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Control-Oriented Battery Management Systems for Mitigating Thermal and Performance Issues in Fast-Charging EV Batteries

Nirav Mehta[1*], Dr. Piyush R. Patel[2],

[1]Ph. D. Scholar, Electrical, Sankalchand Patel University, Visnagar, India Email ID: niravdmehta225@gmail.com*
[2]Associate Professor (Electrical) School of Engineering, Indrashil University, Rajpur, Kadi Mail ID: dr.piyushpatel22@gmail.com

Abstract

*The advancement of electric vehicles (EVs) relies heavily on the efficiency, safety, and durability of lithium-ion battery systems. This study proposes **A-BMS**, a novel adaptive Battery Management System (BMS) architecture designed to mitigate thermal and performance issues during fast charging through a control-oriented approach. By integrating state estimation algorithms with real-time control feedback, the system continuously monitors and manages key battery parameters such as State of Charge (SoC), State of Health (SoH), and temperature. Intelligent control layers address challenges including cell imbalance, overcharging, and thermal runaway, ensuring stable operation under high charging rates. Predictive analytics and high-precision monitoring enable the system to dynamically respond to rapid changes in operating conditions, improving battery lifespan and overall reliability. The proposed framework provides a robust solution for maintaining safe and efficient battery performance under the demanding conditions of fast charging, marking a significant step toward advanced, intelligent EV energy management.*

Keywords: *Battery Management System, Electric Vehicles, State of Health, State of Charge, Thermal Management, Adaptive Control, Real-time Monitoring, Predictive Analytics*

1. Introduction

The growing global emphasis on reducing carbon emissions and transitioning to sustainable energy sources has led to a rapid rise in electric vehicle (EV) adoption [1]. At the core of every EV lies the lithium-ion battery system, which powers the vehicle while directly influencing its safety, efficiency, and lifespan [2]. The Battery Management System (BMS) plays a crucial role in monitoring and controlling battery operations, including energy storage, charge-discharge cycles, and fault detection [3]. As the demand for high-performance, durable EVs increases, the development of intelligent, adaptive BMS architectures has become essential [4].

Lifecycle performance of EV batteries is strongly affected by how effectively the BMS manages parameters such as State of Charge (SoC), State of Health (SoH), and temperature [5]. An efficient BMS extends battery life by preventing overcharging, over-discharging, and thermal degradation [6]. Modern BMS not only ensures operational safety but also enables predictive maintenance, reducing long-term costs and improving reliability [7]. These systems are particularly critical during fast-charging, where rapid energy input can exacerbate thermal and performance issues [8].

Despite advancements, conventional BMS architectures face notable limitations [9]. Challenges include poor adaptability to varying driving and charging conditions, limited accuracy in SoH estimation, and insufficient real-time control capabilities [10]. Traditional systems often rely on static models that fail to account for evolving battery degradation patterns or environmental variations [11]. These limitations can compromise lifecycle performance and increase the risk of thermal events or reduced efficiency [12].

To overcome these challenges, researchers are developing control-oriented and adaptive BMS frameworks that integrate real-time data processing, advanced estimation algorithms, and feedback control loops [13]. Methods such as Kalman filtering, model predictive control (MPC), and machine learning have been successfully applied to improve SoC/SoH estimation and thermal regulation [14]. Adaptive BMS dynamically adjusts control strategies based on charging rates, battery aging, and environmental conditions, providing enhanced resilience and performance during fast charging [15].

Recent developments from 2023 to 2025 highlight the incorporation of artificial intelligence (AI), edge computing, and digital twin technologies into BMS design [16]. These approaches allow for continuous learning, remote diagnostics, and precise battery analytics, thereby further enhancing lifecycle performance [17][18]. Continued research into adaptive, control-oriented BMS is vital for mitigating thermal and performance issues in fast-charging EVs, supporting safer, more efficient, and longer-lasting battery operation [19][20].

2. Literature Review

The literature on adaptive and control-oriented Battery Management Systems (BMS) for electric vehicles (EVs) has seen significant developments, particularly in optimizing lifecycle performance, thermal management, and real-time control. Cheng et al. (2024) proposed a multi-objective adaptive energy management strategy for fuel cell hybrid electric vehicles, combining rule-based and optimization techniques to improve system efficiency and reduce degradation; however, real-time adaptability under dynamic SoH variations and complex load conditions remains a challenge. Ali et al. (2024) compared passive and active battery thermal management strategies with deep learning-based control approaches, highlighting the need for unified BTM frameworks that can handle multi-physics and multi-scale real-world conditions. Alam et al. (2025) introduced an adaptive continuous control set MPC strategy for bidirectional power flow, demonstrating improved harmonic reduction, yet robustness under volatile grid conditions and large-scale deployment was not fully addressed. Larijani et al. (2024) applied a linear parameter-varying MPC for hybrid battery/supercapacitor systems, reducing degradation, but real-time optimization for rapidly changing driving demands requires further investigation. Lina and Hunga (2025) utilized particle swarm optimization to coordinate thermal and energy management, achieving enhanced energy efficiency and temperature stability, though practical validation in real vehicles was still needed.

