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Efficient SOC estimation for electric vehicles: Extended Kalman filter approach for lithium-ion battery systems

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ABSTRACT

This study investigates the estimation of the state of charge (SOC) in lithium-ion batteries by utilizing the extended Kalman filter (EKF) algorithm. A simulation model was developed in MATLAB, integrating the Thevenin model with the EKF algorithm to assess SOC levels. The results from the simulations confirm the accuracy and reliability of the proposed approach in estimating SOC. Moreover, a Simulink-based model of the Thevenin equivalent circuit and the EKF algorithm was implemented to further verify the effectiveness of the EKF in SOC estimation. This research underscores the potential of the EKF algorithm to deliver precise SOC estimates, which is crucial for optimizing battery management systems, particularly in electric vehicles.

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1. INTRODUCTION

The global shift towards sustainable energy solutions has positioned electric vehicles (EVs) at the forefront of efforts to reduce greenhouse gas emissions and dependence on fossil fuels [1]. The United States, Japan, and China have emerged as the primary markets driving the adoption of EVs, with sales showing a consistent upward trend since the early 2000s [2]. Despite these gains, the widespread adoption of EVs is still constrained by significant challenges, including high manufacturing costs, limited driving range, and concerns regarding battery longevity and reliability [3]. Central to these challenges is the performance of lithium-ion batteries [4], which play a critical role in determining the efficiency, range, power output, and overall cost-effectiveness of EVs [5]. Lithium-ion batteries are widely favored for energy storage in EVs because of their exceptional energy density, excellent power performance, and minimal self-discharge rates [6]. The evolution of these batteries, particularly through the use of organic electrolytes, has led to significant improvements in energy density, enabling longer driving ranges and contributing to the increasing popularity of plug-in hybrid electric vehicles (PHEVs) and fully electric vehicles [7]. Organic electrolytes allow for stable operation at higher voltages, which has been instrumental in the advancement of lithium-ion technology [8]. However, despite these advances, the inherent limitations of lithium-ion batteries, such as degradation over time and sensitivity to operating conditions, continue to pose challenges to their widespread adoption [9].

An essential component of battery management in electric vehicles is accurately estimating the state of charge (SOC), which provides real-time information on the remaining energy capacity of the battery [10]. Accurate SOC estimation is vital for maximizing battery efficiency, prolonging its lifespan, and ensuring the safe and effective operation of EVs. Several techniques have been developed to estimate SOC, each with distinct strengths and weaknesses [6], [11]. Coulomb counting is among the simple methods used to determine the battery's state of charge (SOC); this approach relies on the integration of input and output currents of the battery over time. Despite its simplicity, this method is prone to cumulative errors, particularly as the battery ages or its capacity changes [12]. Another widely used technique is the open-circuit voltage (OCV) method, which estimates SOC by measuring the battery's terminal voltage [13], [14]. The nonlinearity between voltage and SOC, temperature fluctuations, and hysteresis effects can impact the accuracy of this method, though it remains cost-effective and easy to use [15]. These challenges highlight the necessity for more advanced approaches to address the complex and nonlinear nature of SOC estimation in lithium-ion batterie [16].

The extended Kalman filter (EKF) is the most applicable method in the field of EVs for estimating battery state of charge, due to its strong capability to handle the nonlinearities characteristic of such battery systems [12], and also for estimating battery parameters and states [17]. It is a nonlinear extension of the linear Kalman filter and operates by linearizing nonlinear functions through the use of partial derivatives and a first-order Taylor series expansion [18]. The EKF was used both for the identification of battery model parameters and for state estimation [19]. The estimation process involves calculation of the Jacobian matrix, which can influence the accuracy of the estimated SOC value [20]. However, the EKF is not without its limitations. Its reliance on first-order approximations can introduce errors, particularly in systems with significant nonlinearities [13]. Moreover, the EKF's performance is highly dependent on the accuracy of prior knowledge regarding system noise, which, if inaccurate, can lead to estimation errors and even divergence from the true SOC [21]. In response to these challenges, various enhancements to the EKF have been proposed in recent years. One such improvement is the EKF which incorporates adaptive parameter updates to account for changes in the battery's characteristics over time, such as aging [22]. This adaptation improves the accuracy of SOC estimation, particularly in real-time applications where the battery's condition may change dynamically [23]. One limitation of the EKF algorithm is that its linearization only provides first-order accuracy, as it relies on first-order Taylor expansion. Consequently, the performance of the EKF is highly dependent on the accuracy of the battery model parameters and prior knowledge of system noise. If the prior knowledge is inaccurate, the estimation process may result in divergence errors [24].

