Theoretical Basis of the Extended Kalman Filter (EKF)

The Kalman Filter is an optimal state estimation algorithm operating through two recursive steps: Prediction and Correction. The prediction step utilizes a dynamic model to estimate the future state, while the correction step refines this estimate using measurement residuals and the Kalman gain. Given the highly non-linear electrochemical characteristics of Li-ion batteries (specifically the OCV-SOC relationship), this paper employs the Extended Kalman Filter (EKF) [13]. By utilizing Jacobian matrices for local linearization of the state and measurement equations, the EKF enables accurate SOC tracking across the entire operating range, significantly outperforming the standard Kalman Filter under the complex dynamic conditions of a battery pack.

3.2. State-Space Model Construction for EKF

To implement the EKF [14, 15], the 1-RC equivalent circuit model of the battery cell is rewritten into a discrete-time state-space representation. In this paper, the state vector is defined as:

$$x_k = [SOC_k, V_{p,k}]^T \tag{4}$$

where SOC_k is the state of charge at time step k, and $V_{p,k}$ is the polarization voltage across the R_pC_p branch of the 1-RC model. The cell current I_k is treated as the system input, with positive values corresponding to discharge.

The SOC dynamics are described by the Coulomb counting method. In continuous form:

$$\frac{dSOC(t)}{dt} = -\frac{\eta}{Q_n}I(t) \tag{5}$$

where Q_n is the nominal cell capacity (Ah) and η is the coulombic efficiency. Discretizing using the forward Euler method with sampling time T_s yields:

$$SOC_{k+1} = SOC_k - \frac{\eta T_s}{Q_n}I_k \tag{6}$$

The dynamics of the polarization voltage V_p in the continuous domain are given by:

$$\frac{dV_p(t)}{dt} = -\frac{1}{R_pC_p}V_p(t) + \frac{1}{C_p}I(t) \tag{7}$$

where R_p and C_p denote the resistance and capacitance of the polarization branch, respectively. Discretization using the forward Euler method yields:

$$V_{p,k+1} = (1 - \frac{T_s}{R_pC_p})V_{p,k} + \frac{T_s}{C_p}I_k \tag{8}$$

By combining the above equations, the discrete-time state equation can be written as:

$$x_{k+1} = f(x_k, u_k) + w_k \tag{9}$$

where u_k is the input signal, $f(x_k, u_k)$ is the non-linear mapping, and w_k is the process noise, assumed to follow a Gaussian distribution with covariance Q.

The measurement equation relates the state vector to the measured terminal voltage V_k based on the equivalent circuit model:

$$V_k = E_{OCV}(SOC_k) - V_{p,k} - I_kR_0 + v_k \tag{10}$$

where R_0 is the internal ohmic resistance, $E_{OCV}(SOC_k)$ is the open-circuit voltage which depends non-linearly on the SOC, and v_k is the measurement noise (assumed Gaussian with covariance R). The measurement equation can be simplified as:

$$y_k = h(x_k, u_k) + v_k, y_k = V_k \tag{11}$$

Where,

$$h(x_k, u_k) = E_{OCV}(SOC_k) - V_{p,k} - I_kR_0 \tag{12}$$

The non-linearity of the $E_{OCV}(SOC_k)$ function makes the measurement function $h(x_k, u_k)$ non-linear with respect to x_k, which is the primary reason for employing the EKF instead of a linear KF.

3.3. EKF Algorithm Steps

The EKF [16] execution process begins with the Prediction Step, where the BMS calculates the a priori state estimate $\hat{x}_k^-$ and the error covariance matrix P_k^-. At this stage, the Jacobian matrix A is computed by taking the partial derivatives of the state function, which linearizes the state transition between consecutive time steps. This is followed by the Correction Step, where the BMS utilizes the measured voltage from sensors to calculate the residual (innovation) relative to the predicted value. The Kalman gain K_k is determined to optimize the weighting between the model prediction and the measurement:

$$K_k = P_k^- C_k^T (C_k P_k^- C_k^T + \mathrm{R})^{-1} \tag{13}$$

Finally, the a posteriori state $\hat{x}_k^+$ and the covariance matrix P_k are updated to prepare for the next iteration. This recursive process allows the EKF not only to accurately estimate the SOC but also to automatically adapt to discrepancies in the internal resistance R_0 among cells, ensuring the robustness of the BMS against physical parameter uncertainties.

