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EV Battery Management using Adaptive Kalman Filter and ECC

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Abstract

This initiative addresses the critical concerns of enhancing battery management and easing the calculation of battery capacity in electric vehicles. By using Coulomb counting method, the State of Charge (SoC) of Electric Vehicle (EV) batteries is estimated by analysing real-time battery data through simulations and interpolation techniques. The primary objective is to offer precise SoC estimation to mitigate the range anxiety. Furthermore, this research proposes methods of estimating the SoC of Lithium-Ion batteries and an enhanced coulomb counting model with Adaptive Kalman Filter to estimate the state of charge with higher accuracy. This comprehensive approach seeks to address critical challenges in EV battery management contributing significantly to the electric vehicle technology for the society.

Keywords: SoC, EV, Lithium-Ion Batteries, Adaptive Kalman Filter, Enhanced Coulomb Counting.

1. Introduction

The prominence of EV’s in today's world is undeniable, driven by the imperative to reduce environmental pollution and dependence on fossil fuels. As society increasingly embraces EV technology, the need for continuous improvement becomes paramount. However, one significant challenge hindering the widespread adoption of EVs is the efficient

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management of their batteries. Despite the numerous advantages EVs offer, such as reduced emissions and lower operating costs, inadequate battery management poses a critical concern.

Without proper maintenance of battery health, the risk of premature battery failure looms large, leading to costly replacements and diminished vehicle performance. Thus, effective battery management is imperative to ensure the longevity and reliability of EVs. R. Xionget al [14] and R.R .Kumar et al [7] reviews on the role of Battery Management Systems (BMS) for EVs and Battery Energy Storage Systems (BESS), focusing on battery modelling, charging strategies, and state estimation were studied . Shrivastava et al [19] emphasizes the importance of accurate battery modelling and state estimation for optimizing charging strategies, identifies challenges in validating BMS under real-world conditions, and suggests future directions for BMS advancement, including the development of a universal BMS and improved predictive techniques.

As the demand for electric vehicles (EVs) continues to rise, there is an increasing need for the advancement of reliable and efficient battery management systems (BMS). A critical aspect of a BMS is determining the accurate charge left in the battery pack. SoC reflects the remaining battery capacity which provides impact in charging strategies, and overall battery health. BMS in EVs play a vital role in ensuring the safety, efficiency, and optimal performance of the battery pack. Mina Naguib et al [5] highlights the importance of accurate cell balancing and charge estimation in lithium-ion battery packs for electric vehicles. Fazel Mohammadi et al [9] and Z. Xia et al [6]. discusses the challenges posed by cell inconsistencies, aging, and presents various SoC estimation and balancing methods. The study intends to explore the latest advancements and difficulties in creating reliable methods for estimating battery charge and balancing lithium-ion battery packs [4].

Movassagh K et al [10] addresses the crucial issue of battery management in EVs, focusing on strategies to optimize battery health and performance. By exploring methods for accurately determining the State of Health (SoH) and State of Charge of EV batteries, to mitigate the risks associated with poor battery management. JEONG LEE et al [1] introduces an enhanced coulomb counting method to improve the accuracy in estimating the state of charge in lithium-ion batteries, illustrating the initial value error of the traditional method by incorporating the open circuit voltage method and considering battery aging, with effectiveness verified through comparative experiments and it was improved by data driven methods by others [2][3][8][9]. C. Lyu et al. [15] gives a new estimation method which combines Coulomb Counting with Fuzzy logic. This technique provided better results with minimized error value. Adjusting the fuzzy control's gain automatically can help decrease the error value [11][16][17]. In [18][21], the authors suggested utilizing the Extended Kalman Filter across all simulation conditions. This involved updating the parameters with the average value of each SOC section, as opposed to the conventional EKF. The simulation results verified that adaptive battery parameters can improve the performance of the SoC estimation. In practice, a variant called the Extended Kalman Filter (EKF) is often used for SoC estimation due to the non-linear nature of Li-ion battery behaviour. The EKF linearizes the non-linear model around the current operating point, allowing the KF framework to be applied.[12][13]. Later this was extended and improved the accuracy [20]. Additionally, this study proposes innovative solutions for enhancing battery efficiency by the AKF method for estimating SOC. Still many researches are going on to improvise the BMS and obviously it is highly essential to have eco-friendly transportation in order to control the environmental pollution and to face the consequences of diminishing fuel.

