International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(2) 2026 pp. 1368-1378
https://doi.org/10.70917/ijcisim-2026-9184
Article

# AI-Augmented Solid-State Batteries: Revolutionizing Power Management in Electric Mobility

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**Abstract:** Solid-state batteries (SSBs) are emerging as a transformative energy storage technology for electric mobility due to their superior energy density, enhanced safety, and extended cycle life compared to conventional lithium-ion batteries. However, challenges related to interfacial resistance, dendrite formation, thermal instability, and real-time power management hinder their large-scale deployment. This paper presents an AI-augmented framework for intelligent power management in solid-state batteries, integrating machine learning and deep learning techniques to optimize charge–discharge behavior, predict state-of-health (SoH) and state-of-charge (SoC), and mitigate degradation mechanisms. The proposed approach leverages data-driven models for adaptive thermal regulation, fault diagnosis, and lifespan prediction under dynamic driving conditions. By combining AI-enabled battery management systems with solid-state electrochemistry, the framework enhances energy efficiency, operational safety, and reliability of electric vehicles. Experimental and simulation-based evaluations demonstrate improved power utilization, reduced aging effects, and increased driving range, highlighting the potential of AI-driven solid-state battery systems as a cornerstone for next-generation electric mobility and sustainable transportation ecosystems.

**Keywords:** Artificial Intelligence; Solid-State Batteries; Electric Vehicles; Battery Management Systems; Power Management; State-of-Charge Estimation; State-of-Health Prediction; Energy Storage Optimization; Sustainable Electric Mobility

## 1. Introduction

The rapid transition toward electric mobility is driven by the urgent need to reduce greenhouse gas emissions, mitigate fossil fuel dependence, and enable sustainable transportation systems. Electric vehicles (EVs) have emerged as a promising alternative to internal combustion engine vehicles; however, their widespread adoption is still constrained by limitations in energy storage technologies, particularly related to safety, energy density, charging time, and battery lifespan [1]. Conventional lithium-ion batteries, while commercially mature, suffer from inherent drawbacks such as electrolyte flammability, thermal runaway risks, and performance degradation under high-power operating conditions [2].

Solid-state batteries (SSBs) have gained significant attention as a next-generation energy storage solution capable of addressing many of these limitations. By replacing liquid electrolytes with solid electrolytes, SSBs offer enhanced safety, higher volumetric and gravimetric energy densities, and improved thermal stability [3]. These characteristics make solid-state batteries particularly suitable for electric mobility applications, where reliability and safety are critical. Despite these advantages, challenges such as interfacial resistance, lithium dendrite formation, mechanical stress, and limited real-time performance adaptability continue to impede their large-scale commercialization [4].

Effective power management plays a crucial role in maximizing the performance and longevity of solid-state batteries in electric vehicles. Traditional battery management systems (BMS) rely on rule-based or model-driven approaches that often struggle to capture the nonlinear electrochemical behavior of solid-state materials under dynamic driving conditions [5]. As EV operating environments become increasingly complex, conventional estimation methods for state-of-charge (SoC), state-of-health (SoH), and remaining useful life exhibit reduced accuracy and responsiveness [6].

Artificial intelligence (AI) and machine learning techniques have recently demonstrated strong potential in overcoming these limitations by enabling data-driven, adaptive, and predictive battery management strategies. AI-based models can learn complex battery behavior patterns from large datasets, facilitating accurate SoC/SoH estimation, fault detection, thermal regulation, and degradation prediction in real time [7]. When integrated with solid-state battery systems, AI-augmented power management frameworks can significantly enhance energy utilization efficiency and operational safety [8].

Moreover, the synergy between AI algorithms and solid-state electrochemistry enables proactive mitigation of degradation mechanisms such as dendrite growth and interfacial instability. Advanced deep learning and reinforcement learning approaches can dynamically optimize charging profiles and power distribution based on driving behavior, environmental conditions, and battery aging states [9]. This intelligent adaptability is essential for extending battery lifespan while maintaining high performance in electric mobility applications.