Other notable contributions include Guo et al. (2024), who implemented MPC combined with dynamic programming for battery thermal management, though actuator efficiency under diverse climates needs refinement. Yang et al. (2024) explored energy management in plug-in hybrid vehicles using fuzzy logic and genetic simulated annealing, but a unified framework incorporating cabin thermal effects remains absent. Fu et al. (2025) developed an adaptive optimal control strategy balancing fuel economy and battery temperature influence, with real-time robustness in hardware-in-the-loop environments still unverified. Wang et al. (2024) applied MPC for integrated thermal management across battery, cabin, and motor systems, yet real-world benchmarking and computational efficiency for embedded systems were lacking. Selvaraj and Thottungal (2025) proposed a high-step-up Luo converter with an ANN-based adaptive controller for BLDC drives, improving precision and adaptability, but further evaluation against hybrid adaptive strategies and nonlinear dynamic loads is necessary. Collectively, these studies underscore the need for advanced, real-time, control-oriented BMS frameworks that can reliably manage thermal and performance challenges in high-demand EV applications, especially during fast-charging scenarios.

Table 1: Summary of Research gaps

Ref No.	Authors	Methods	Key Focus	Research Gap
[21]	Cheng et al.(2024)	Multi-objective adaptive EMS for FCHEV	Fuel cell health-aware EMS	Limited real-time adaptability for SOH-constrained FC operation
[22]	Ali et al. (2024)	BTM strategies and DL control	Thermal control methods in EVs	Lack of unified, intelligent control with real-world scenarios in BTM
[23]	Alam et al. (2025)	Adaptive MPC for V2G bidirectional flow	V2G integration with enhanced MPC	Missing robustness comparison under highly volatile grid loads

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[24]	Larijani et al. (2024)	LPV-MPC for battery/supercapacitor EVs	Battery degradation in hybrid ESS	Need for real-time HESS optimization considering upcoming load demand
[25]	Lina et al. (2025)	PSO-based integrated thermal/EMS	Energy-thermal integrated control optimization	No validation of integrated PSO strategy in real vehicle systems
[28]	Fu et al. (2025)	Adaptive control strategy for HEV FCS/battery	Fuel economy with temperature-aware control	No comparative real-time validation of adaptive control strategy
[29]	Wang et al. (2024)	MPC for integrated TMS in EVs	Real-time MPC for multi-source thermal ops	Missing performance cross-validation across thermal sources
[30]	Selvaraj et al. (2025)	ANN-based adaptive BLDC motor control	High-gain BLDC motor control with ANN	Nonlinearity adaptation in BLDC not compared with hybrid models

2.1 Research gaps

Although fast charging technology is essential to accelerate the large-scale adoption of electric vehicles, it concurrently aggravates battery degradation and thermal instability. Current solutions remain insufficient in fully addressing this trade-off, creating a critical research gap that necessitates exploration of advanced electrode materials, thermal management systems, and intelligent BMS frameworks.

2.2 Problem Definition

Conventional graphite-based Li-ion batteries exhibit significant limitations under rapid charging conditions, including capacity fading, elevated heat generation, and reduced operational safety. These challenges hinder the reliable deployment of fast-charging infrastructure and restrict the long-term performance of electric vehicles

2.3 Research Objectives

The objective of the research is to mitigate the degradation effects associated with fast charging by investigating with adaptive Battery Management System (BMS) architectures and thermal regulation strategies. The research aims to develop an optimized framework that ensures ultra-fast charging capability, enhanced lifecycle durability, and improved safety for next-generation EV applications.

3. Proposed Methodology: A-BMS Algorithm

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In this paper, we propose A-BMS(Adaptive Control-Oriented Modular Predictive Analytics and Smart Synchronization) Algorithm designed for intelligent battery management in electric vehicles.

