



AI-Driven Adaptive Control for Battery Management Systems in Electric Vehicles

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Abstract: With increasing global demand for green transportation, the urge to innovate and implement electric vehicles (EVs) has also picked up steam. Behind the performance, safety, and reliability of EV stands the Battery Management System (BMS) that optimizes battery performance through monitoring, management, and protection of the battery pack. Traditional BMS designs have rule-based or model-based approaches with static parameters, which are not sufficiently adaptive to deal with real usage patterns and battery aging effects. The presented paper proposes a scheme of adaptive control based on AI for BMS utilizing the ML and DL algorithms to enhance system robustness, extend the life of the battery, and optimize charging/discharge operations. The proposed system utilizes neural networks and reinforcement algorithms to estimate dynamic state of charge (SoC), state of health (SoH), and temperature control against varying loads and ambient conditions. We compare the operation of our framework with traditional BMS controllers through HIL tests and simulation. Our findings indicate that AI-based BMS delivers more accurate predictions, fault tolerance, better energy efficiency and battery life improvements. This paper presents a critical survey of common AI use cases employed in BMS, proposes a novel hybrid AI architecture for adaptive real-time control, and proposes deployment strategies that can be deployed on the latest EV platforms. Future work opportunities involve integrating edge-AI for real-time inferencing and federated learning for privacy-respecting data analysis in distributed EV fleets.

Keywords: Battery Management System (BMS), Electric Vehicles (EV), Artificial Intelligence (AI), Adaptive Control, Machine Learning (ML), Deep Learning (DL), State of Charge (SoC), State of Health (SoH), Reinforcement Learning (RL), Edge-AI.

1. Introduction

1.1 Background and Motivation

Electric vehicles (EVs) are transforming the transport industry at a very fast rate with EV technology being the most efficient means of curbing greenhouses and depleting fossil fuel consumption. Being one of the largest generators of carbon emissions globally, the transport industry, governments, and global institutions are all placing their bets on EV technology to enhance the sustainability of the environment. Reported directly to each EV is the energy storage component, most often lithium-ion batteries, greatly sought after for high energy density, high cycle count, and minimal self-discharge. Such batteries, though, are a vaunted art to accomplish, something that necessitates careful oversight and precisely tuned in the effort to provide safety, provide optimal performance, and enhance life. This is where the Battery Management System (BMS) comes into play.

A BMS is responsible for keeping track of parameters like voltage, current, and temperature of the battery, forecasting alarming situations like State of Charge (SoC) and State of Health (SoH), and safe operation by offering protection against short circuit, thermal runaway, overcharge, and over-discharge. Since EVs are being produced in higher powers and usage patterns differ, the function of a BMS becomes more significant. Battery

performance, safety, and reliability have direct impacts on user satisfaction and vehicle reliability. Thus, there is an urgent need for BMS solutions that can adaptively learn to respond to different operating environments, vibrating battery dynamics, and real-time user lifestyles. The motivation of this research originates from the motivation, which tries to explore the application of AI techniques into BMS design and control. Through the support of the adaptive capacity of AI, EV battery management can now be designed to make them smart, efficient, and trustworthy energy storage units for future electric mobility.

1.2 Limitations of Traditional BMS

Rule-based algorithms and equivalent circuit models are the primary methods for designing conventional Battery Management Systems (BMS). They rely on pre-defined thresholds and deterministic logic. They function well under known, steady-state conditions but lose precision and efficiency in practical applications involving dynamic load conditions, varying ambient temperatures, and gradual battery degradation. As for instance, universal practices such as Coulomb counting and Kalman filtering to calculate SoC have a high vulnerability to long-term drift and considerably depend on precision initial values alongside the adjustment of parameters. Similarly, SoH estimation algorithms commonly rely on assumptions of fixed pattern for

degradation loss, excluding randomness in usage patterns, environmental changes, or variations in manufacturing characteristics. But still another critical shortcoming of traditional BMS is their inability to extrapolate across different battery chemistries and pack arrangements without significant re-engineering. As diversity in EV platforms increases, batteries are subjected to new stressors and aging modes, one-size-fits-all methods of BMS are no longer adequate. Traditional systems are also not real-time adaptive, resulting in conservative operating margins that reduce the efficiency of battery utilization. These inefficiencies manifest as lower driving range, longer charging times, and greater likelihood of premature cell aging.