1.1 Efficient BMS and It's Challenges

In the realm of powering electric vehicles and energizing our daily devices, lithium-ion batteries stand out as a cornerstone technology. Electric vehicle (EV) battery packs are complex electrochemical systems that require careful management to ensure safety, optimal performance, and extended lifespan. Accurately determining the remaining usable energy within the battery pack is crucial for maximizing driving range, preventing over-discharge, and optimizing charging strategies. However, achieving highly accurate SoC estimation presents a challenge due to the non-linear relationship between battery voltage, SoC, temperature dependence, and battery aging effects.

In an efficient battery management system, several key parameters are monitored and managed to ensure optimal battery health and safety. The state of charge reflects the remaining usable energy within the battery pack, crucial for maximizing driving range and preventing over discharge. The SoH indicates the battery's capacity relative to its original design capacity, reflecting its health and overall degradation time. The individual cell voltages are monitored to identify any imbalances within the pack that could impact battery performance or safety up to an extent.

Temperature significantly affects battery performance and life span. Maintaining optimal operating temperature is most important. Efficient battery management system continuously monitors battery's temperature and implements cooling strategies to prevent overheating. For lithium-ion batteries additional parameters like cell balancing currents or internal resistance are monitored for the betterment to form a bench mark.

The challenges in an efficient BMS includes the accuracy in estimation of the SoC as the advanced techniques require higher computational power than the traditional methods to analyze various parameters in providing accuracy. Thermal management complexity is one of the crucial aspects for the management of batteries for its performance. Also, the cell balancing challenges and reliability with software for standardized communication with the BMS and EV are essential in increasing the performance of the battery.

BMS assumes the role of an invaluable data collector, gathering insights on cell health, usage patterns, and environmental conditions. This data not only enhances our understanding of battery behaviour but also serves as a foundation for future improvements. With various communication protocols and standardized interfaces, BMS facilitates seamless integration with other systems in applications like electric vehicles (EVs).

1.2 Lithium-Ion Batteries: Dominance, Challenges, and Future Perspectives

Lithium-ion batteries have unequivocally become the driving force in the electric vehicle (EV) industry owing to their superior characteristics compared to alternative battery technologies. These batteries strike a balance between performance, longevity, and environmental benefits, solidifying their dominance in the EV landscape. Lithium-ion battery technology has witnessed significant advancements in recent years, particularly in terms of energy density. This metric refers to the amount of energy a battery can store per unit volume. As the energy density increases, the range covered by an electric vehicle increases and this reduces the anxiety of EV adopters.

Early EVs had average lithium-ion battery energy densities around 100-120 Wh/kg. By the advancements technologies have led common densities are improvised up to 300 Wh/kg, with some exceeding 400 Wh/kg. Batteries with high energy density may need advanced thermal management systems to maintain ideal operating temperatures during both charging and operation

Li-ion batteries undergo a natural degradation process over time. High temperatures exacerbate this process, leading to faster capacity fade and reduced overall battery lifespan. The elevated temperatures intensify chemical reactions within the battery, accelerating the breakdown of electrode materials and electrolytes. In high-performance lithium-ion batteries, organic carbonate electrolytes are commonly used, which are flammable and serve as fuel. When subjected to external heating, overcharging, or internal short circuits, the battery generates heat and experiences higher temperatures due to exothermic chemical reactions. Figure 1.1 Internal Structure of Lithium ion Battery

