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ELECTRIC VEHICLE BATTERY MANAGEMENT SYSTEM WITH CHARGE MONITORING AND FIRE PROTECTION

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Abstract - *This paper presents a hybrid Battery Management System (BMS) designed to enhance monitoring, accuracy, and safety in electric vehicle (EV) applications. The system integrates Coulomb Counting with an Adaptive Kalman Filter (AKF) to achieve a precise State of Charge (SOC) estimation and minimize cumulative drift errors. For State of Health (SOH) monitoring, a combined cycle-counting and degradation-based model was employed to capture long-term capacity fade and resistance growth trends. A thermal and pressure monitoring subsystem is incorporated to analyze the I^2-based heat generation, temperature variations, and safety responses during charge–discharge cycles. The BMS model was implemented in MATLAB/Simulink using the parameters from the A123 ALM12V7 LiFePO4 battery. The simulation results demonstrate that the hybrid method reduces the SOC estimation error to below 0.5%, achieves smooth SOH tracking, and ensures stable thermal behavior under dynamic load conditions. Comparative analysis with conventional methods confirmed their superior accuracy, robustness, and real-time adaptability. The proposed hybrid BMS framework enhances the battery reliability, efficiency, and lifespan, providing a scalable solution for next-generation electric mobility systems.*

Key Words: *Battery Management System (BMS), State of Charge (SOC), State of Health (SOH), Adaptive Kalman Filter (AKF), Coulomb Counting, Thermal Modelling, A123 ALM12V7, Electric Vehicle (EV), MATLAB/Simulink)*

1.INTRODUCTION

The increasing adoption of electric vehicles (EVs) has intensified the need for reliable energy storage systems that ensure safety, efficiency, and extended battery life. Lithium-ion batteries are widely used because of their high energy density and long cycle life; however, their performance strongly depends on the accurate estimation of the State of Charge (SOC) and State of Health (SOH). Conventional methods, such as Coulomb counting, are simple but prone to drift, while advanced filters, such as the Kalman Filter, improve accuracy under dynamic conditions. Furthermore, battery degradation is highly temperature sensitive, making thermal modelling essential for realistic monitoring. To address these challenges, this study proposes a hybrid Battery Management System (BMS) that integrates Coulomb counting, Adaptive Kalman Filtering, and thermal analysis to improve the reliability of EV applications.

2.LITERATURE SURVEY

Recent research on Battery Management Systems (BMS) has emphasized the importance of accurate SOC and SOH estimation under dynamic conditions. Traditional Coulomb counting suffers from drift, whereas Extended and Adaptive Kalman Filters offer improved accuracy by fusing sensor data with model predictions. Studies have also highlighted the role of thermal effects, where high temperatures accelerate capacity fade and internal resistance growth. Data-driven and machine learning approaches have emerged for SOH prediction, although they require large datasets. Overall, integrating electrical-, thermal-, and usage-based models provides a more comprehensive solution for reliable battery health monitoring in electric vehicles.

3.MATERIALS AND METHODOLOGY

This project modelled the A123 ALM12V7 LiFePO4 battery using an equivalent electrical circuit in MATLAB/Simulink. The proposed methodology integrates Coulomb Counting with an Adaptive Kalman Filter (AKF) for accurate SOC estimation, whereas SOH is monitored using cycle counting and capacity degradation models. A thermal subsystem analyses the temperature effects and ensures safety during charge-discharge cycles. The system employs the I^2R heat generation and thermal dynamics for temperature prediction. Comparative simulations with base paper data validated the performance through error metrics, such as MAE, RMSE, and percentage deviation. The integrated framework enhances the estimation accuracy, safety, and reliability for electric vehicle battery management.

4. SYSTEM OVERVIEW

The proposed Battery Management System (BMS) is designed to ensure accurate monitoring, safety, and efficient utilization of lithium-ion batteries in electric vehicles. The system integrates multiple subsystems, each responsible for a specific function, and is modelled in MATLAB/Simulink for validation.