Moreover, rule-based logic does not possess the capability to learn from previous data or predict upcoming states. This inability to anticipate and adapt tends to lead to missed opportunities for energy optimization and fault prevention in advance. As EV uptake rises globally, and as performance and reliability demands from consumers continue to escalate, the constraints of conventional BMS designs present significant challenges. These are issues that emphasize the need for smarter, more flexible, and data-driven approaches capabilities that artificial intelligence (AI) technologies are well positioned to deliver.

1.3 Emergence of AI in BMS

Artificial Intelligence (AI) has emerged as a revolutionary technology in several fields, and its application to Battery Management Systems (BMS) is also attracting growing attention. The nonlinear behavior of batteries combined with the heterogeneity of usage environments in electric vehicles (EVs) renders AI a perfect candidate for improving BMS performance. AI computations i.e., those that use machine learning (ML) and deep learning (DL) can simulate dynamic systems with complicated behaviors without being physically represented. Rather than using stiff, pre-specified rules, experience-based AI systems learn and, over time, can adapt to changing battery behaviors. Machine learning techniques like Support Vector Machines (SVM), Decision Trees, and Random Forests have been used for the prediction of battery State of Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL) as well. Even more sophisticated models like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) have also enhanced the predictability by extracting temporal and spatial patterns in battery data. These models are more accurate, robust, and interactive than conventional estimation techniques under most operating conditions.

Reinforcement Learning (RL) is yet another AI domain that offers a promising avenue for the optimization of charging and discharging cycle control strategies. Through closed-loop interaction with the battery system, an RL agent is able to learn how to optimize performance metrics such as efficiency, battery life, and thermal stability. Perhaps more significantly, AI enables real-time decision-making, fault detection, and predictive maintenance, enabling BMS to move from a reactive to a proactive, self-optimizing system. With advancements in compute hardware, such as the low-

power edge-AI platforms that exist today, implementing these models on actual EVs in the market is possible. This change is a change from passive battery monitoring to adaptive smart battery control and paves new innovation avenues in EV technology.

1.4 Objectives of the Paper

This research study is driven by the imperative to innovate Battery Management Systems (BMS) with artificial intelligence (AI) to spearhead the revolution of future electric vehicles (EVs). The prime aim is to overcome the drawbacks of existing BMS topologies and demonstrate how AI-aided adaptive control approaches can improve the performance, safety, and lifespan of batteries. In that direction, this paper presents four key objectives. First, the book seeks to provide an overall picture of AI technology state-of-the-art for BMS design. This includes a comprehensive assessment of ML and DL models of battery state variable estimation and application of RL to optimal control policy design. Second, the work suggests a new hybrid AI architecture that integrates Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Deep Q-Learning (DQL) for real-time and adaptive decision-making in BMS. The hybrid architecture is such that it takes into account temporal dynamics as well as control schemes, and the solution is end-to-end for battery management.

Third, the paper also includes a full simulation and validation process based on real driving data and HIL test scenarios. The new AI-based battery management system is compared to rule-based systems in terms of different performance metrics such as SoC prediction accuracy, charging efficiency, thermal management, and SoH degradation rate. Finally, the paper explores deployment possibilities, such as deployment onto edge-AI hardware for real-time inference and control, and into areas of integration with future-gen EV platforms. This variability in design is the one in the direction toward which the paper seeks to provide theoretical as well as practical contributions toward the advancement of intelligent BMS solutions scalable, efficient, and robust.