For instance, the authors in [18] proposed an Improved EKF for online SOC estimation, which adapts battery model parameters in real time to account for battery aging. The I-EKF method demonstrated that the SOC estimated from a single cell could be accurately used to represent the SOC of an entire battery pack in EVs. Additionally, a robust EKF was utilized for SOC estimation using a five-RC battery model to evaluate the algorithm's performance [25]. The study explored the sensitivity of SOC estimation to different initial conditions, and the results showed that robust EKF could effectively minimize errors caused by incorrect initial SOC values.

In this study, we propose developing a comprehensive equivalent circuit model (ECM) of a lithium-ion battery, incorporating the dynamic characteristics of the battery, such as resistance, capacitance, and voltage sources. This model will serve as the basis for formulating a state equation model, which will then be implemented in MATLAB/Simulink for simulation. The simulation results will provide a foundation for integrating the model into an EKF algorithm to estimate SOC. The effectiveness of the proposed method will be evaluated by comparing the estimated SOC values with actual SOC values obtained from experimental measurements. This work contributes to the existing body of knowledge by introducing a refined battery model that more accurately captures the nonlinear behavior of lithium-ion batteries, and by proposing an improved EKF algorithm that accounts for battery aging and other dynamic factors, thereby enhancing the accuracy and reliability of SOC estimation. Finally, the study provides a rigorous evaluation of the proposed method through simulations and experimental validation, demonstrating its potential applicability in real-world EV battery management systems.

The structure of this manuscript is as follows: i) Section 2 offers a comprehensive review of the literature, discussing both the strengths and limitations of previous research on SOC estimation; ii) In section 3, the methodology is outlined, covering the development of the battery model and the application of the EKF algorithm; iii) Section 4 presents the simulation and experimental results, while section 5 provides an in-depth discussion of these findings; and iv) Lastly, section 6 concludes the paper, summarizing the main contributions and proposing directions for future research.

2. METHOD

To accurately estimate the SOC of a battery, it is necessary to construct an equivalent model that not only offers high precision but also accurately captures the dynamic behavior of the battery. Moreover, to facilitate practical implementation in engineering applications, the model's complexity must be kept in check. The most commonly used equivalent models for Li-ion batteries include the Rint model [26], the Thevenin model [27], and the Rngv model [28]. Among these, the Thevenin model is particularly effective in quickly capturing the operating state of the Li-ion battery without introducing significant delays, thus ensuring reliable accuracy over extended simulations.

The equivalent circuit model is a well-established approach, frequently applied across various applications depending on the type of battery. Researchers in the field have created several models, often refining them through extensive testing to generalize their use for different battery types. The following section outlines some of the models discussed in the literature. One of the most commonly used models is Thevenin’s model, depicted in Figure 1. In this model, the components of the equivalent circuit are considered constant, with differences between the charging and discharging states. However, in reality, these parameters also vary according to the battery’s state of charge and discharge rate [29].