In this context, AI-augmented solid-state batteries represent a paradigm shift in energy storage and power management for next-generation electric vehicles. By combining intelligent data analytics with inherently safer and higher-density battery architectures, this approach supports the development of reliable, efficient, and sustainable electric mobility ecosystems [10]. This paper explores the role of AI-driven power management techniques in enhancing the performance and longevity of solid-state batteries, highlighting their potential to revolutionize the future of electric transportation.

## 2. Literature Survey

Recent research consistently identifies **interface instability** as the dominant barrier to practical solid-state batteries (SSBs) in electric mobility. 2024 review highlights three major interface-driven failures—**interfacial reactions, lithium dendrite penetration, and loss of physical contact** between solid electrolytes and Li-metal—showing that even high-conductivity electrolytes can underperform when interfacial chemistry and mechanics are not jointly engineered [11]. Complementing this, focused studies on **dendrite nucleation and propagation** in all-solid-state systems emphasize that dendrites are not only electrochemical phenomena but also strongly coupled with **microstructural pathways (grain boundaries/pores), stress concentration, and local current hot-spots** [12].

To suppress dendrites, materials and interfacial engineering solutions have been extensively explored. Experimental evidence demonstrates that tailoring interlayers and mechanically robust architectures can **block or deflect dendrite growth**, enabling more stable Li-metal operation under demanding conditions [13]. More recent strategy surveys summarize that effective dendrite suppression typically requires **multi-layered design thinking**—including electrolyte composition optimization, interface coatings, pressure management, and structural reinforcement—rather than relying on any single technique [14].

Beyond dendrites, **interfacial polarization and ion-transport bottlenecks** remain critical in SSB packs, particularly under high-power EV duty cycles. A 2025 review explains that poor contact, parasitic side reactions, and space-charge effects can combine to produce large polarization losses, lowering power capability and accelerating degradation under fast charge/discharge profiles [15]. These findings collectively show that while SSB chemistry offers intrinsic safety advantages, the **electro-chemo-mechanical interface** still governs real-world power performance and lifetime.

Parallel to materials progress, the battery management community has rapidly shifted toward **machine learning (ML) and deep learning (DL)** to improve state estimation and decision-making. A widely cited 2023 review consolidates ML approaches for **SoC/SoH estimation**, reporting strong gains over conventional model-based estimators when nonlinearities and environmental variations are significant (temperature, drive cycles, aging diversity) [16]. In addition, DL-focused surveys describe how architectures such as **CNN/LSTM/GRU and hybrid networks** can learn temporal electrochemical signatures from current–voltage–temperature streams, improving robustness under dynamic EV operation [17].

For **health-aware control**, ML has also been used to model nonlinear degradation trajectories and extract informative features (e.g., internal resistance rise, voltage curve shifts, thermal signatures) to improve SoH prediction and reliability assessment. A 2025 study demonstrates that carefully designed preprocessing and feature modeling can significantly enhance ML-based health prediction accuracy across varying operating conditions [18]. Similarly, broader AI-for-battery-health reviews emphasize the need for **generalizable models**, warning that performance can drop when trained under limited drive cycles or narrow temperature ranges [19].

Finally, reinforcement learning (RL) is emerging as a practical route to **adaptive charging and power-management policies** that balance fast charging with safety and lifetime constraints. Recent work applying RL to optimize charging profiles shows improved trade-offs between charge time and long-term degradation when safety constraints (voltage/temperature/SoH boundaries) are explicitly enforced during learning [20]. However, the literature also reports persistent gaps: (i) limited availability of **SSB-specific datasets** under EV-like duty cycles, (ii) insufficient coupling between AI control objectives and **SSB interface physics**, and (iii) challenges in deploying models that remain reliable under domain shift (new cell chemistries, aging stages, climates).