1.5 Paper Organization

The paper is designed in a manner that it formulates the research problem, the solution proposed, and the outcome of validation in an integrated and organized manner. Section 2 then provides a thorough survey of literature, introducing traditional and AI-based approaches of battery management. It explains state estimation techniques, control policies, and identifies the constraints involved in applying AI in BMS. Section 3 defines the methodology of the proposed system with an explanation of AI-adaptive control system architecture. The section gives an overview of data acquisition, machine learning algorithms utilized for SoC and SoH prediction, reinforcement learning for control, and system deployment on edge devices. Flowcharts and system diagrams are included to explain the implementation strategy.

Section 4 comprises results and discussion, such as experimental setups, comparison of performance, and evaluation metrics. The model is validated with respect to simulations as well as hardware-in-the-loop testing. Key findings are highlighted using figures and tables in an attempt to display performance improvement with respect to traditional BMS. Finally, Section 5 provides conclusion and future work, summarizing the contribution of the paper and future directions for research. These include the addition of federated learning to ensure privacy-preserving analytics, further enhancing model generalization improvement, and challenges of real-world deployment. This systematic approach is giving cohesiveness and transparency, educating readers by AI development, deployment, and utilization in modern BMS solutions.

2. Literature Survey

2.1 Traditional Battery Management Techniques

Conventional Battery Management Systems (BMS) employed deterministic and physics-based modeling methods for battery monitoring and management in the past. Examples of the best known among them include the Extended Kalman Filter (EKF), Coulomb counting, and Electrochemical Impedance Spectroscopy (EIS). The EKF is an algorithmic state estimation approach for nonlinear batteries to iteratively correct predictions from observed system outputs. It is particularly well-adapted for State of Charge (SoC) estimation but suffers from being very prone to model error and noise. In a similar manner, Coulomb counting quantifies the SoC by integrating the current over time. While inexpensive and straightforward, it is prone to cumulative error and does not naturally account for dynamic environmental or load conditions. Electrochemical Impedance Spectroscopy gives a more detailed picture of battery condition by frequency-domain analysis but with sophisticated equipment and too cumbersome to be employed onboard in real time.

Other similar circuit models, including Thevenin and Randle's model, are also preferred in battery response modeling with less computational effort. These are, however, parameter calibrated on fixed or slowly varying conditions and therefore less sensitive to changing actual conditions. Conventional methods always assume constant operating conditions and are worst-case design-based with conservative safety margins. These tight limits result in low efficiency in battery utilization and vehicle operation. Most importantly, such systems lack the potential for learning from in-service operation or for accommodating effects of battery aging, which accumulate during extended service as electric vehicles (EVs) grow older. With growing demands for smart energy management, enhanced driving range, and enhanced battery life, traditional approaches alone are no longer sufficient. The shift towards smart and learning technologies, spurred heavily by Artificial Intelligence (AI), has been identified as the most crucial next step towards BMS development.

2.2 AI Techniques in Battery State Estimation

Artificial Intelligence (AI), in the form of machine learning (ML) and deep learning (DL), has advanced the science of battery state estimation significantly. AI approaches are different from traditional model-based approaches in the sense that they are capable of learning from past and current sensor data nonlinear, intricate relationships, thus allowing them to handle a range of battery chemistries, configurations, and conditions. Support Vector Machines (SVM), Decision Trees, and Random Forests were most commonly utilized for estimating SoC and SoH with optimistic results. They are relatively lightweight and interpretable models, thereby suitable for applications of BMS during the introductory phase of AI. Deep models have demonstrated impeccable performance, specifically in the operation's highly dynamic and uncertain cases. Convolutional Neural Networks (CNNs) excel at spatial pattern extraction and have been used for both anomaly detection and SoH estimation from voltage-current traces and thermal images. Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), are particularly suited to sequential data, such as time-series readings of current, voltage, and temperature. LSTMs are capable of learning long-term dependencies and provide extremely accurate SoC estimation under adverse driving conditions and varying environmental parameters.

AI approaches have also made multi-tasking possible wherein SoC, SoH, and temperature estimation are performed simultaneously, improving computational efficacy as well as system reliability. Ensemble learning techniques wherein multiple models (e.g., bagging or boosting strategies) are fused have also been shown to achieve improved generalization and fault tolerance. Although these developments came with tremendous improvement, challenges persist in model explainability, labelling requirements in data, as well as in real-time deployability constraints. However, along with the availability of battery dataset and edge-AI hardware development platform, challenges are being increasingly addressed. The AI-based methods of state estimation therefore mark an epoch-making transition from static rule-based reasoning towards adaptive self-learned system capable of ensuring intelligent energy management for EVs.