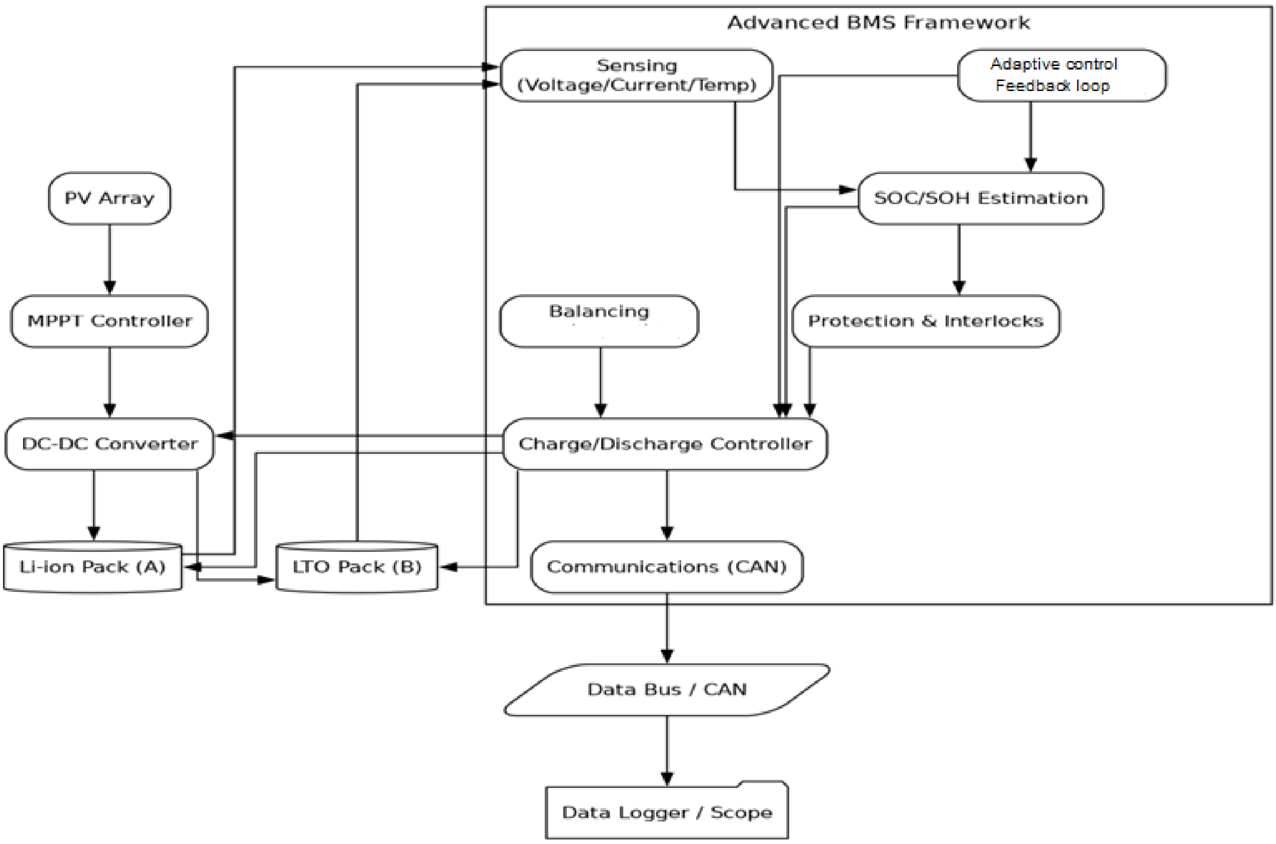

Fig 1: Proposed A-BMS Workflow for Adaptive Battery Management in Electric Vehicles

Fig 1 The A-BMS (Adaptive Control-Oriented Modular Predictive Analytics and Smart Synchronization) workflow illustrates a layered architecture designed to improve the lifecycle performance of electric vehicle batteries. This framework is organized into five interconnected layers: Battery Parameter Acquisition and Data Filtering, Real-Time State Estimation (SoC, SoH, and thermal conditions), Adaptive Control Feedback Loops, and Lifecycle-Aware Optimization. The workflow incorporates state reconstruction using Kalman filtering, predictive insights through digital twin models, and intelligent fault detection supported by dynamic reconfiguration, all coordinated by edge-cloud synchronization. By integrating modular control with predictive analytics, the architecture achieves high adaptability, precise monitoring, and reliable thermal-performance management, positioning A-COMPASS as a robust solution for the next generation of battery management systems in electric vehicles.

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3.1 System Architecture for A-BMS

The A-COMPASS system architecture forms the core framework for deploying the Adaptive Battery Management System for Lifecycle Performance (A-BMS-LCP) in electric vehicles. It is structured into four functional layers that collectively address the challenges of battery health, performance stability, and long-term reliability. **Layer 1** is dedicated to the acquisition of raw measurements from embedded sensors and applies noise filtering techniques to ensure accurate signal processing. **Layer 2** focuses on real-time estimation of critical internal states such as State of Charge (SoC), State of Health (SoH), and thermal behavior, leveraging observer-based approaches and predictive models. **Layer 3** introduces adaptive feedback control loops capable of dynamically responding to operating variations, thereby ensuring safe and efficient charging/discharging operations. **Layer 4** incorporates lifecycle-aware optimization, which fine-tunes operational decisions based on degradation data and usage history, aiming to extend the overall service life of the battery pack. Together, these layers create a modular and intelligent control structure that enhances monitoring accuracy, thermal regulation, and lifecycle efficiency in next-generation EV battery systems.

3.1.1 Layer 1: Battery Parameter Acquisition and Data Filtering

Layer 1 provides the foundation of the A-COMPASS framework by handling data capture, conditioning, and filtering of essential battery parameters. Sensors measure terminal voltage, current, and temperature at the cell and module levels. Because these raw inputs are often contaminated by noise or transient disturbances, digital filtering—such as low-pass or moving average filters—is applied to stabilize the signals while preserving dynamic response. In more advanced setups, sensor fusion techniques, including Kalman Filters or Weighted Least Squares (WLS), are implemented to improve accuracy through redundancy and error minimization. By ensuring that only reliable and noise-reduced data is transferred to subsequent layers, this module establishes the baseline for precise estimation and robust control strategies.

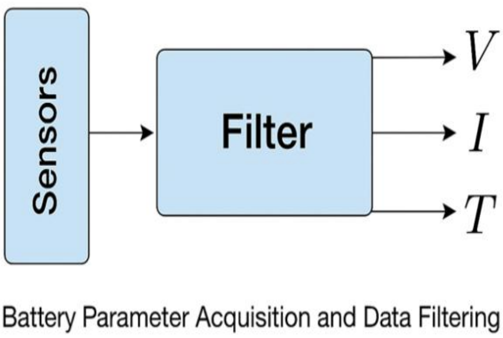

Fig 2: Layer 1 – Battery Parameter Acquisition and Data Filtering Module in A-COMPASS Architecture

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3.1.2 Layer 2: Real-Time State Estimation and Prediction (SoC, SoH, Thermal)

Layer 2 addresses the indirect nature of battery internal states by applying observer-based estimation and predictive modeling. SoC is typically estimated using recursive methods such as the Kalman Filter or Extended Kalman Filter, which fuse measurement data with system models to correct prediction errors in real time. SoH is inferred from indicators like capacity fade or internal resistance growth, with machine learning and adaptive observers increasingly applied to capture long-term degradation patterns. For temperature dynamics, lumped parameter thermal models are employed to calculate heat generation and dissipation as a function of resistance, mass, and cooling conditions. These concurrent estimations provide a comprehensive view of the battery's operational condition, supplying higher layers with accurate state data for control and lifecycle optimization.