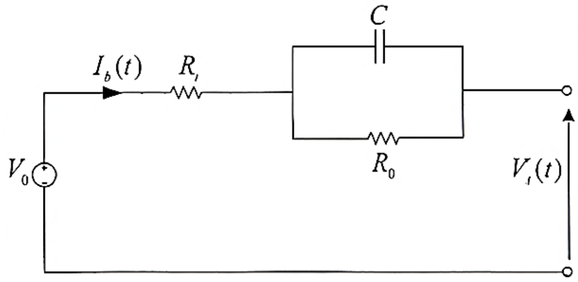


Figure 1. Thevenin battery model

2.1. State of charge estimation based on EKF

The EKF algorithm represents the advanced Kalman filter designed to accommodate non-linear system models. It finds extensive application in addressing state estimation challenges, particularly in estimating the SOC for lithium-ion batteries in EVs. Operating on a mathematical model of the battery's behavior, the EKF integrates real-time measurements with predicted states, undertaking iterative updates to enhance the precision of state estimates [30]. The procedural steps involved in implementing the EKF algorithm for battery state estimation are as follows:
- State and measurement models definition: Specify the state vector, outlining the parameters of interest for estimation.
- Initialization: Set the initial values for the state vector and its covariance matrix, reflecting the preliminary estimate and uncertainty regarding the battery's SOC and other parameters.
- Prediction phase: Employ the non-linear system model to project the subsequent state (SOC and other parameters), taking into account the present state estimate and system inputs (e.g., current, voltage).
- Covariance prediction: Utilize the Jacobian matrix and the covariance matrix of the present state to project the covariance matrix for the subsequent state estimate. This matrix quantifies the uncertainty associated with the projected state.
- Update phase: Collect real-time measurements from sensors (e.g., battery voltage, current) and compare them with the projected measurements derived from the measurement model.
- State update: Enhance the state estimate by combining the projected state with the Kalman gain-weighted measurement residual. This process yields an improved estimate of the battery's SOC and other parameters.
- Covariance update: Adjust the covariance matrix of the state estimate using the Kalman gain and the covariance matrix of the sensor measurements. This step minimizes the uncertainty in the state estimate after incorporating real-time measurements.

The application of the EKF serves to alleviate the influence of noise, yielding accurate SOC estimation outcomes. When dealing with nonlinear systems, the discrete-time state space model is expressed in (1).

$$X_t = f(X_{t-1}, U_{t-1}) + W_{t-1}, Y_t = g(X_t, U_t) + V_t \quad (1)$$

Where, the function X_t is the battery dynamics state equation, and the function Y_t is the battery output state equation. The function $f(X_{t-1}, U_{t-1})$ is the state transition function, and the function $g(X_t, U_t)$ is the measurement or observation function of the nonlinear system. The parameters of the state space model are: X_t is the state vector, Y_t denotes the observation vector, U_t signifies the input vector, W_t stands for process noise, and V_t represents Gaussian white measurement noise. The Taylor series expansion of the nonlinear observation function, as shown in (2)-(7).

$$g(X_t, U_t) \approx g(\hat{X}_t, U_t) + \frac{\partial g(X_t,U_t)}{\partial x_t}\bigg|_{x_t=\hat{x}_t} (x_t - \hat{x}_t) \text{ and } C_t = \frac{\partial g(X_t,U_t)}{\partial x_t}\bigg|_{x_t=\hat{x}_t} \quad (2)$$

$$Y_t = C_t x_t + g(\hat{X}_t, U_t) - C_t\hat{x}_t + V_t \quad (3)$$

of them, $g(\hat{X}_t, U_t) - C_t\hat{x}_t$ has no functional relationship with x_t, so it is directly regarded as D_tU_t.

$$Y_t = C_t x_t + D_t U_t + V_t \quad (4)$$

$$\begin{bmatrix} SOC_t \\ U_{ct} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{(\frac{\Delta t}{R_2 C})} \end{bmatrix} \begin{bmatrix} SOC_{t-1} \\ U_{ct-1} \end{bmatrix} + \begin{bmatrix} \frac{-\Delta t}{Q_r} \\ R_2 - (1 - e^{\frac{\Delta t}{R_2 C}}) \end{bmatrix} I_{t-1} + \begin{bmatrix} W_{1\,t-1} \\ W_{2\,t-1} \end{bmatrix} \quad (5)$$

$$U_{co\,t} = \begin{bmatrix} \frac{\partial F(SOC_t)}{\partial SOC_t} & -1 \end{bmatrix} \begin{bmatrix} SOC_t \\ U_{c\,t} \end{bmatrix} - I_t R_1 + V_t \quad (6)$$

The formula and the process of the extended Kalman calculation as (7).

$$\begin{aligned} \hat{x}_{\bar{t}} &= A_{t-1}\hat{x}_{t-1} + B_{t-1}U_{t-1} \\ \hat{P}_{\bar{t}} &= A_{t-1}\hat{P}_{t-1}^{+}A_{t-1}^{T} + Q_t \\ K_t &= \hat{P}_t^{-}C_t^T(C_t\hat{P}_t^{-}C_t^T + R_t)^{-1} \\ \hat{x}_t &= \hat{x}_t^{-} + K_t(Y_t - C_t\hat{x}_t^{-} - D_kU_k) \\ P_t &= (I - k_tC_t)P_t^{-} \end{aligned} \quad (7)$$

The functioning of the EKF adheres to a fundamental principle encompassing multiple stages. Initially, it computes the a priori estimate value based on the state quantity from the preceding time step and subsequently ascertains the covariance matrix of the estimation error. These computed values are then employed in the formulation of the temporal update equations. Subsequently, the gain coefficient Kt is derived based on the existing observation matrix Ct. Following this, the optimal temporal value is computed utilizing the a priori estimate value of the state quantity and the current observation value, ultimately, the covariance error matrix is adjusted accordingly.