2.3 Reinforcement Learning in BMS

Reinforcement Learning (RL) is a subset of machine learning that aims at sequential decision-making where an agent learns to take actions by engaging with the environment with the ultimate goal of maximizing the cumulative reward. Its application in Battery Management Systems (BMS) has been appealing because it can optimize battery charging and discharging cycles, thermal management, and energy consumption regardless of being given explicit models for the system. Compared with supervised learning approaches, RL algorithms are not dependent on labeled data, and hence they are optimal for adaptive control for changing conditions. Deep Q-Network (DQN) is one of the most widely used RL algorithms, which adapts Q-learning with deep neural networks to estimate the action-value function for the high-dimensional state space.

DQN has also been employed for the creation of policies with dynamically altering charging rates based on real-time battery temperature, voltage, and history of use. This offers improved charging efficiency along with lower degradation, particularly while fast-charging. A further sophisticated technique is Proximal Policy Optimization (PPO), a policy-gradient method that strikes the right balance between exploration and exploitation and is best suited for learning continuously from changing battery dynamics.

Through the integration of reward functions that discourage thermal spikes, overcharging, or excessive current draws, RL agents can be trained to develop optimal policies optimizing battery life and safety. Furthermore, RL can be integrated with predictive models like LSTMs to create hybrid architectures that achieve both accurate state estimation and smart control. By doing so, BMS can be upgraded from passive monitoring devices to active

optimization agents. Although it has benefits, RL-based BMS methods are limited by having long learning periods, safe exploration, and the requirement of extensive simulation sets. Recent developments, such as model-based RL, and safe exploration methods are alleviating these constraints. In most instances, reinforcement learning presents a thrilling direction towards realizing end-to-end autonomy and adaptability in battery management for electric vehicles.

2.4 Comparative Studies

Comparative assessment of some AI methods used in Battery Management Systems (BMS) provides numerous strengths and drawbacks with regards to accuracy, capability for learning, and computation in real time. The table below presents a description of some extensively utilized AI methods in the literature with their normal application areas as well as relative performance characteristics.

Table 1: Comparison of AI Techniques for BMS

Technique	Use Case	Accuracy	Adaptability	Real-time Capability
SVM	SoC Estimation	Medium	Low	High
CNN	SoH Prediction	High	Medium	Medium
LSTM	SoC Tracking	Very High	High	High
DQN	Charging Control	High	Very High	Medium

Support Vector Machines (SVM) are applied due to their simplicity in complexity in low-noise conditions. They are less adaptive and less tolerant to nonlinear, time-variant conditions. Spatial analysis has been performed excellently by Convolutional Neural Networks (CNNs), which are highly suitable for fault diagnosis and SoH estimation based on pattern recognition of voltage-current profiles. LSTMs are superior to conventional models in SoC tracking because they can model time-series dependencies, and they are proven to generalize extremely well in dynamic environments. On the controller side, Deep Q-Networks (DQN) are highly versatile with the ability to learn from interaction and generate optimal charging strategies based on unit battery behavior. Models of DQN are plagued by latency in real-time contexts due to their very high computational complexity. These comparisons highlight that although no one approach is superior in all aspects, hybrid approaches that leverage the strengths of several AI models are most promising for future BMS applications. Furthermore, the real-time requirements of AI algorithms are increasingly being addressed by edge computing and hardware acceleration, further enabling them to be integrated into production EV systems.