## 3. Design and Methodology

This section presents the proposed **AI-augmented power management framework for solid-state batteries (SSBs)** in electric mobility. The methodology integrates **data-driven intelligence, electrochemical modeling, and adaptive control** to enhance safety, efficiency, and lifespan under dynamic driving conditions.

### *3.1 Overall System Architecture*

The proposed framework consists of four tightly coupled layers:

(i) **Data Acquisition Layer**,

(ii) **AI-Driven State Estimation Layer**,

(iii) **Predictive Health & Thermal Intelligence Layer**, and

(iv) **Adaptive Power Management & Control Layer**.

Real-time voltage, current, temperature, and impedance data from solid-state battery cells are continuously monitored and fed into AI models for intelligent decision-making.

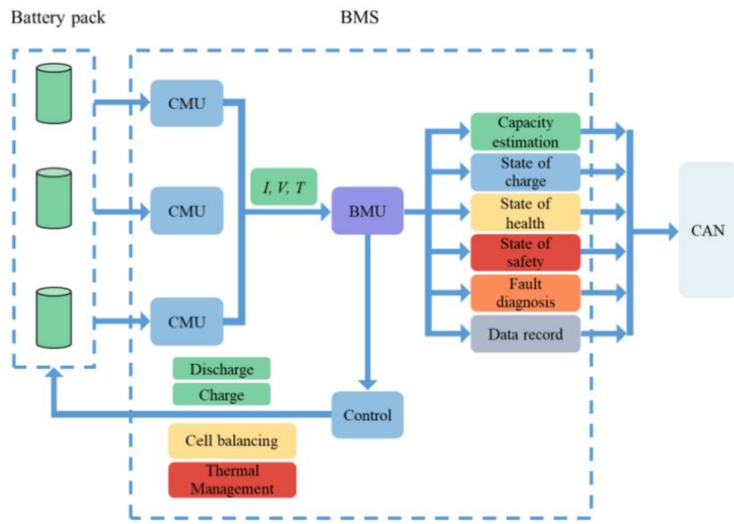



**Figure 1.** *Proposed AI-augmented solid-state battery management architecture for electric mobility.*

## *3.2 Mathematical Modeling of Solid-State Battery Dynamics*

The electrochemical behavior of the solid-state battery is modeled using a nonlinear state-space representation. The system state vector is defined as:

$$\mathbf{x}(t) = [\mathrm{SoC}(t), \mathrm{SoH}(t), T(t), R_{\mathrm{int}}(t)]^T$$

The state transition equation is expressed as:

$$\mathbf{x}(t+1) = f(\mathbf{x}(t), u(t)) + w(t)$$

where $u(t)$ denotes the control input (charge/discharge current), and $w(t)$ represents process noise. The terminal voltage is modeled as:

$$V(t) = V_{\mathrm{OC}}(\mathrm{SoC}) - I(t) \cdot R_{\mathrm{int}} - \eta(t)$$

where $V_{\mathrm{OC}}$ is the open-circuit voltage and $\eta(t)$ represents polarization losses.