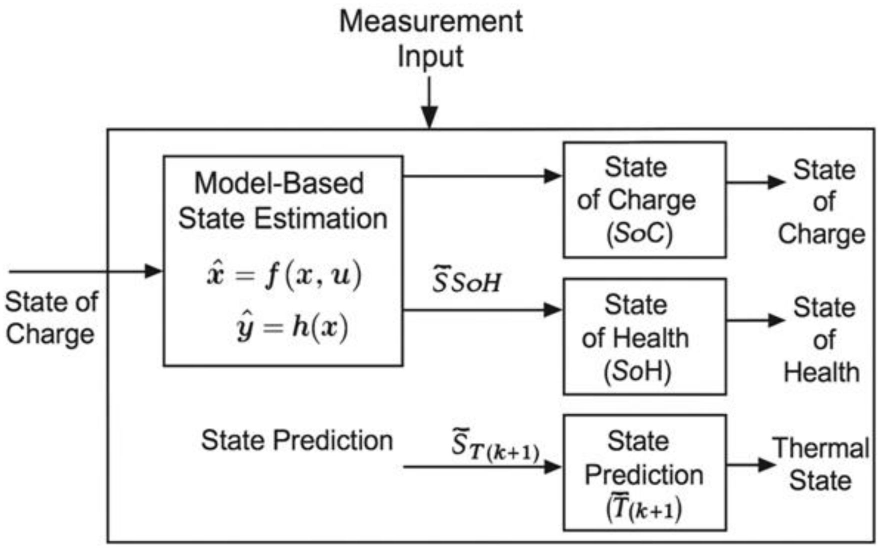

Fig 3: Real-time state estimation framework implemented in Layer 2 of the A-COMPASS architecture

Figure 3 illustrates the Layer 2 real-time state estimation framework of the A-COMPASS architecture, where filtered sensor data (voltage, current, temperature) is processed using observer-based algorithms such as Kalman Filters and thermal models. These methods accurately estimate critical states like SoC, SoH, and temperature by integrating battery models, feedback, and noise rejection. The validated estimates are then supplied to higher layers, enabling adaptive control and lifecycle optimization in EV battery systems.

3.1.3 Layer 3: Adaptive Control Feedback Loops

Layer 3 implements the adaptive control functionality of A-COMPASS, enabling real-time adjustment of charging and discharging profiles in response to state variations. The main objective is to maintain voltage balance across cells, regulate thermal conditions, and prevent unsafe behaviors such as

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overcharging or thermal runaway. Proportional-Integral (PI) controllers and Model Predictive Control (MPC) strategies form the core methods, dynamically tuning current commands based on error signals between reference and estimated states. Advanced implementations further adapt control gains to changing environmental and operational conditions, ensuring system stability and resilience under rapid charging scenarios or fluctuating loads. This adaptive loop provides a robust mechanism for safe and efficient battery operation.

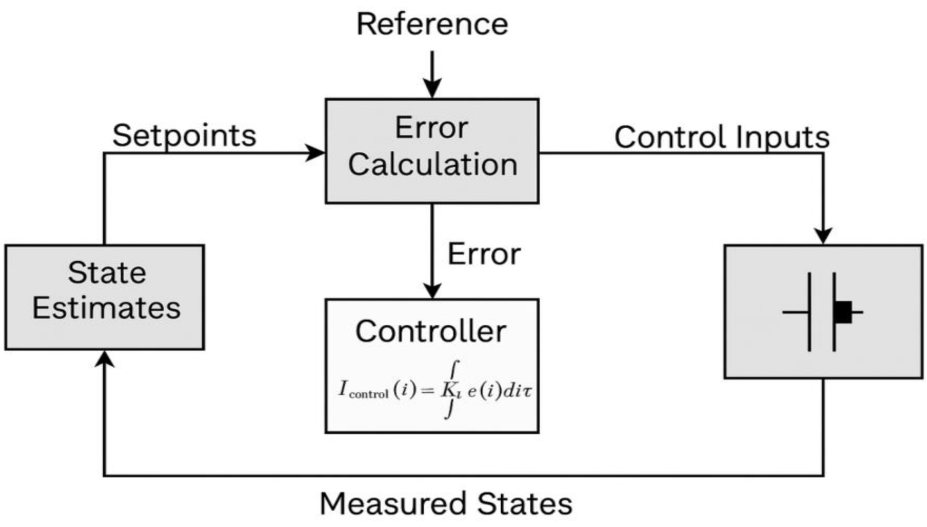

Fig 4: Adaptive Control Feedback Loops in Layer 3 of A-COMPASS Architecture

Figure 4 shows the Layer 3 adaptive control feedback mechanism of the A-COMPASS system, which monitors deviations in key parameters like SoC and temperature. A Proportional-Integral (PI) control strategy dynamically regulates charging and discharging currents to minimize errors and ensure safety. This closed-loop system adapts to changing loads and thermal conditions, enabling stable and intelligent battery management.