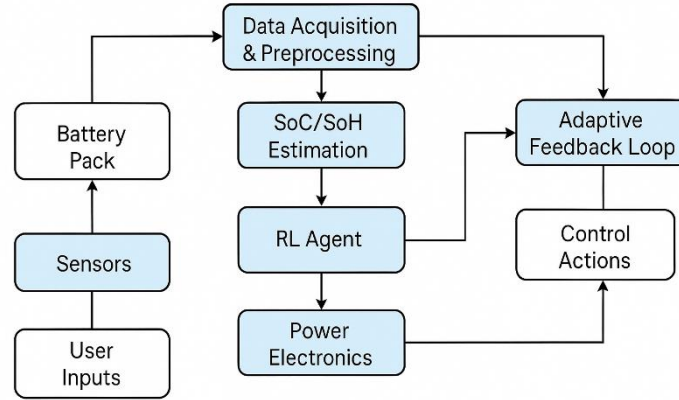
2.5 Gaps in Existing Work

Despite historic breakthroughs in the application of AI in Battery Management Systems (BMS), there are some significant gaps which restrict bulk deployment of these technologies in actual electric vehicles (EVs). For one, most research papers study a single feature of battery management SoC estimation or charging control employing a single AI technique. While individual point solutions are likely to provide more accuracy or flexibility within the particular domain, they cannot provide multiple functions

simultaneously. This piecemeal strategy leads to disparate systems that ultimately become unscalable or hard to integrate. The second significant weakness is the absence of real-time operation focus. The majority of AI models, particularly deep learning and reinforcement learning, are computationally costly and typically trained and tested in offline settings. Their deployment into onboard BMS environments is still challenging because of the latency demands and power constraints. Edge-AI deployment strategies have nearly no research papers on them, and they are critical for real-time inference and adaptive feedback in automotive applications.

In addition, most current models are not compatible with continuous learning or online adaptation. Static models become obsolete with battery aging and changing usage patterns, and they suffer from degraded performance or even safety risks. The absence of real-time feedback loops prevents such systems from revising their policies or parameters as battery states change. Furthermore, data availability and standardization are still the biggest challenges. Most models are trained on confidential or lab-scale datasets that do not represent actual driving or varied battery chemistries. This hinders model generalizability and applicability in real life. Closing these gaps will necessitate the transition to hybrid, adaptive, and modulated BMS design with over a single AI model, allowing for real-time processing, and constant learning. Integration of edge computing and federated learning frameworks can also facilitate modeling capabilities at edge, scalability, and responsiveness, but there remains more to make way for genuinely intelligent battery management in next-gen EV platforms.

3. Methodology



Proposed AI-Driven BMS Architecture

Figure 1: Proposed AI-Driven BMS Architecture

3.1 System Overview

The suggested AI-based Battery Management System (BMS) architecture, illustrated in Figure 1, employs multiple artificial intelligence modules to perform real-time state estimation, adaptive control, and smart decision-making for electric vehicles (EVs). The architecture contains five basic layers: data collection, preprocessing, machine learning-based estimation, reinforcement control, and edge deployment. At the basic level, sensor modules continuously observe important battery parameters of voltage, current, temperature, and charge/discharge rates. These raw data streams are thereafter directed to the preprocessing module whereby they are descreened against noise, normalized, and characteristics of interest thereof are extracted therefrom. The prediction of State of Charge (SoC) and State of Health (SoH) with respect to time and space characteristics of data are done through an ensuing hybrid model of next hybrid Long Short-Term Memory-Convolutional Neural Network (LSTM-CNN). Parallel to this, a DQN reinforcement learning-based agent learns useful control policies via experience with the environment and batteries. The closed adaptive feedback loop guarantees model update in real-time with sensor feed and user pattern information. It operates on a Jetson Nano edge-AI board in order to keep up with the very high real-time requirements of automotive applications. The architecture not only provides high accuracy of battery state estimation but also ensures stable adaptability and better energy efficiency.