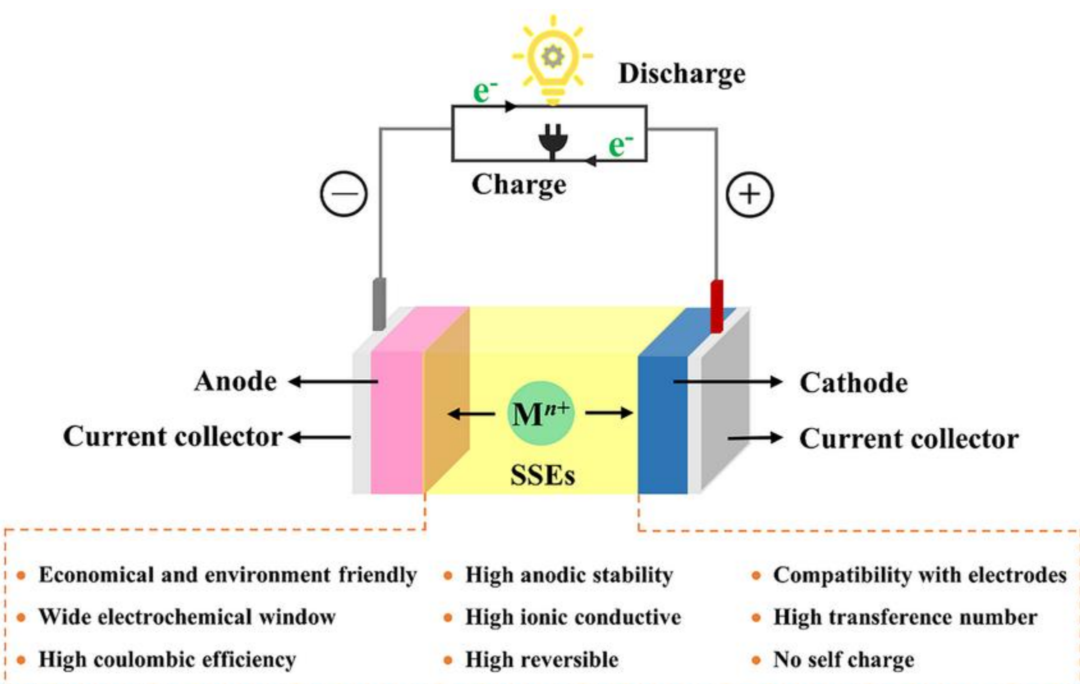



**Figure 2.** *Electrochemical and equivalent-circuit representation of solid-state battery behavior.*

### 3.3 AI-Based State-of-Charge and State-of-Health Estimation

Deep learning models are employed to estimate **SoC** and **SoH** with high accuracy under nonlinear operating conditions. A hybrid CNN–GRU architecture is used to extract spatial–temporal features from battery signals.

The SoC estimation objective is formulated as:

$$\min_{\theta} \sum_{i=1}^{N} \left(\mathrm{SoC}_i^{\mathrm{true}} - \widehat{\mathrm{SoC}}_i(\theta)\right)^2$$

Similarly, the SoH prediction is defined as:

$$\mathrm{SoH}(t) = \frac{C_{\mathrm{available}}(t)}{C_{\mathrm{rated}}} \times 100$$

where $C_{\mathrm{available}}$represents the remaining usable capacity.