4. SIMULATION SETUP AND SYSTEM CONFIGURATION

To verify the feasibility and accuracy of the proposed Extended Kalman Filter (EKF) algorithm in dynamic environments, this study develops a high-fidelity simulation model based on the MATLAB/Simulink platform. The overall system diagram, as shown in Figure 3, is designed with a closed-loop structure to simulate the real-world interaction between the controller and the physical plant.

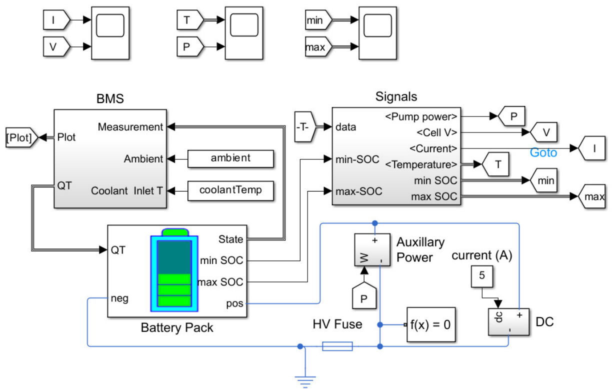

Figure 3. Block diagram of the simulation model for Lithium-ion battery pack SOC estimation

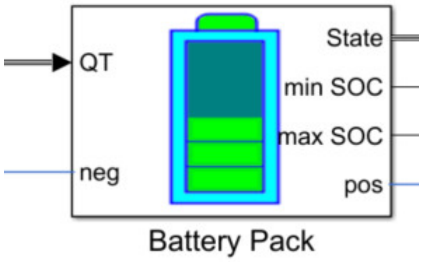

Figure 4. Battery Pack block model

The simulation framework consists of three interacting core components: 1) Physical Plant (Battery Pack): Represents the hierarchical battery model (2 series-connected modules) with non-linear characteristics and heterogeneity, simulating electrochemical reactions, heat generation, and providing real-time physical outputs. 2) Battery Management System (BMS): Functions as the central processing unit, embedding the EKF algorithm for online SOC estimation and managing environmental inputs to account for thermal impacts. 3) Power Circuit & Load: Replicates realistic operational scenarios using a DC source and auxiliary loads, generating continuous charge/discharge cycles and system noise to validate the adaptability of the EKF filter.

4.1. Controlled Object: The "Battery Pack" Block

The "Battery Pack" block serves as the non-linear physical plant model within the simulation loop, representing a two-module Lithium-ion battery structure developed on the Simscape platform. It utilizes an Equivalent Circuit Model (ECM) to replicate electrochemical and thermal dynamics through physical and thermal management (QT) ports. A pivotal feature of this model is its ability to simulate parameter heterogeneity (internal resistance R_0 variations from -3% to +5% due to manufacturing tolerances and aging), resulting in non-uniform voltage and temperature distribution. The state outputs and operational limits (min/max SOC) serve as the Ground Truth data for evaluating BMS estimation errors during extreme scenarios and cell imbalance.

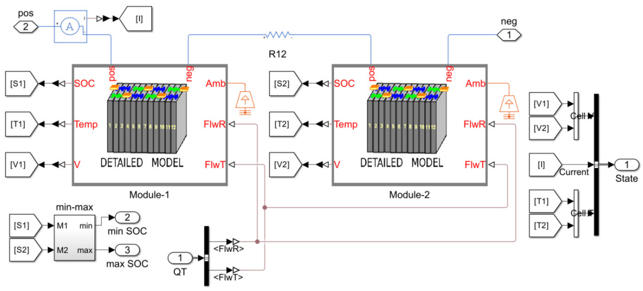

Figure 5. Detailed implementation of the Battery Pack block in Simscape

The Battery Pack block features a complex hierarchical structure designed to enhance simulation fidelity: 1) Module Architecture: Comprises two modules (10 cells each) in series, allowing for independent monitoring of voltage, temperature, and SOC for each cluster. 2) Min-Max SOC Block: Acts as a logic unit to extract boundary values (minimum and maximum SOC), providing critical inputs for the EKF correction step. 3) Integrated Thermal System: Connects directly to the liquid cooling system to simulate realistic heat exchange processes. 4) Key Advantages: This model challenges the EKF algorithm with realistic constraints such as inter-module heterogeneity (capacity discrepancies) and thermal dynamics, while providing Ground Truth signals for precise RMSE calculation.