3. RESULTS AND DISCUSSION

In this research, a MATLAB-based simulation platform was used to design and implement a SOC estimation model that integrates the Thevenin equivalent circuit with EKF algorithms. This method involved coupling the lithium-ion battery model with the EKF algorithm, as depicted in Figure 2. The Thevenin model simplifies the battery into an equivalent circuit comprising a series resistance and an internal voltage source, allowing for accurate simulation of the battery's electrical response under varying operating conditions. The EKF algorithm processes measured data alongside the battery's dynamic models to provide more accurate SOC estimates than conventional methods. Utilizing these tools in the MATLAB environment enables comprehensive simulation of lithium-ion battery performance, the fine-tuning of model parameters based on experimental data, and improved precision in SOC estimation. This approach overcomes the limitations of static estimation techniques by considering dynamic SOC fluctuations, delivering reliable outcomes for practical applications such as energy management in electric vehicles.

Figure 2 illustrates the simulation model used for estimating the SOC of the battery. To assess the effectiveness of the proposed estimation model, the simulation results for SOC were evaluated by analyzing the input current and load voltage, as shown in Figures 3 and 4. This process involves verifying the accuracy of the SOC estimation model by examining how variations in input current and load voltage affect the SOC results. The data presented in the referenced figures enable a comparison between the estimated SOC values and the actual measurements, which helps determine the model’s performance under different operational conditions. By analyzing the input current and load voltage, insights can be gained into how well the model adapts to various operating scenarios and maintains accurate SOC estimations. This validation ensures the model’s robustness and its suitability for practical applications such as energy management in battery systems.

The SOC estimation model proposed, as depicted in Figure 2, was assessed based on simulation results obtained under specific conditions of load input current and load voltage. To evaluate the model's performance, load voltage and current profiles, derived from EA power control, were analyzed. The data acquisition process was managed through the LabView interface.

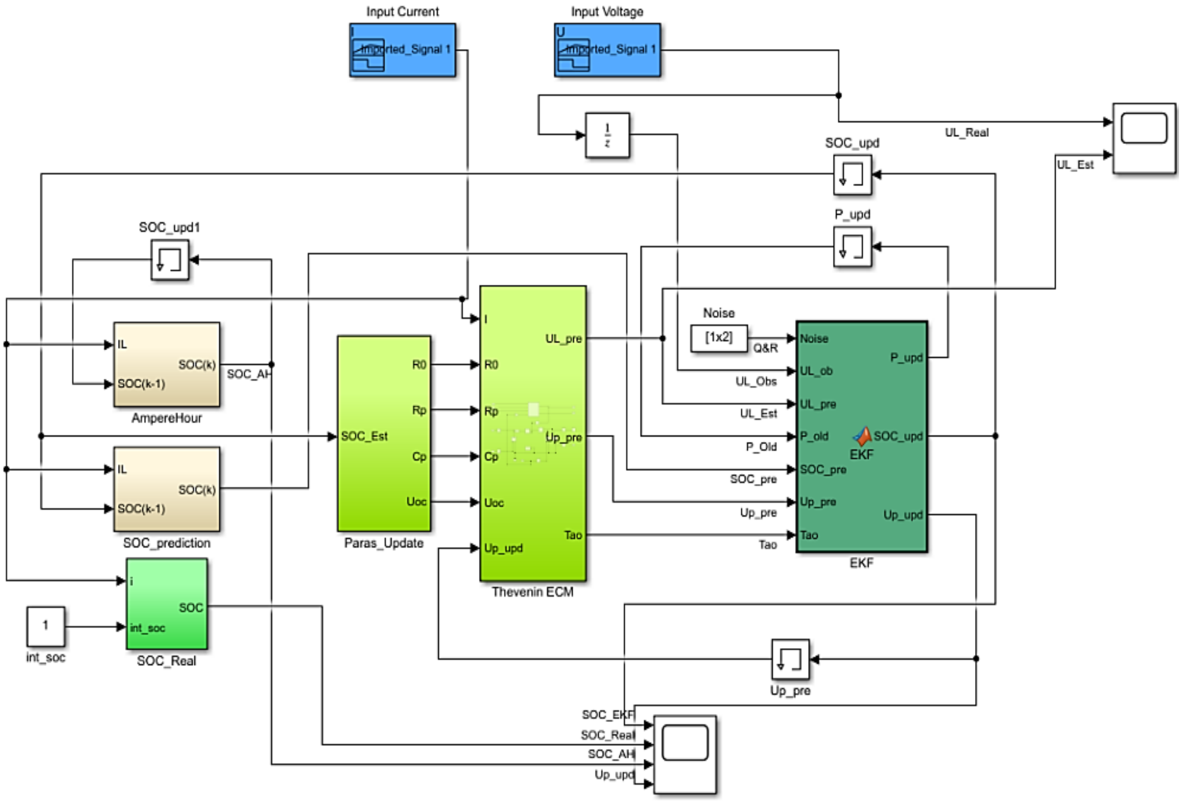
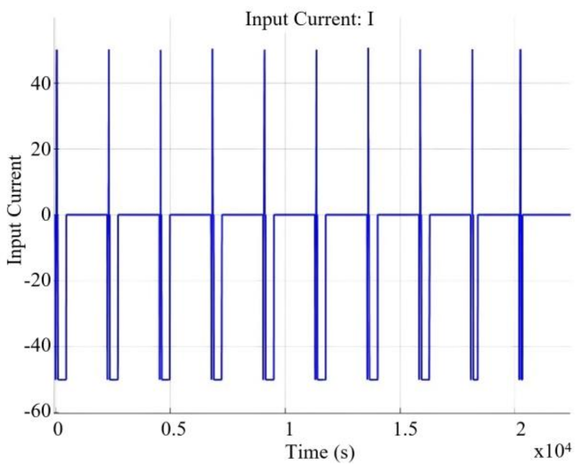