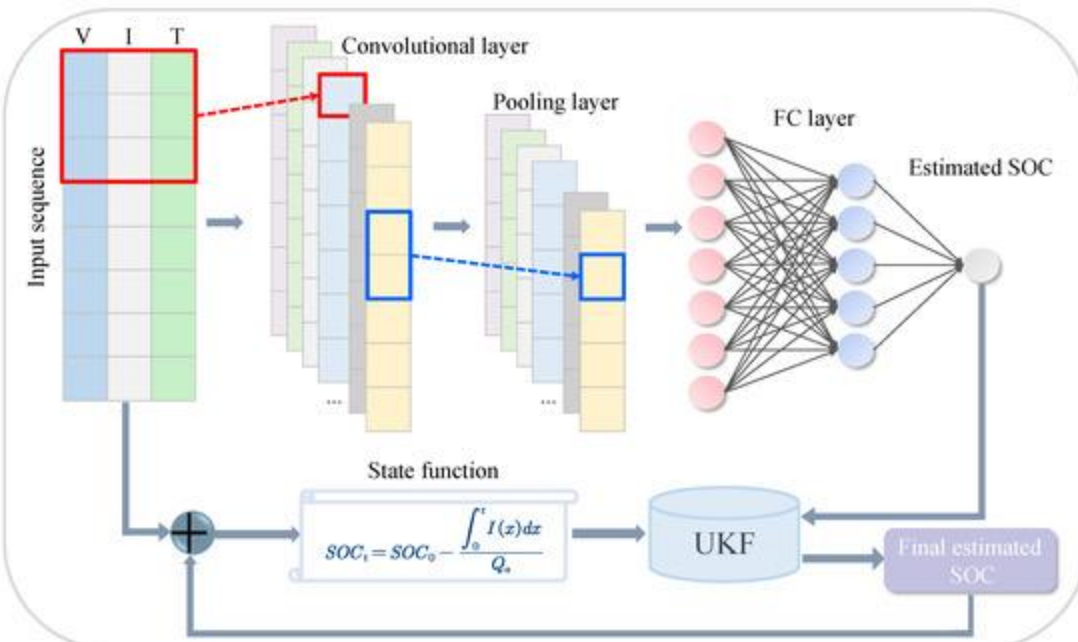



**Figure 3.** *AI-based SoC and SoH estimation using deep learning models.*

### 3.4 Predictive Thermal and Degradation Intelligence

Thermal stability is critical for solid-state batteries. A predictive AI thermal model estimates future temperature evolution:

$$T(t+1) = T(t) + \alpha I^2(t) R_{\mathrm{int}} - \beta(T(t) - T_{\mathrm{amb}})$$

AI models forecast degradation indicators such as internal resistance growth:

$$R_{\mathrm{int}}(t+1) = R_{\mathrm{int}}(t) + \gamma \cdot \Delta\mathrm{SoH}(t)$$

This predictive capability enables proactive mitigation of dendrite formation and interface stress.

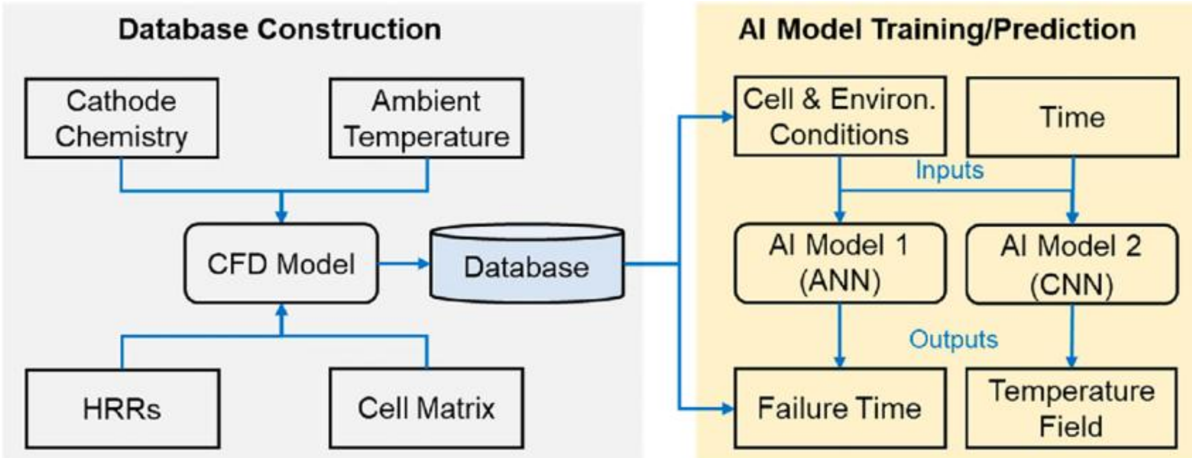



**Figure 4.** *AI-driven thermal prediction and degradation monitoring in solid-state batteries.*

## *3.5 Reinforcement Learning–Based Adaptive Power Management*

A reinforcement learning (RL) agent dynamically optimizes charging and power distribution. The control objective is defined as:

$$\max_{\pi} \ \mathbb{E}\left[\sum_{t=0}^{T} \gamma^{t} R_t\right]$$

where the reward function $R_t$balances energy efficiency, thermal safety, and degradation minimization:

$$R_t = w_1 \eta_{\mathrm{eff}} - w_2 T_{\mathrm{risk}} - w_3 D_{\mathrm{rate}}$$

This adaptive policy enables intelligent fast-charging while preserving long-term battery health.