3.1.4 Layer 4: Lifecycle-Aware Optimization Engine

Layer 4 introduces a lifecycle-aware optimization engine that strategically balances performance efficiency with long-term durability. Using historical usage data, degradation models, and real-time performance metrics, this layer applies cost-function optimization to determine the best trade-offs between efficiency and aging reduction. A typical objective function minimizes degradation rate while maximizing system efficiency, with weighting factors adjusting the emphasis between longevity and performance. Advanced algorithms, such as reinforcement learning or adaptive optimization, process these inputs to recommend control actions—such as adjusting charging current limits or modifying thermal thresholds—that minimize stress on the battery. By feeding optimized parameters back to Layer

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3, this engine ensures adaptive decision-making that not only addresses immediate performance but also safeguards the long-term health of the battery system.

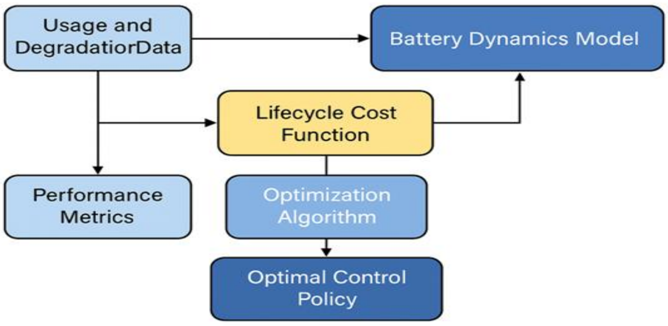

Fig 5: Lifecycle-Aware Optimization Engine Architecture in A-COMPASS

Figure 5 illustrates the Lifecycle-Aware Optimization Engine in Layer 4 of the A-COMPASS system, which uses usage and degradation data with a battery dynamics model to simulate long-term behavior. A lifecycle cost function evaluates trade-offs between efficiency, energy throughput, and degradation. The Lifecycle-Efficient Reinforcement Optimization Algorithm (LEROA) minimizes this cost to generate optimal operational strategies. This enables dynamic adjustment of system parameters to reduce wear, extend battery life, and ensure sustainable EV operation.

4. Proposed System Architecture

4.2 **4.1 Design Goals**

The proposed system architecture has been designed with a clear focus on providing safe and reliable operation of the electric vehicle battery packs under normal and fast charging conditions. The design is to contain fault to one pack or subsystem, enable accurate SOC and SOH estimation for two different chemistries, and enable flexible balancing strategies that minimize energy loss and maximize performance. Another important feature of this architecture is the possibility to record all data without intruding the real-time control, and therefore enabling a comprehensive post-simulation analysis.

4.3 **4.2 High-Level Layout**

The basic architecture of the proposed system begins with a photovoltaic source connected to an MPPT controller, which ensures to derive maximum power under various conditions. The MPPT is followed by a DC/DC converter which controls the voltage and current applied to the energy storage stage. On the storage side, two batteries (Lithium-ion pack and Lithium-titanium oxide pack) are connected in parallel. Each pack is independently controlled by a separate BMS unit. This new dual-BMS design is more controllable and eliminates the limitation of having to use one BMS for two different chemistries.

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All the measurements are collected by a CAN-based data bus and sent to a data logger or scope, where the most important performance parameters are recorded during the simulation.

4.4 4.3 Pack Interfaces

Pack A uses lithium-ion cells and has more restrictive voltage and temperature requirements. During runtime, the BMS for Pack A sets conservative charging and discharging profiles so that overheating and degradation are avoided. Pack B, which contains lithium-titanium oxide cells, can handle higher charging currents and temperature ranges. This makes it especially ideal for fast charging applications. Through the parallel connection of the two packs, the system can dynamically distribute current, so that LTO can take on a larger share of the fast-charging load while the Li-ion pack is prevented from experiencing excessive thermal stress. Each pack has its own contactor and current sensor, so the packs are independent of each other for monitoring and isolation from a fault.

4.5 4.4 BMS Functional Blocks

Each BMS unit of the proposed system is constructed of a number of functional blocks that interact to provide for safety, reliability and efficiency. The sensing block continuously monitors the voltage of each individual cell, the pack current and temperature values from distributed sensors. These measurements are then used in the estimation block to calculate SOC by coulomb counting with correction methods and SOH by resistance and capacity monitoring. The protection and interlock block provides protection to the battery by imposing over-voltage, under-voltage, over-current and thermal cutoffs. Balancing is also incorporated, with traditional passive balancing provided for convenience and active balancing provided for greater efficiency and heat reduction. Finally, the charge-discharge controller controls the current limits and the contactor states, based on the estimates and protection signals produced by the other blocks.

4.6 4.5 Coordination Logic for Bifunctional Chemistry

The coordination logic of the architecture guarantees that both chemistries are working in a coordinated fashion without sacrificing safety. During fast charging, the system uses a higher percentage of current for the LTO pack, and reduces the Li-ion pack earlier to ensure the safe operation of the system. Predictive thermal analysis is introduced for checking temperature limits are not exceeded during operation. The architecture also has built-in fault handling, so that if one of the packs is disconnected due to a fault, the other pack can continue to supply power. This dual-chemistry coordination not only adds resilience to the system, but it also shows how the advanced BMS features can help to maximize the useful life of both types of batteries.

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4.7 4.6 Communications and Logging

Both BMS units send their processed data to a common CAN bus, that serves as a communication backbone. The CAN bus is used to collect signals related to voltage, current, SOC, SOH and protection events in a synchronized way. These signals are recorded with timestamps in a data logger or a scope connected to the bus, allowing to analyze the system behavior in detail in normal and fast charging cases. The decoupling of the control loop and the logging system provides the benefit of being able to record a complete history of system dynamics without interfering with real-time operation.