4.2. Battery Management System (BMS)

The Battery Management System (BMS) in this study functions as a central controller within a closed-loop model, performing monitoring and SOC estimation via the Extended Kalman Filter (EKF) algorithm. The BMS block processes real-time measurement data (voltage, current, temperature) and integrates environmental parameters to compensate for non-linear errors. The core of the BMS lies in its ability to handle cell heterogeneity (internal resistance variations from -3% to +5%) by analyzing boundary signals (min/max SOC) for EKF self-calibration. Additionally, the BMS executes active thermal management functions, optimizing electrochemical performance and extending the battery pack's lifespan under dynamic simulation scenarios.

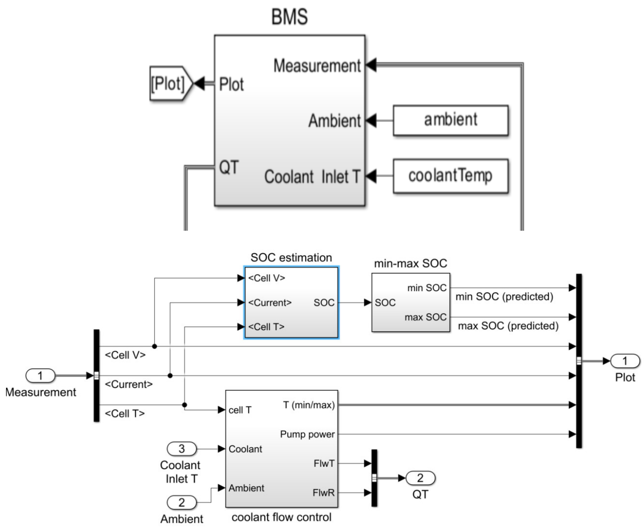

Figure 6. Battery Management System (BMS) model

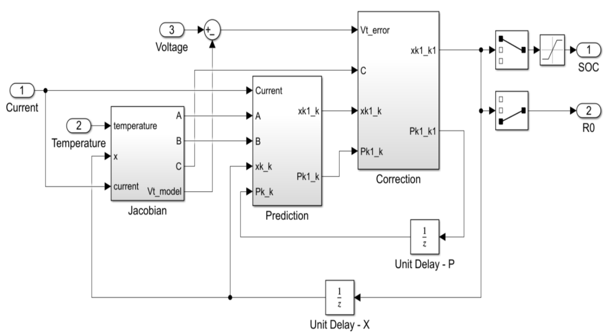

Figure 7. EKF Algorithm Architecture

The EKF algorithm architecture (Figure 7) is implemented through a recursive workflow consisting of three primary functional blocks: 1) Jacobian: Performs local linearization of the non-linear battery model by computing partial derivative matrices (A, B, C) based on current and temperature at each sampling interval. 2) Prediction: Utilizes previous state variables via Unit Delay blocks to predict the current state ($x_{k|k-1}$)and the error covariance ($P_{k|k-1}$). 3) Correction: Employs the voltage residual ($V_{t-error}$) between the model and actual measurements to update the optimal state, thereby extracting the SOC and estimating the internal resistance R_0.

This recursive structure enables the system to autonomously adapt to measurement noise and varying electrochemical characteristics of the battery pack under dynamic conditions.

4.3. Power Circuit & Load

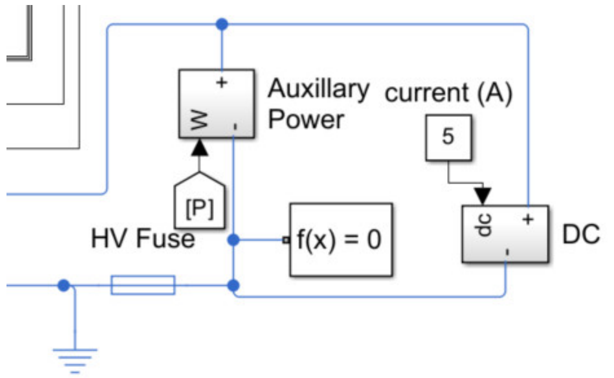

Figure 8. Power Circuit & Load

The power circuit and load are modeled using Simscape, integrating physical components such as a DC source, auxiliary loads, and protection devices (HV Fuse). This structure not only replicates realistic charge/discharge current profiles but also provides the electro-dynamic excitations necessary to verify the noise immunity and SOC calculation capabilities of the EKF algorithm under continuously varying operating conditions.