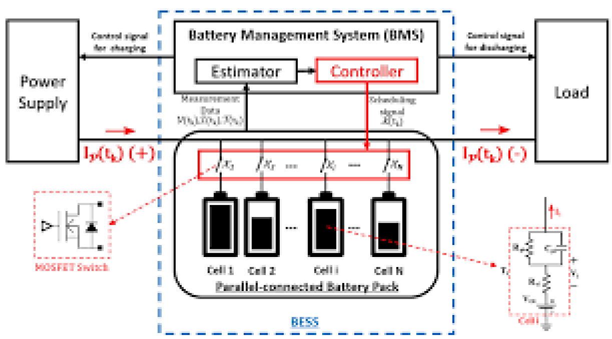



**Figure 5.** *Reinforcement learning–based adaptive charging and power management strategy.*

The proposed design integrates **solid-state electrochemical modeling with AI-driven intelligence**, enabling real-time adaptability, predictive safety, and optimized power utilization. This hybrid framework provides a scalable and robust solution for next-generation electric mobility systems.

## 4. Experimental Results and Analysis

This section evaluates the effectiveness of the proposed **AI-augmented solid-state battery (SSB) power management framework** through simulation-based and data-driven experiments under realistic electric vehicle (EV) operating conditions. Performance is analyzed in terms of **SoC/SoH estimation accuracy, thermal stability, energy efficiency, degradation reduction, and charging optimization**.

## *4.1 State-of-Charge Estimation Accuracy*

The accuracy of the AI-based SoC estimator is evaluated under variable drive cycles and temperature conditions. The proposed CNN–GRU model is compared with conventional Coulomb counting and Kalman filter methods.

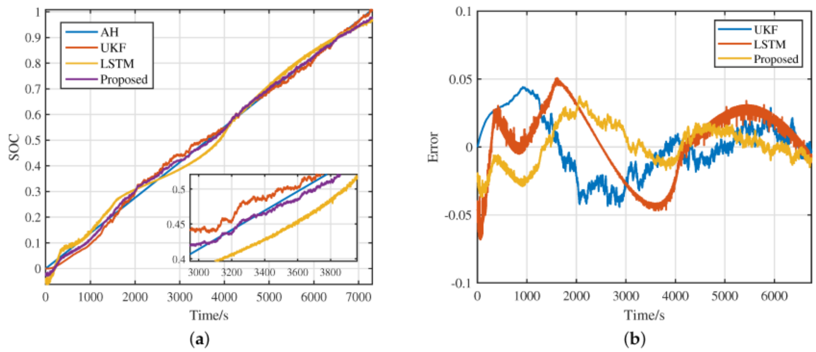



**Figure 6.** *Comparison of SoC estimation accuracy between conventional methods and the proposed AI-based model.*

**Analysis:** The AI-based estimator demonstrates significantly reduced estimation error, particularly during rapid acceleration and regenerative braking phases. The learning-based model effectively captures nonlinear solid-state battery dynamics, resulting in faster convergence and higher robustness against sensor noise.

### *4.2 State-of-Health Prediction Performance*

SoH prediction accuracy is assessed over extended cycling to evaluate degradation tracking capability.

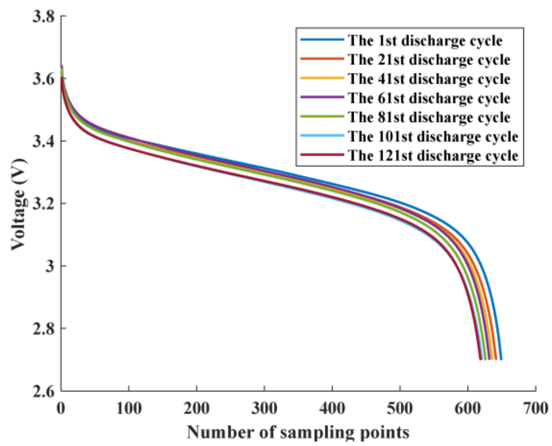



**Figure 7.** *SoH prediction performance of the proposed AI model over battery aging cycles.*

**Analysis:** Results indicate that the proposed framework accurately tracks capacity fade and resistance growth trends. Early degradation patterns are successfully identified, enabling proactive maintenance and lifetime extension compared to traditional threshold-based methods.