Figure 2. Simulink model



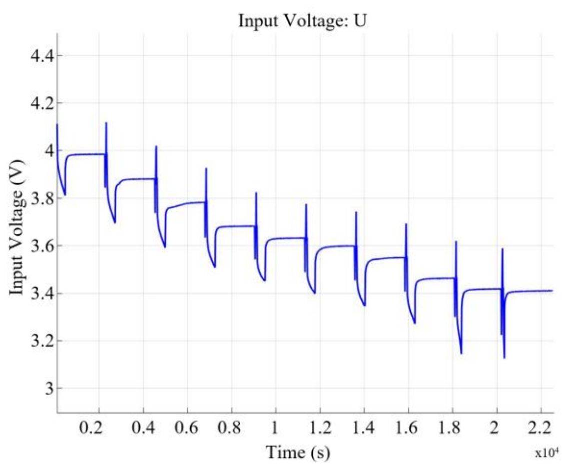


Figure 3. Current profile

Figure 4. Voltage profile

Furthermore, the accuracy of the EKF algorithm was evaluated, and the effectiveness of the SOC estimation methods was determined by examining the estimation results presented in Figure 5. This evaluation involved a detailed analysis of the model's performance in predicting the SOC and its ability to accurately reflect changes in load conditions. By comparing the estimated SOC outcomes with actual measurements, the study assessed the reliability and precision of the proposed estimation model and algorithm. Figure 6 illustrates the comparison between the real voltage and the estimated voltage of the battery, demonstrating the accuracy of the estimation model. The close alignment between both voltage profiles indicates that the estimation algorithm effectively tracks the actual battery voltage, which is essential for reliable SOC prediction and optimal battery management.