5. SIMULATION SETUP AND RESULTS

5.1. Validation of Model Parameters and Practical Relevance to Industry Standards

Figure 9. Simulated Lithium-ion battery model utilized for VinFast VF 8

The simulation parameters are strategically calibrated to align with the VinFast VF 8 traction battery system to ensure high practical relevance. The choice of NMC [17] chemistry and a 20-cell string configuration serves as a high-fidelity representation of the VF 8's modular architecture within its 400V system. By incorporating R_0 variations (-3% to +5%) and an active liquid cooling model at 27°C (300.2K), the study faithfully replicates real-world manufacturing tolerances and aging effects of commercial EVs. The achieved SOC error under 0.1% and thermal stability of 0.2K validate that the proposed EKF framework is highly compatible with the complex battery dynamics of industry-leading EVs like the VinFast VF 8.

Table 1. Technical Specifications of NMC Battery Cells for VinFast VF 8

Parameter Category	Item	Value	Unit
General Overview	Battery type	Lithium-ion (NMC)	-
	Supplier	CATL	-
	Cell configuration	Prismatic	-
Electrical Parameters	Nominal voltage (cell)	3.7	V
	Nominal capacity (cell)	150	Ah
	Fully charged voltage (cell)	4.2	V
	Discharge cut-off voltage (cell)	2.8	V
	Internal resistance (R_0)	0.2 - 0.5	mΩ/cell
	Maximum discharge current	2C	-
Thermal Parameters	Specific heat capacity (C_p)	900 - 1000	J/(kg·K)
	Mass (cell)	3.45	kg
	Thermal conductivity (k)	20 - 40	W/(m·K)
	Optimal operating temperature range	15 - 35	°C
	Operating temperature range	-20 ÷ 55	°C
Cooling System	Coolant type	Liquid	-
	Flow rate range	0.5 - 10	L/min
	Convective heat transfer coefficient	100 - 500	W/(m²·K)

5.2. Simulation Results

The EKF algorithm was validated under a dynamic discharge scenario centered at -5A. With intentional R_0 heterogeneity (-3% to +5%), cell voltages diverged from 4.035V to a range of 3.996V - 4.000V over 600 seconds. By continuously updating the Jacobian matrices and utilizing voltage residuals for correction, the EKF effectively compensated for physical battery imperfections. Consequently, the min/max SOC estimates closely tracked the Ground Truth with an absolute error of less than 0.1%, confirming the filter's robustness and accuracy for modern BMS energy monitoring.