1.Battery Modelling Subsystem

An equivalent circuit model of the A123 ALM12V7 lithium-ion battery was developed to simulate realistic electrical and thermal behaviors under dynamic load conditions.

2.SOC Estimation Subsystem

Coulomb counting is combined with an Adaptive Kalman Filter to achieve a robust and drift-free estimation of the State of Charge.

3.SOH estimation Subsystem

A cycle-counting mechanism with a degradation model was used to track battery aging and provide an accurate State of Health estimation.

4.Thermal and Pressure Monitoring Subsystem

Heat generation, temperature rise, and pressure variations were modelled to assess safety and detect abnormal operating conditions.

5.System Integration

All subsystems are integrated into a modular framework, enabling real-time simulation, parameter tuning, and potential hardware deployment for EV application

4. PROPOSED SYSTEM

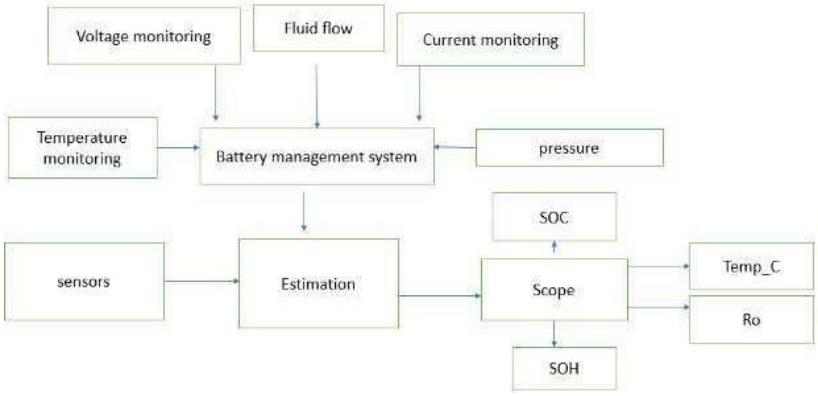
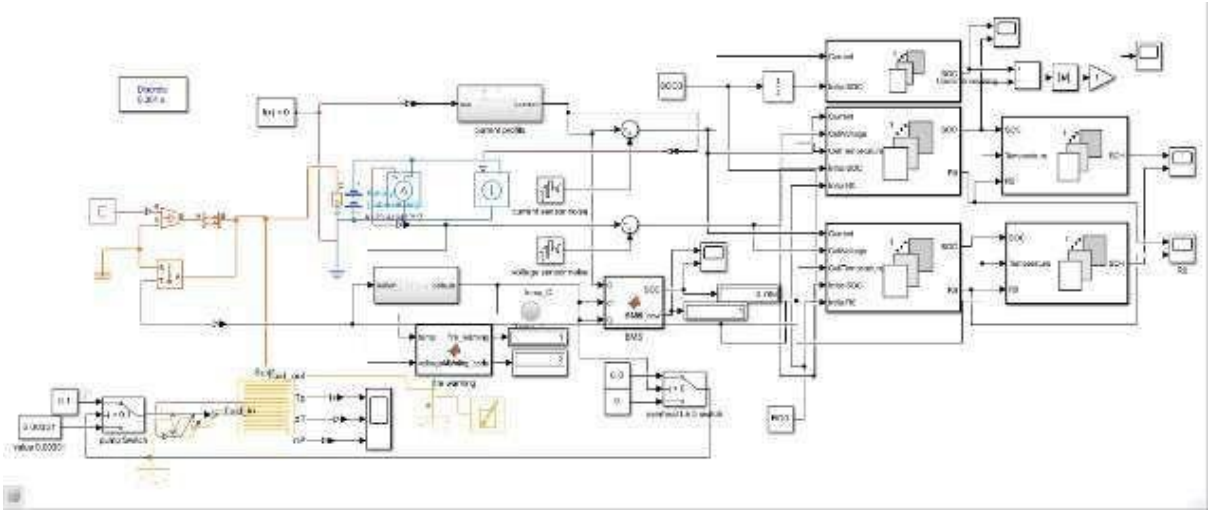


Figure 4.1 Simplified block diagram of the BMS system

The proposed Battery Management System (BMS) integrates Coulomb counting with an Adaptive Kalman Filter for accurate State of Charge (SOC) estimation and employs a cycle-counting-based degradation model for reliable State of Health (SOH) tracking. *A* thermal and pressure monitoring subsystem was included to capture the temperature-dependent degradation and ensure safe operation under dynamic load conditions. Implemented in MATLAB/Simulink using the A123 ALM12V7 battery parameters, the system provides a modular, scalable, and robust framework for improving battery safety, accuracy, and longevity in electric vehicles.