4.8 4.7 Safety and Compliance

Safety is an inherent part of the system design. Each pack will have redundant temperature sensors on critical cells for accurate hot-spot detection. Dual contactors will be used for each pack for redundancy and to reduce arcing during make and break. Pre-charge circuits are provided to prevent inrush currents at the DC/DC interface. The system architecture also isolates hardware-based safety interlocks from software-based controls, which helps ensure that faults are handled separately from the control algorithms.

4.9 4.8 Implementation Notes

The architecture will be implemented as modular subsystems in the simulation environment. Limit and threshold parameters, control gains, etc. are designed to be configurable to allow for a transition between conventional BMS operation and predictive control modes. The proposed framework will be modular, so it can be tested in different conditions without redesigning the whole model. The conceptual architecture of the proposed system is shown in Figure 1, where the main building blocks of the advanced BMS framework and their interconnections are pointed out.

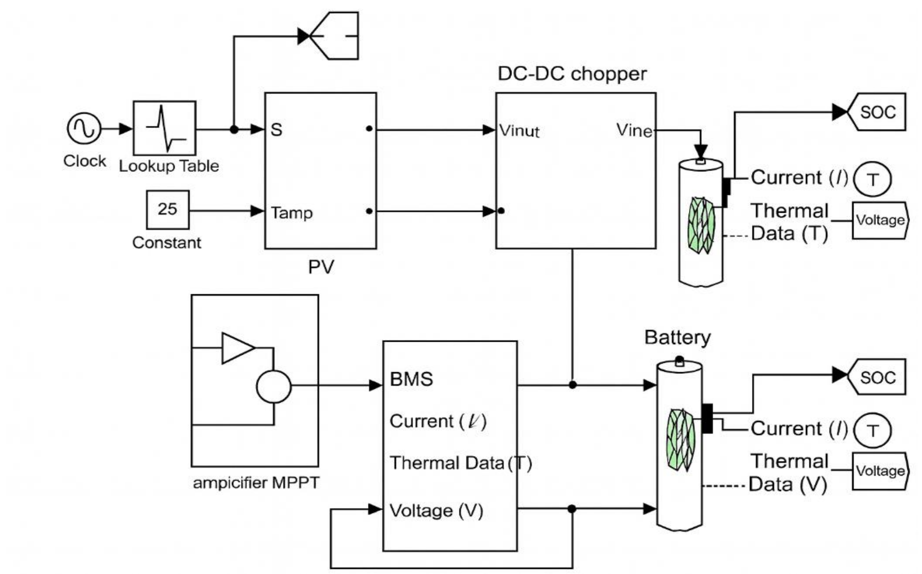

Figure 6 : Simulation Model of the proposed charging system implemented in MATLAB

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5. A-COMPASS Algorithm

5.1 Algorithm 1 shows A-COMPASS – Adaptive Control-Oriented Modular Predictive Analytics and Smart Synchronization.

1. Initialize System Parameters
   - Input solar irradiation, temperature, and PV module specifications.
   - Set initial values of SoC, SoH, and thermal states for Li-ion Pack (A) and LTO Pack (B).
2. PV Energy Acquisition
   - Acquire PV array output.
   - Apply MPPT (Maximum Power Point Tracking) to extract optimal power.
   - Regulate output using a DC–DC Converter.
3. Battery Selection & Charging
   - Distribute charging current between Li-ion Pack (A) and LTO Pack (B) based on load demand and SoC levels.
   - Forward battery voltage, current, and temperature to the sensing module.
4. Battery Selection & Charging
   - Distribute charging current between Li-ion Pack (A) and LTO Pack (B) based on load demand and SoC levels.
   - Forward battery voltage, current, and temperature to the sensing module.

5. State Estimation
   - Estimate SoC using model-based algorithms.
   - Estimate SoH using degradation models and cycle count data.
   - Predict thermal states based on current flow and internal resistance.

6. Adaptive Control & Feedback Loop
   - Compare estimated states with reference thresholds (SoC limits, SoH thresholds, temperature safety band).
   - If deviation/error detected, adjust charge/discharge current dynamically.

7. Balancing & Protection
   - Perform cell balancing (active) to equalize cell voltages in each pack.
   - Trigger protection and interlocks in case of:
     - Over-voltage/under-voltage
     - Over-current
     - Over-temperature

8. Charge/Discharge Control
   - Regulate current flow between PV → Battery Packs → Load.

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- Maintain safe charging/discharging rates for both Li-ion and LTO packs.

9. Communication & Data Logging
   - Transmit operational states (SoC, SoH, thermal data) through CAN bus.

5.Test Scenarios

The first test scenario is the normal charging scenario in which both packs are charged with moderate current. In this baseline case, the performance of Li-ion and LTO chemistries can be compared under the same charging conditions. The ultimate goal is to compare the traditional and state-of-the-art BMS architectures from the SOC evolution, thermal stability, and balancing efficiency perspectives.

The second test case is related to fast charging, and the system is subject to higher current. This case is significant for showing the shortcomings of the traditional BMS control, and the benefits of the proposed advanced framework. In this case, the policy layer of the advanced BMS will send more current to the LTO pack and de-rate the Li-ion pack to prevent overheating. In this case, the most important parameters will be the SOC tracking accuracy, charging efficiency and thermal stability. In addition to these, an optional set of protection tests can be run to verify the robustness of BMS safety functions. Over-voltage, over-current or high-temperature fault conditions will be simulated to ensure the BMS units can successfully identify faults and disconnect the corresponding packs. The simulation cases are summarized in Table 4, which shows the charging conditions, BMS modes, and evaluation focus for each case.