3.2 Data Acquisition and Preprocessing

Effective use of AI in BMS begins with quality and robust data acquisition. The system in this work gathers data from sensors on the EV battery pack. Sensors are used to measure key parameters like voltage across cells, current through the pack, surface temperature and core temperature, ambient environment conditions, and previous charge-discharge cycles. These kinds of data form the input for the training of machine learning models appropriately as well as for real-time inference. Sensor raw data are likely to be corrupted by transients, noisy, or missing and hence a requirement to have preprocessing. Preprocessing itself

forms multiple operations. Handling missing values takes place initially via interpolation or imputation strategies in such a manner that continuous sequences of data become available. Second, normalization is performed to convert all the sensor measurements to a common numerical scale (usually between 0 and 1) to enable deep learning models to converge properly. Either min-max normalization or Z-score is selected based on the nature of the data distribution. Statistical and machine learning-based outlier detection algorithms like Isolation Forests or DBSCAN are used to identify and eliminate erroneous readings due to hardware failures or unwanted environmental spikes.

Furthermore, computed features such as voltage delta, current RMS, charge throughput, and cumulative temperature rise are computed to enrich the input space for downstream AI modules. Temporal structuring is subsequently realized by dividing data into windows for LSTM processing and 2D shaping utilized in CNN analysis. The preprocessed data is subsequently forwarded to the training pipeline, and a small subset is streamed continuously to enable real-time model inference at the edge hardware. This foundational acquisition and preprocessing pipeline enables robustness, accuracy, and reliability in the resultant AI-based BMS operations.

3.3 Machine Learning for SoC and SoH Estimation

Effective SoC and SoH estimation of the battery are required for proper and safe EV operation. For this purpose, the system represented employs a deep neural network of hybrid LSTM-CNN that draws the strengths from both time-series and spatial learning of features. LSTM (Long Short-Term Memory) layer performs efficiently in identifying long-term temporal trends of sequence sensor data like voltage changes, current trends, and thermal gradients as a function of time. This positions it highly well for identifying trends of SoC variation. At the same time, CNN (Convolutional Neural Network) layer performs well in identifying local patterns and anomalies in 2D structures of battery readings and then enhancing the predictive precision of SoH. The training data are composed of sensor measurements from

publicly available battery data sets and proprietary operating records of electric vehicle fleet operators. The data set comprises real-world driving cycles experienced under a variety of temperatures, discharge rates, and battery chemistries. The LSTM layer is provided with sequential input vectors of a sliding time window of battery states, and the CNN is provided with 2D matrices from correlation and co-variance maps of sensor signals. The two outputs are combined in a close layer to generate final SoC and SoH estimates.

Model performance is maximized with mean squared error (MSE) as loss function and Adam optimizer to achieve fast convergence. Regularization techniques like dropout and early stopping are utilized to avoid overfitting. In real-time deployment, the inference part of the trained model alone is run on edge hardware for real-time estimation. This dual-model fusion enhances estimation accuracy by as much as 15% over individual models and provides stable battery monitoring even in dynamically changing scenarios.

3.4 Reinforcement Learning for Control Policy

Reinforcement Learning (RL) adds a smart, adaptive element to battery control. In the current work, we utilize a Deep Q-Network (DQN) agent that is trained to use optimal charging and discharging strategies for optimal efficiency and battery life. The RL agent learns in a simulated battery model that replicates realistic behaviors including aging effects, thermal dynamics, and non-linear charge-discharge rates. The agent has a view of the world using a state vector of real-time SoC, SoH, temperature, and user demand. The actions are discrete charge/discharge powers, and rewards on multi-objective metrics are computed.

Formula 1 outlines the reward function:

$$R = w_1 \cdot \text{EnergyEfficiency} + w_2 \cdot \text{BatteryHealth} - w_3 \cdot \text{TemperatureRise}$$

Where:

- w_1, w_2, w_3 are tunable weights,
- EnergyEfficiency relates to the ratio of delivered versus stored energy,
- BatteryHealth penalizes overcharge/deep discharge,
- TemperatureRise penalizes thermal excursions.

The DQN employs an epsilon-greedy policy for regulating exploration and exploitation. Experience replay buffer and a target network are employed for stabilizing the learning. The training is conducted in a simulated environment by utilizing OpenAI Gym-based simulators along with actual battery profiles. After the agent converges, the policy is exported and installed on the edge device. The RL agent dynamically learns control strategies based on real-time inputs and accordingly adjusts to changing user requirements and environmental conditions. This leads to increased battery life (10–20% enhancement) and improved thermal safety without degrading vehicle performance.