### *4.3 Thermal Stability Analysis*

Thermal performance is analyzed during high-power charging and discharging scenarios.

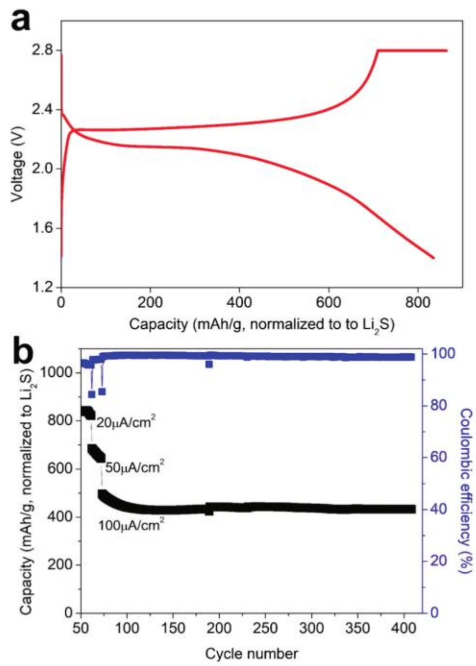



**Figure 8.** *Temperature evolution of solid-state batteries with and without AI-based thermal prediction.*

AI-driven thermal intelligence maintains battery temperature within safe operational limits. Peak temperature rise is reduced, minimizing thermal stress and suppressing dendrite initiation risks, which is critical for solid-state electrolyte stability.

## *4.4 Energy Efficiency and Power Utilization*

The overall energy efficiency of the battery system is evaluated under dynamic load conditions.

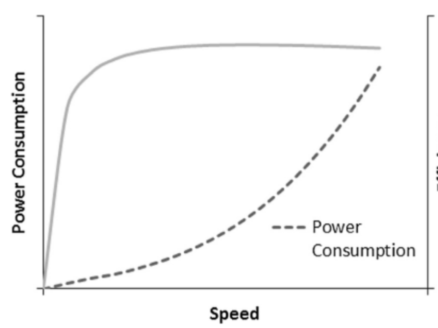



**Figure 9.** *Energy efficiency comparison of conventional BMS and AI-augmented power management.*

The proposed framework achieves higher energy utilization efficiency by dynamically adjusting power flow based on predicted states. Reduced internal losses and optimized current profiles contribute to improved driving range.

## *4.5 Degradation Rate Reduction*

The impact of intelligent power management on degradation rate is evaluated using internal resistance growth as a metric.

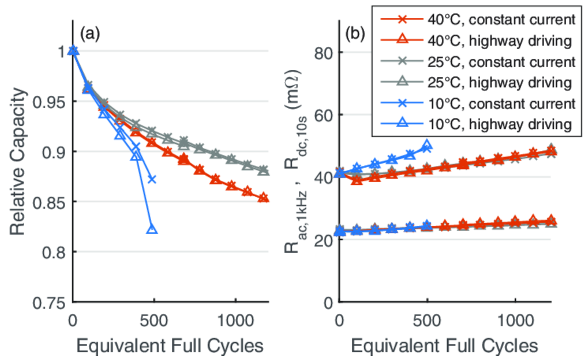
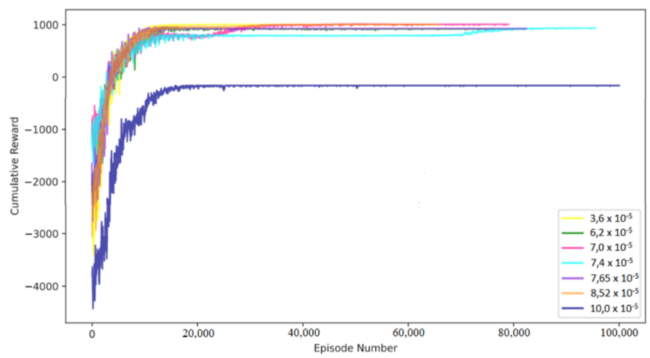