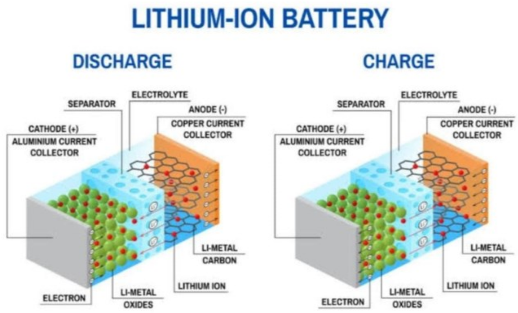

Figure 1.1. Internal Structure of Lithium-Ion Battery

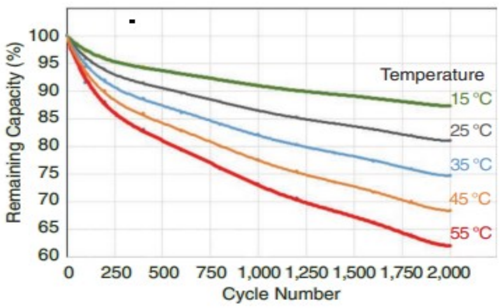

Figure 1.2. Battery Capacity Loss at Different Temperatures [4]

This shows high temperature accelerates the natural degradation of these batteries, shortening their lifespan and reducing overall capacity. This vulnerability also increases the risk of thermal runaway, a dangerous scenario where a self-heating loop within the battery leads to fire or explosion. EV performance suffers too, with reduced power output and driving range at high temperatures. To ensure safety and optimal performance, most EVs aim to maintain battery temperatures within a moderate range, typically between 15°C and 25°C (59°F and 77°F). EV manufacturers combat heat through various thermal management systems, including liquid cooling loops or air circulation strategies. Maintaining temperatures below 50-60°C is paramount to prevent accelerated degradation and potential safety risks associated with excessive heat. Maintaining temperatures below 50-60°C is essential to prevent accelerated degradation and potential safety risks associated with excessive heat during fast charging. The internal structure of the Lithium-Ion Battery during charge and discharge state in shown in Fig 1.1. The loss of battery capacity at different temperatures is shown in Fig 1.2 and it is observed that when temperature increases the rate of discharging capacity of the battery increases and vice versa.

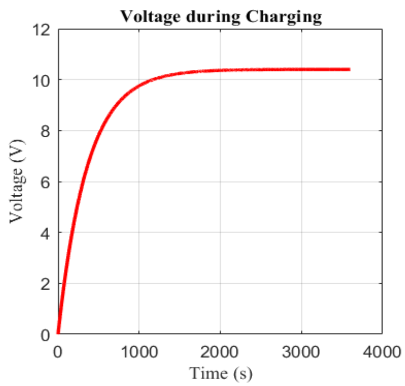

Figure 1.3. Charging Rate of Lithium-Ion Battery

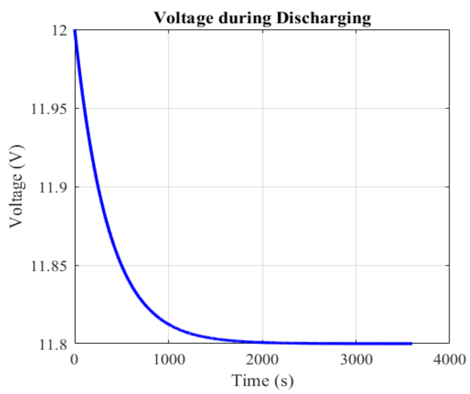

Figure 1.4. Discharging Rate of Lithium-Ion Battery

The discharge rate of lithium-ion batteries typically falls within the range of 1C to 5C, with high-performance EVs reaching up to 10C during rapid acceleration. However, higher discharge rates introduce heat, impacting both performance and battery lifespan. Temperature management becomes paramount, with optimal operation occurring within a range of 20°C to 40°C. Below 0°C, performance drops significantly, and above 45°C, degradation accelerates, while exceeding 60°C poses the risk of thermal runaway. Presently, EV batteries range from 40kWh to 100kWh, offering distances of 200 to 500 km per charge. Ongoing research and development aim to increase battery capacity for extended range. Leading companies like Tesla, BYD, LG Chem, and Panasonic employ advanced technologies, such as 2170 cylindrical cells or blade battery tech. Despite advantages like high energy and power density, long cycle life, and low self-discharge, challenges persist, including cost considerations, the need for efficient thermal management, and sustainability concerns in sourcing and recycling. The change in voltage during charging and discharging of a battery with respect to time graph is shown in Fig 1.2 and Fig 1.3.