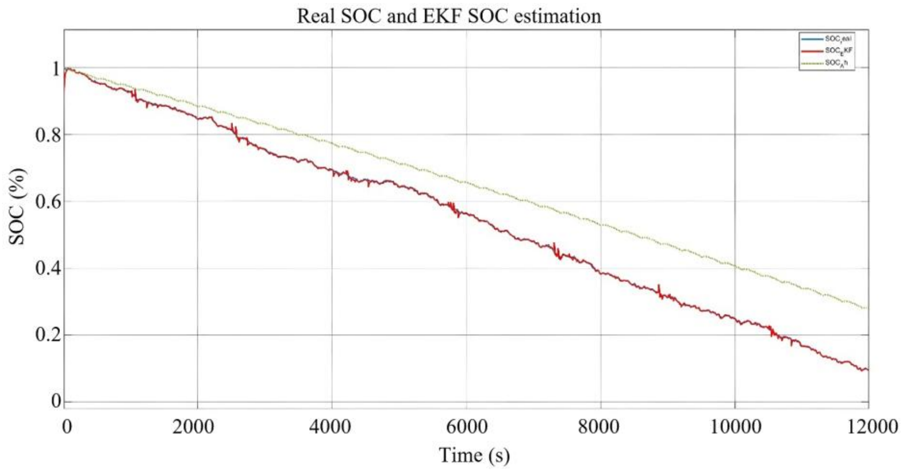


Figure 5. SOC estimation using EKF algorithm

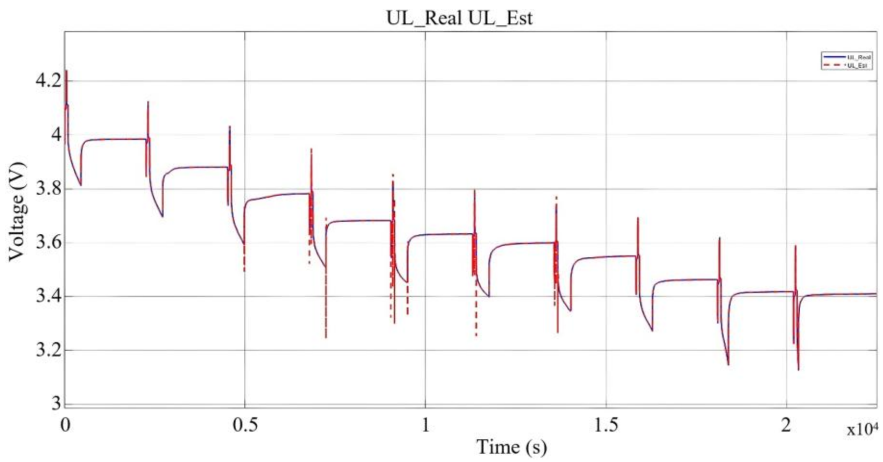


Figure 6. Real voltage and estimated voltage

4. CONCLUSION

The EKF method exhibits resilience to variations in the initial SOC value and demonstrates the ability to rectify SOC errors, as corroborated through distinct input adjustments. In the simulation results, the proposed approach demonstrates its effectiveness and accuracy in addressing the outlined objectives, the SOC estimated by the extended Kalman filter for the battery is indicated at 90% and 10%, respectively. These figures portray the values the extended Kalman filter estimated, the actual SOC value, and the SOC value in ampere-hours plotted together. When relying solely on the ampere-hour integration method, an erroneous initial value perpetuates errors, significantly compromising SOC estimation precision. However, utilizing the EKF for SOC estimation demonstrates resilience to initial values, facilitating rapid correction of the SOC estimate provided by the EKF. Data analysis of data indicates that even when the initial SOC differs from the actual SOC by 50%, the EKF adeptly rectifies the discrepancy to under 5%. Following error correction by the EKF, the estimation error fluctuates, primarily influenced by added Gaussian noise. Nonetheless, the EKF error gradually diminishes, and the estimated SOC value consistently converges toward the true value. The experimental findings validate the efficacy of the EKF algorithm in capturing the dynamic characteristics of lithium-ion batteries, encompassing variables such as charge and discharge cycles, varying temperature conditions, and non-linear voltage-SOC relationships. In comparison to traditional methods, the EKF approach mitigates cumulative errors and addresses uncertainties in both the battery model and measurements, yielding more accurate SOC estimation. Moreover, the adaptability of the EKF algorithm to various battery chemistries and configurations enhances its applicability across diverse electric vehicle scenarios. Its computational efficiency and real-time suitability ensure practical implementation in battery management systems, contributing to more efficient energy utilization, extended driving range, and increased battery lifespan.

These findings hold significant implications for the electric vehicle industry, where accurate SOC estimation is essential for efficient battery usage, reliable range forecasting, and overall vehicle performance. The EKF algorithm emerges as a practical and reliable solution for SOC estimation in electric vehicles, paving the way for greener and more sustainable transportation systems. Future research endeavors in this domain may explore the algorithm's performance under diverse driving conditions, investigate the incorporation of machine learning techniques for further enhancement, and explore potential integration with smart grid technologies to optimize energy utilization even further. Continued efforts in this direction promise accelerated advancements in battery management and energy efficiency, thereby fostering the widespread adoption of environmentally friendly transportation solutions.

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