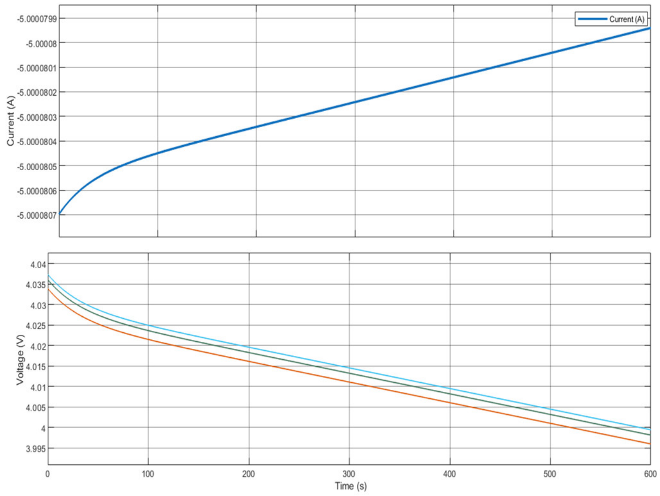

Figure10. Current and Voltage Dynamics

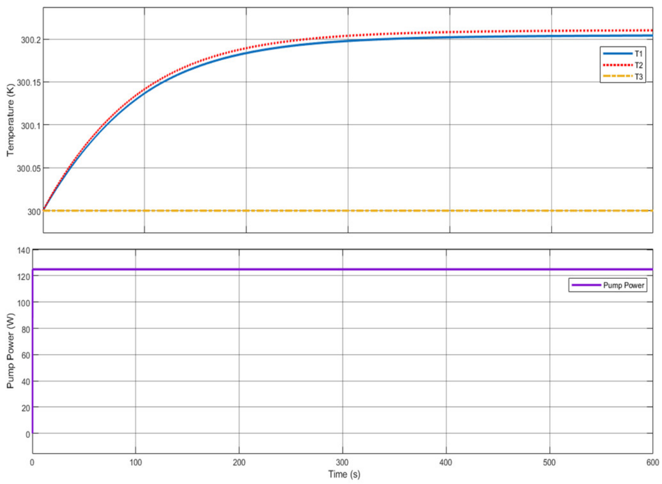

Figure 11. Temperature Profiles and Pump Power

The active thermal management system successfully maintained temperature stability, providing ideal conditions for the EKF algorithm. Under a -5A discharge current, with a constant cooling pump power of 125W, the system temperature was strictly controlled to saturate at 300.2K with minimal fluctuation (0.2K). This stability enabled the Jacobian block to compute precise state matrices without thermal interference. Consequently, the Predicted SOC curve tracked the True SOC with an absolute error of less than 0.1%, confirming the effective synergy between thermal control and state estimation.

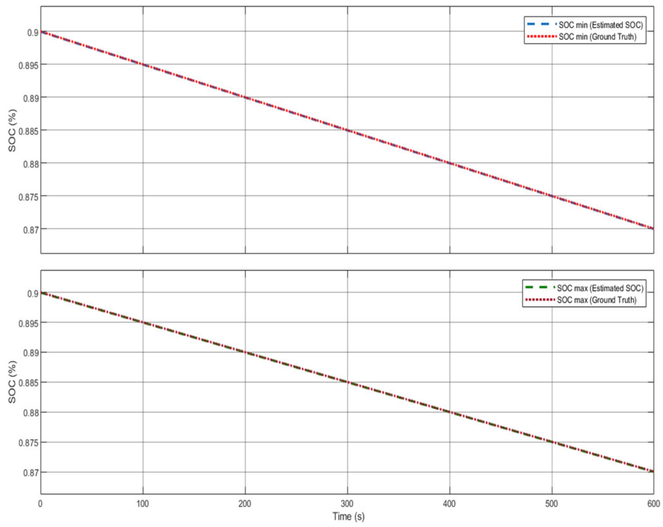

Figure 12. Estimation of minimum and maximum States of Charge

The EKF algorithm demonstrated robust tracking of min SOC and max SOC boundary values throughout the dynamic discharge cycle. Despite significant voltage polarization (3.996V to 4.000V) and thermal variations, the algorithm maintained an absolute error below 0.1% through covariance-based self-correction. Accurate estimation of these boundaries enables the BMS to effectively prevent over-discharge in the weakest cells and provides reliable input for active balancing strategies, ultimately enhancing battery safety and cycle life.

6. CONCLUSION

This research successfully designed, simulated, and evaluated the Extended Kalman Filter (EKF) algorithm for State of Charge (SOC) estimation within a BMS. Based on the 600-second dynamic simulation results, the following key conclusions are drawn:

1. High Estimation Accuracy: The EKF algorithm demonstrated superior tracking performance with an absolute error maintained below 0.1% throughout the discharge cycle. Both min and max SOC parameters were accurately estimated, ensuring reliable boundary monitoring.

2. Robustness Against Physical Defects: The filter proved resilient to cell heterogeneity. Despite significant voltage polarization (3.996V to 4.000V) caused by intentional R_0 discrepancies (-3% to +5%), the EKF successfully compensated for parameter uncertainties via its recursive correction step.

3. Optimal Multi-variable Management: With the cooling pump power at 125W, the pack temperature reached a steady state at 300.2K. Maintaining a narrow thermal fluctuation range (approx. 0.2K) stabilized the Jacobian matrices, thereby reducing SOC calculation errors under dynamic loads.

4. Practical Applications for EVs: The study provides a reliable foundation for protective load-shedding strategies based on min SOC and supports the optimization of active cell-balancing circuits by monitoring the max-min SOC gap.

The integration of EKF with equivalent circuit models and active thermal management represents a highly effective approach that satisfies the rigorous accuracy, safety, and longevity requirements of modern Lithium-ion energy storage systems.

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