2. Methods of Estimating State of Charge

Accurate state of charge (SoC) estimation is crucial for lithium-ion battery management. SoC estimation methods include direct measurement, Coulomb Counting, data-driven, and model-based approaches. Direct measurement, such as Open Circuit Voltage (OCV), offers simplicity but lacks online estimation capability. Coulomb Counting integrates current over time but requires initial SoC knowledge and is prone to integration errors. Enhanced Coulomb Counting improves accuracy using adaptive algorithms and battery modeling.

$$\mathrm{Soc}\,(t) \;=\; SoC_{(t_0)} \;+\; \left(\int_{t_0}^{t} \quad I\,dt \;/\; Q_n\right)$$

Where,

- $\mathrm{Soc(t)}$ - charge at specified time
- $\mathrm{I(t)}$ - battery current
- $\mathrm{SoC_{(t_0)}}$ - Initial SoC

- Q_n - nominal battery capacity

Discharging the battery for 1 hour at a constant current of 2 A yields an SOC of 80% after 1 hour. However, the accuracy of this method relies heavily on an accurate initial SOC, often necessitating calibration methods.

The Kalman Filter (KF) estimates lithium-ion battery State-of-Charge (SoC) accurately by combining information from multiple sources. However, it's not ideal for nonlinear systems, leading to increased calculation time with more variables. To address this, methods like Extended and Unscented Kalman filters are used. The Dual Extended Kalman Filter (DEKF) enhances traditional EKF by updating both system state and parameters using observed measurements in prediction and update steps

State Prediction:

$$\widehat{x_{\bar{k}}} = f(\widehat{x_{k-1}, u_k})$$

Where,

- $\widehat{x_{\bar{k}}}$ = predicted state of time step k
- f = system dynamics model
- $\widehat{x_{k-1}}$ = estimated state at the previous time step *k-1*, and
- u_k = control input at time step k

Parameter Prediction:

$$\hat{\theta}_{\bar{k}} = f(\theta_{\hat{k-1}})$$

The parameters are assumed to be constant over time.

Kalman Gain Calculation:

$$k_k = P_{\bar{k}}\ H_k{}^T(H_k{}^T P_{\bar{k}} H_k{}^T + R_k)$$

Where,

- K_k = Kalman gain at step k
- $P_{\bar{k}}$ = predicted covariance matrix of the state and parameter estimates,

- H_k = measurement Jacobian Matrix
- R_k = measurement noise covariance matrix

State and parameter update:

$$\widehat{x_k} = \widehat{x_{\bar{k}}} + K_k \left(Z_k - h\,(\widehat{x_{\bar{k}}}\right)$$

$$\widehat{\theta_k} = \widehat{\theta_{\bar{k}}} + K_k \left(Z_k - h\,(\widehat{x_{\bar{k}}}\right)$$

Where,

- $\widehat{x_k}$ and $\widehat{\theta_k}$ are the updated state and parameter estimates
- Z_k is the measurement on time step k-1

h is the measurement function mapping the state to the measurement space

These equations are iteratively applied at each time step to estimate both the state and parameters of the system, enabling more accurate and robust state estimation in nonlinear systems such as lithium-ion batteries. In recent years, data driven methods such as Neural Networks and Convolutional neural networks (CNN) replaces the traditional methods in estimating the SoC as they use machine learning algorithms and are trained with large datasets, they can predict the SoC accurately at different operating conditions.