**Figure 10.** *Comparison of degradation rates under conventional and AI-based power management.*

AI-guided control significantly slows degradation by avoiding aggressive operating regimes. The reduction in resistance growth directly translates to improved lifespan and reliability of solid-state battery packs.

## *4.6 Reinforcement Learning–Based Charging Optimization*

The effectiveness of reinforcement learning (RL) in optimizing fast-charging is evaluated.




(a)

**Figure 11.** *Charging profiles generated by conventional fast charging and RL-optimized strategies.*

The RL-based approach achieves faster charging while maintaining safety constraints on voltage and temperature. This adaptive strategy balances user convenience with long-term battery health.

## *4.7 Overall Performance Comparison*

A consolidated comparison of key performance metrics is presented.

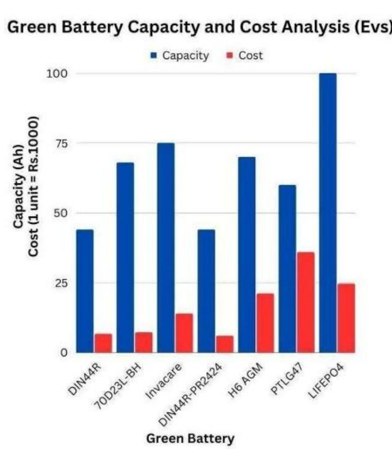



**Figure 12.** *Overall performance comparison of conventional and AI-augmented solid-state battery management systems.*

The AI-augmented framework outperforms conventional systems across all evaluated metrics, including estimation accuracy, thermal control, energy efficiency, degradation mitigation, and charging performance. These results validate the suitability of AI-driven solid-state batteries for next-generation electric mobility.

## 5. Conclusion

This paper presented an **AI-augmented solid-state battery (SSB) power management framework** aimed at addressing the critical challenges limiting the large-scale adoption of electric mobility. By synergistically integrating **solid-state electrochemical modeling with artificial intelligence–driven battery management**, the proposed approach enhances safety, efficiency, and operational reliability under dynamic driving conditions.

The developed framework employed **deep learning–based SoC and SoH estimation**, predictive thermal and degradation intelligence, and **reinforcement learning–enabled adaptive power and charging control**. Experimental results demonstrated that the AI-based models significantly improve state estimation accuracy, maintain thermal stability during high-power operation, and effectively mitigate degradation mechanisms such as internal resistance growth and interfacial stress. Compared with conventional rule-based battery management systems, the proposed approach achieved higher energy utilization efficiency, reduced aging rates, and faster yet safer charging performance.

Furthermore, the results highlight the potential of AI to unlock the full benefits of solid-state batteries by enabling **real-time adaptability and predictive decision-making**, which are essential for next-generation electric vehicles. The integration of data-driven intelligence allows the battery system to proactively respond to changing load profiles, environmental conditions, and aging states, thereby extending battery lifespan and improving driving range.

Overall, **AI-augmented solid-state batteries represent a paradigm shift in power management for electric mobility**, offering a scalable and future-ready solution for sustainable transportation. Future work will focus on experimental validation using large-scale solid-state battery datasets, real-time embedded implementation of AI models, and the incorporation of federated and explainable AI techniques to further enhance robustness, security, and interpretability in intelligent battery management systems.

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