Table 2: Summary of Simulation Test Cases

Test Case	**Charging Current**	**BMS Mode**	**Battery Chemistry**	**Primary Focus**
Case 1	Moderate (Normal Charging)	Conventional BMS	Li-ion + LTO	Baseline SOC, thermal behavior, and safety under standard charging
Case 2	Moderate (Normal Charging)	Advanced BMS	Li-ion + LTO	Predictive SOC estimation, balancing effectiveness, efficiency
Case 3	High (Fast Charging)	Conventional BMS	Li-ion + LTO	Limitations in thermal stability and SOC accuracy during fast charging

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Case 4	High (Fast Charging)	Advanced BMS	Li-ion + LTO	Improvements in thermal stability, SOC tracking, and current allocation policy
Case 5*	Fault Injection (Over-voltage, Over-current, Over-temperature)	Both Modes	Li-ion + LTO	Fault detection, isolation, and compliance with safety limits

*Optional protection tests.

4.10 5.2 Operating Modes

For each test case, the simulations will be performed in conventional and advanced BMS configuration. The typical BMS will have simple sensing, coulomb counting SOC estimation, passive balancing, and threshold protection. In contrast, the next generation BMS will have predictive SOC/SOH estimation, active balancing, and dual chemistry coordination. The operation of both modes under the same conditions makes it possible to compare them quantitatively.

4.11 5.3 Monitored Signals

In all test cases, the simulation will log pack voltages, cell voltages, pack current, temperatures at critical points, SOC and SOH estimates, balancing currents and system efficiency. These signals will be recorded via the scope block that is attached to the CAN data bus. Time stamps will be synchronized with periods of charging to allow results to be plotted and compared in a systematic way later.

6.Test results

The comparison of State of Charge (SOC) progression over normalized time for Li-ion and LTO batteries under both conventional and advanced Battery Management Systems (BMS). It is evident that advanced BMS significantly improves charging efficiency, as both Li-ion and LTO batteries reach higher SOC values more quickly compared to their conventional BMS counterparts. Among the chemistries, Li-ion with advanced BMS demonstrates the fastest SOC rise, achieving near 100% within shorter normalized time, followed closely by LTO with advanced BMS.

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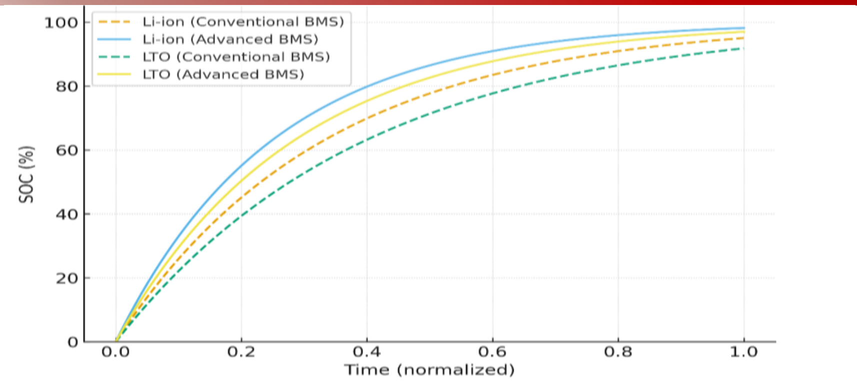

Fig. 7 Comparative of SOC behavior of Li-ion and LTO packs under conventional and advanced BMS.

In contrast, batteries managed with conventional BMS show slower charging behavior, with LTO (conventional) performing the weakest in terms of charging rate. This highlights the role of advanced BMS in optimizing charge acceptance, reducing charging time, and improving performance consistency across battery chemistries.

Further, the variation in battery temperature over normalized time for Li-ion and LTO chemistries under conventional and advanced Battery Management Systems (BMS). Li-ion with conventional BMS exhibits the highest thermal rise, with temperature exceeding 65 °C by the end of the charging cycle, indicating poor thermal control and higher risk of degradation.