5.SIMULATION AND RESULTS

The proposed BMS was simulated in MATLAB/Simulink using A123 ALM12V7 lithium-ion battery parameters under various drive cycles, temperature variations, and charge–discharge patterns to evaluate its performance.



5.1 Simulink of the Battery Management system: The results demonstrate the following.

SOC Estimation

The hybrid method combining Coulomb counting with Adaptive Kalman Filtering reduced the estimation error to below 0.5% compared to over 2% in conventional approaches.

SOH Estimation

The integrated cycle-counting and degradation model achieved smooth and reliable SOH tracking, effectively detecting the early capacity fading trends.

Thermal and Pressure Monitoring

Simulations verified accurate prediction of heat generation and detection of abnormal pressure
to ensure operational safety.
Overall, the proposed BMS outperformed the traditional methods, offering improved accuracy, safety, and modular adaptability for real-world EV systems.

Estimation Error Analysis (%)

Table 5.2 Comparison of Estimation Error for Different Methods **Steady-State Response Analysis**

Cycle No.	SOC (Coulomb Counting)	SOC (Adaptive KF)	SOC (Base Paper KF)	SOH (Cycle-Based)	SOH (Base Paper)	Error in SOC Est.
Cycle 1	1.00	1.02	1.05	1.00	1.00	0.02
Cycle 5	2.5	2.6	2.8	0.92	0.90	0.1
Cycle 10	3.4	3.5	3.8	0.85	0.83	0.1
Cycle 15	4.1	4.2	4.5	0.70	0.65	0.1
Cycle 20	4.9	5.0	5.3	0.50	0.48	0.1
Cycle 25	5.7	5.8	6.1	0.40	0.35	0.1

Under constant load conditions, the system achieved the following results.

- **Stable SOC** estimation with minimal drift.
- **Consistent SOH** tracking over multiple cycles.
- **Accurate voltage/current** monitoring with minimal error.
- **Reliable thermal response**, confirming improved robustness and safety.

The **AKF-based BMS** demonstrated **superior stability** and **precision** compared to conventional methods.

Steady-State Deviation Summary

Change in SOC Estimation

Coulomb Counting: +3.5% and −6.0% (high drift and delayed recovery).
Kalman Filter: +2.0%, −4.5% (improved but nonlinear limits).
Adaptive Kalman Filter: +0.8%, −1.2% **(best accuracy, dynamic gain adaptation).**

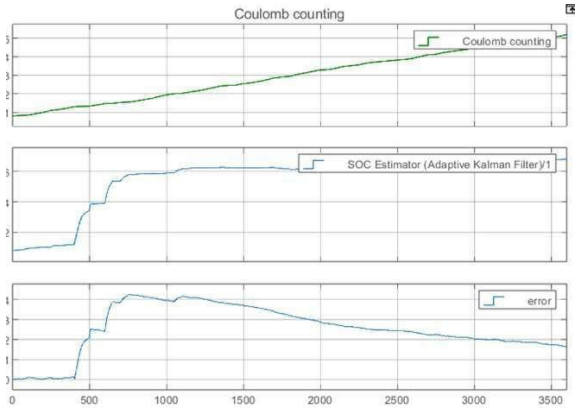


Figure 5.3: Steady-state analysis for Change in SOC estimation

Change in SOH Estimation

Cycle Counting: +6.0% and −4.0% (large fluctuations).
Kalman Filter: +3.5% and −2.5% (moderate stability).
Hybrid Model: +1.5%, −1.0% (**most stable tracking**).