3. The Enhanced Coulomb Counting Method: Estimating SoC with Precision

Considerations for the Coulomb counting method encompass limitations such as dependence on precise initial SoC and inadequate accommodation for changes in battery capacity due to aging. Enhanced accuracy is pursued through advanced approaches incorporating corrections for temperature effects and aging. The method may become less accurate near 0% and 100% SoC due to the non-linear behaviour of the battery. In practical applications, approximating the integral in the formula involves numerical methods based on the sampling rate of current measurements. A thorough understanding of the principles, formula, and limitations of the coulomb counting method empowers effective SoC estimation in lithium-ion batteries, with continuous advancements in battery management technologies refining SoC estimation methods for heightened accuracy and reliability in monitoring battery performance. The variation of Current, Voltage and SoC of a battery with respect to time is shown in Table 3.1. From the table it is observed that the current and voltage changes irrespective of the time varies and SoC decreases linearly with the increase in time.

Table 3.1. State of Charge Analysis on a Battery

S. No.	**Time (min)**	**Current (mA)**	**Voltage (Volts)**	**SoC %**
1	1	1.397	12.04	99.99
2	10	10.237	11.84	99.78
3	20	38.75	11.19	98.73
4	30	68.63	10.68	96.58
5	40	66.64	10.94	93.77
6	50	65.12	11.25	91.04
7	60	63.63	11.59	88.37
8	70	62.06	11.90	85.77
9	80	60.71	12.19	83.22
10	90	59.48	12.49	78.48
11	100	58.36	12.79	70.49
12	110	57.36	12.95	63.89
13	120	56.43	13.18	60.5

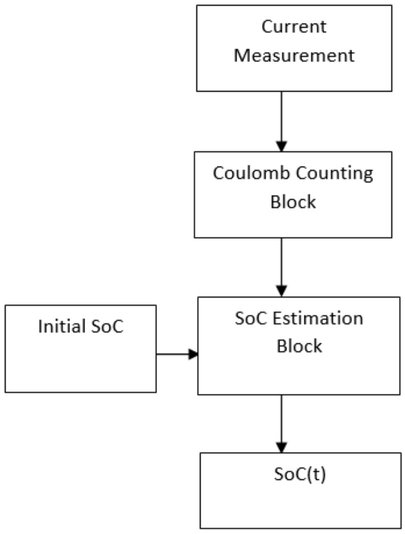

Figure 3.1. Block Diagram of Coulomb Counting Method

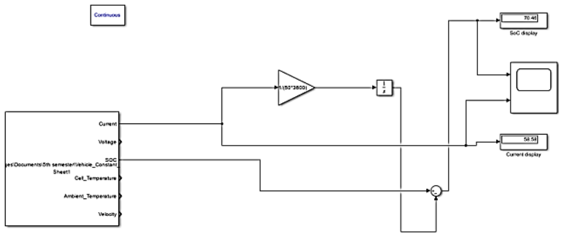

Figure 3.2. Simulink Model of Coulomb Counting Method to Estimate State of Charge

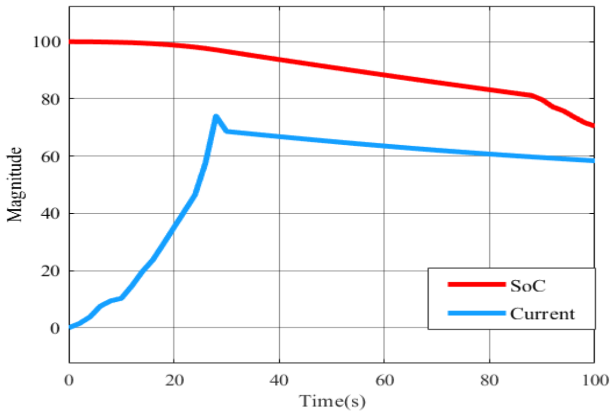

Figure 3.3. SoC and Current Discharge Rate of Lithium Ion Battery (CCM)

The SoC estimation with Enhanced Coulomb Counting (ECC) with an Adaptive Kalman Filter (AKF) provides improved accuracy compared to traditional Coulomb counting methods. The integration errors and initial SoC dependence, temperature effects, battery's degradation capacity due to aging are reduced by this method.