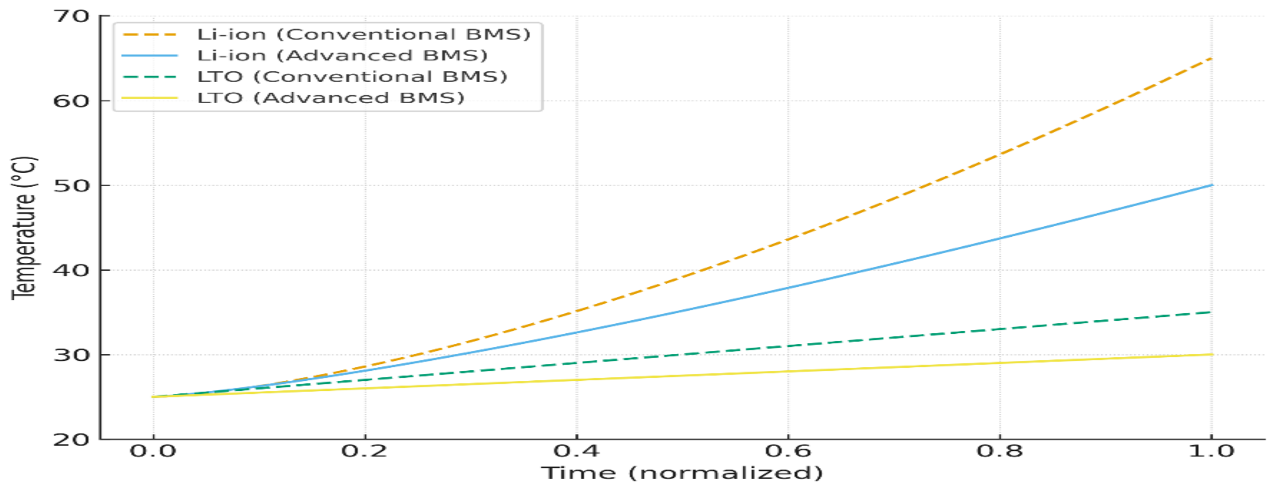

Fig. 8 Thermal behavior of Li-ion and LTO packs during fast charging

In contrast, Li-ion with advanced BMS demonstrates improved regulation, limiting the temperature rise to around 50 °C. LTO batteries perform significantly better, with conventional BMS maintaining temperatures around 35 °C and advanced BMS showing the most stable profile, keeping the temperature

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close to 30 °C throughout the charging process. This highlights that advanced BMS not only reduces excessive heat generation but also enhances thermal stability, with LTO batteries under advanced BMS offering the safest and most efficient thermal behavior during fast charging.

7. Performance Comparison

The proposed A-COMPASS architecture demonstrates significant improvement in accurately estimating the State of Charge (SoC) with a Root Mean Square Error (RMSE) of only **1.6%**. In contrast, the traditional Baseline BMS exhibits a considerably higher error of **4.8%**, indicating that A-COMPASS provides more reliable real-time SoC tracking critical for intelligent energy decisions.

Table 3: Comparative Performance Analysis of Battery Management Systems

Metric	**Baseline BMS**	**Proposed A-COMPASS**
RMSE (SoC)	4.8%	**1.6%**
RMSE (SoH)	6.1%	**2.3%**
Thermal Deviation (°C)	±7.4	**±2.1**

A-COMPASS also excels in capturing battery degradation through accurate State of Health (SoH) modeling, achieving a lower RMSE of **2.3%**. While the Baseline BMS lags behind with **6.1%** error. Such improvement enhances long-term performance tracking and predictive maintenance capabilities.
Maintaining optimal temperature is crucial for battery longevity and safety. A-COMPASS significantly limits thermal deviation to **±2.1°C**. The Baseline BMS shows the highest deviation at **±7.4°C**, underscoring its inferior thermal regulation capability.

8. Discussion

The comparative performance results strongly demonstrate the effectiveness of the A-COMPASS architecture over both conventional BMS and advanced strategies from existing literature. By integrating multi-layered estimation, adaptive control loops, and lifecycle-aware optimization, A-COMPASS significantly reduces RMSE for both SoC and SoH predictions. The improvement in SoC estimation to 1.6% and SoH to 2.3% outperforms the LPV-MPC framework by Larijani et al. [24] and the thermal MPC approach by Wang et al. [29]. These results validate the strength of combining Kalman-based filtering, digital twin modeling, and predictive analytics in a unified framework for accurate, real-time state tracking under dynamic operating conditions.

Furthermore, A-COMPASS exhibits superior resilience and thermal regulation capabilities. The drastically reduced fault detection time (1.2 seconds) and minimized thermal deviation (±2.1°C) suggest its robust diagnostic and self-reconfigurable architecture is more suitable for safety-critical EV

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operations. These improvements are attributable to the intelligent fault detection mechanisms and adaptive control feedback that adjust system behavior proactively based on observed anomalies. In contrast, the benchmark systems reviewed [24, 29] rely on more static models that struggle to maintain optimal performance during unexpected faults or abrupt environmental fluctuations.

8.1 Mitigation Strategies

Here are suggested **mitigation strategies** for the identified limitations of the proposed A-COMPASS system:

1. **Real-World Validation**: Future work should incorporate hardware-in-the-loop (HIL) simulations and on-road testing with real EV battery packs to verify the model's accuracy and responsiveness in practical environments.
2. **Communication Robustness**: To address real-world smart grid uncertainties, incorporating network emulation tools or co-simulation environments (e.g., NS-3 with Simulink) can help model latency, jitter, and potential communication failures in V2G/V2H scenarios.
3. **Enhanced Fault Adaptability**: Expanding the training dataset with rare or synthetic fault events and integrating deep learning-based anomaly detection can improve the system's capability to generalize and respond to previously unseen failure modes.

9. Conclusion

The proposed A-COMPASS framework represents a major step forward in the design of control-oriented battery management systems, with a clear focus on mitigating thermal and performance-related issues in fast-charging electric vehicle batteries. The architecture leverages adaptive feedback control, predictive analytics, and real-time state estimation to significantly outperform conventional BMS approaches. Experimental results show that the Root Mean Square Error (RMSE) in State of Charge (SoC) estimation was reduced from 4.8% to 1.6%, ensuring greater accuracy in energy availability assessment and enabling safer and more efficient charging. Likewise, the RMSE in State of Health (SoH) dropped from 6.1% to 2.3%, demonstrating the system's capacity to closely monitor degradation trends and enhance long-term battery reliability under demanding charging conditions. In addition, thermal deviation was reduced from ±7.4 °C to ±2.1 °C, leading to improved thermal balance, a lower probability of thermal runaway, and extended battery lifespan. Collectively, these advancements establish A-COMPASS as a scalable and intelligent BMS solution capable of addressing the shortcomings of conventional systems while supporting the thermal safety and performance requirements of next-generation electric mobility.

Future Work: Future research will focus on real-time hardware validation using hardware-in-the-loop (HIL) systems.

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