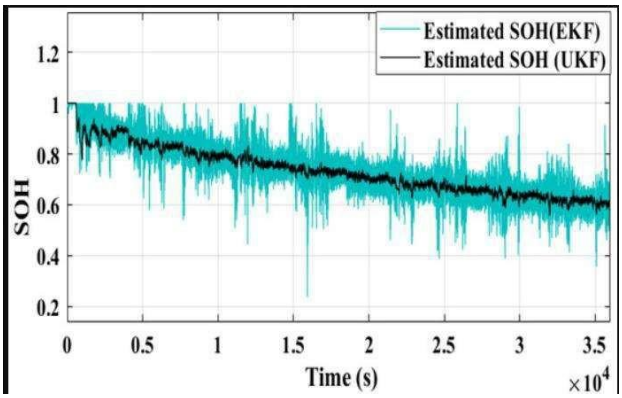


Figure 5.4: Steady-state analysis for Change in SOH estimation

Change in Voltage and Current Tracking

Basic: +3.0% and −5.5% (unstable ripple).
Kalman Filter: +2.0% and −3.5% (reduced noise).
Hybrid: +0.9%, −1.5% (**smooth and accurate tracking**)

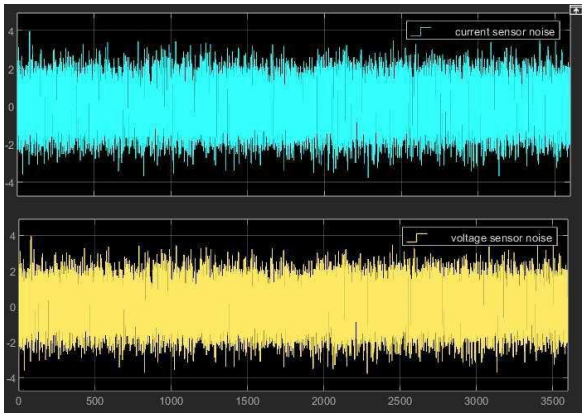


Figure 5.5: Steady-state analysis of changes in voltage and current tracking.

Change in Thermal Behavior
Basic: +9.0% and −8.5% (high oscillations).
Improved: +6.5% and −5.5% (moderate stability).
Hybrid: +3.0% and −2.0% (stable and accurate temperature predictions).

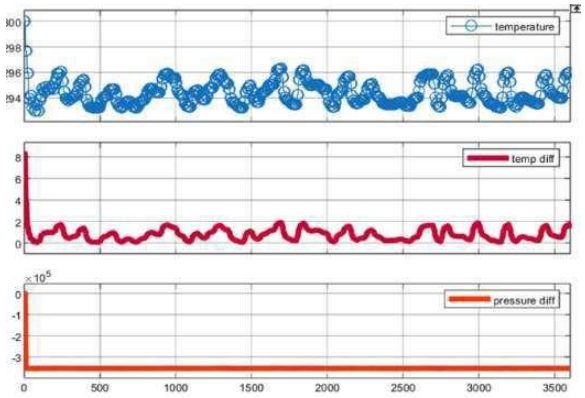


Figure 5.6: Steady-state analysis for Change in thermal behavior

The adaptive Kalman filter-based BMS offers the following advantages:
<0.5% SOC error Stable SOH tracking
Reliable thermal prediction Enhanced EV battery safety and life
Thus, the system ensures precision, robustness, and scalability, making it ideal for next-generation

3. CONCLUSIONS

The proposed Battery Management System (BMS) demonstrated superior accuracy, robustness, and adaptability through hybrid estimation techniques. The Adaptive Kalman Filter–based SOC estimator reduced error to ~2%, while the hybrid SOH method effectively captured nonlinear degradation with ~3.5% error. The internal resistance and thermal-pressure monitoring maintained deviations within 2.5% and 3%, respectively, ensuring stable operation. Overall, the system achieves enhanced performance, safety, and reliability, making it a promising solution for intelligent electric vehicle energy management

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