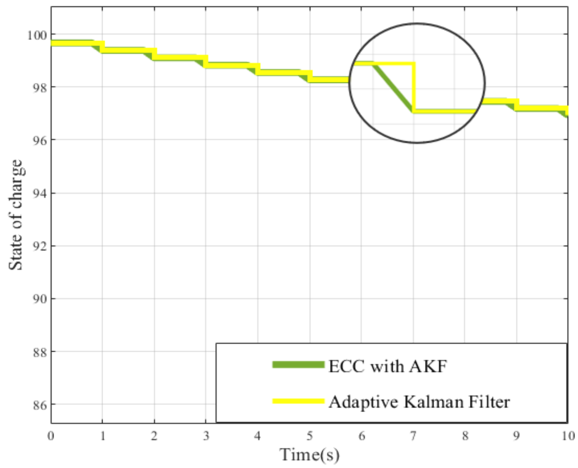

Figure 3.4. State of Charge Estimation by AKF and ECC with AKF with Improved Accuracy

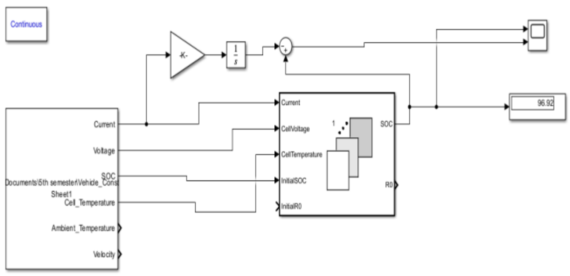

Figure 3.5. Simulink Model of Estimating SoC by ECC with AKF Method

The limitations in the Enhanced Coulomb Counting method such as inaccurate initial SoC, integration errors and nonlinearities in battery behaviour which causes gradual drift in estimating the State of charge can be overcome by combining the Adaptive Kalman filters. The estimation of SOC of a battery 's simulation using Coulomb counting method and ECC with AKF method in shown in Fig 3.2 and Fig 3.4 and corresponding simulation results are shown in Fig 3.3 and Fig 3.5.

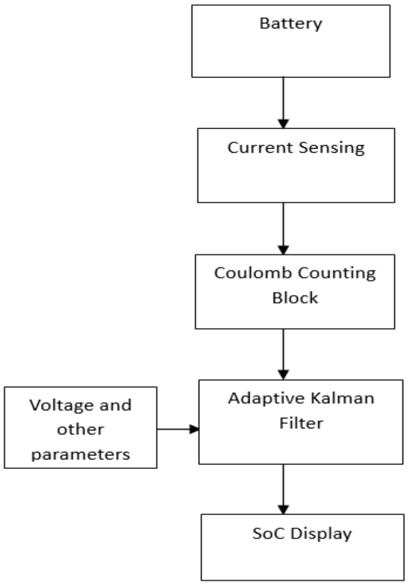

Figure 3.6. Block Diagram of ECC with AKF

This model tackles the issues in traditional methods of estimating the State of Charge by utilizing the battery model and real time measurements. By incorporating the Adaptive Kalman Filter, the accuracy is increased by measuring the temperature, noise and other parameters thereby, providing more robust and accurate estimation of State of Charge over time.

4. Conclusion

This study proposes a novel solution for estimating the SoC of lithium-ion batteries in EVs using an Enhanced Coulomb counting method with an adaptive Kalman filter. The integration of real-time data collection and analysis illustrates the dynamic adjustments of the SoC estimation based on various operating conditions and it helps in improving the accuracy and reliability compared to other existing methods. The future scope would focus on the adoption of Hybrid Dual extended Kalman filter for utmost accuracy which helps in introducing various advancements in battery management.

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