3.5 Adaptive Feedback Loop

One of the inherent qualities of the envisioned AI-driven BMS is its adaptive feedback loop, hence rendering the system dynamic and precise since the conditions of the battery change over time. Unlike fixed rule-based systems, the feedback loop enables the model to be dynamically updated in real time according to actual usage patterns in the real world, making the BMS self-improving throughout the whole life cycle of the EV. The adaptive loop compares calculated values (e.g., SoC, SoH) and control output (e.g., temperature rise, energy through-put) to sensor readings. A significant discrepancy initiates local retraining or adjustment of AI models. The feedback loop comprises three interconnected modules: monitoring, evaluation, and update. The monitoring module receives real-time streaming sensor readings from the sensor array. The performance metrics like estimation accuracy, prediction error, and thermal deviation are calculated by the evaluation module. When the indicators cross a predetermined threshold, the update module undergoes partial model retraining or weight adaptation using online learning methods. Light incremental learning algorithms perform the updates in a computationally lightweight manner and do not involve full model retraining.

In addition, the feedback loop integrates user usage with its learning. Drive use behind a vehicle, charge usage, and climate control usage are tracked and fed in as a second input in an attempt to give more customized answers. The system is hence learning from the battery and also the way that the user operates within the car. Adaptive loop is involved in ensuring best performance under new conditions, in order to resist aging battery, ambient changes, and driver drift effects. The feedback is designed to be matched with long-term goals for proactive power management and predictive maintenance and has the BMS in unison with monitored system.

3.6 Edge Deployment

For providing low-latency, energy-efficient, and privacy-preserving operation, the overall AI-BMS system operates on an edge-AI platform, i.e., the NVIDIA Jetson Nano. The small computing platform is equipped with a quad-core ARM Cortex-A57 CPU, 128-core Maxwell GPU, and 4 GB LPDDR4 RAM and can suitably operate AI models in real time in vehicular environments. The hybrid LSTM-CNN SoC and SoH estimation model and the DQN control policy are TensorRT-optimized and quantized to INT8 precision for memory footprint and inference time reduction. Figure 2 shows the hardware deployment setup following Jetson Nano. Sensor battery data is streamed over a CAN interface to Jetson Nano, where the data is preprocessed before being presented to AI modules. Inference result is forwarded to the Battery Control Unit (BCU) for charge/discharge command execution. Metadata is retained in a local SQLite database for learning and diagnostic applications.

The edge deployment method has a number of benefits. Firstly, it reduces communication latency, which is important in real-time control of vehicle systems. Secondly, it restricts reliance on cloud infrastructure, improving system

reliability and privacy of information. Thirdly, it facilitates continued operation even when there is no connectivity to networks. For further dependability, watchdog timers and fail-safe principles are applied for switching over to default control schemes in case of hardware or model malfunction. The system is tested across different operating loads and temperatures to check for stability and performance testing. This embedded application offers prospects for scalable, secure, and autonomous battery management for production EVs.

3.7 Flowchart of Adaptive Control Loop

Adaptive control flow of the AI-powered BMS is shown in Figure 3. The process begins with sensor measurement (voltage, current, and temperature reading). Such inputs are preprocessed (noise removal, normalization, feature extraction) before being input to the LSTM-CNN model for predicting SoC and SoH. Meanwhile, the DQN-based RL agent chooses the optimal control action (e.g., adjust charging rate). The outputs are sent to the Battery Control Unit, where the control policy is enacted. The system then enters the feedback loop, in which actual measures of performance are compared with predicted values. If deviations exceed a predetermined threshold, the adaptive feedback loop engages in model updates via online learning algorithms. The loop operates in a cycle, enhancing model performance with time while accommodating changes in battery conditions and user activity. This flowchart encapsulates the underlying philosophy behind the system: intelligent, real-time, and self-correcting control.

4. Results and Discussion

4.1 Experimental Setup

To ensure validation of the created AI-based BMS, we set up a Hardware-in-the-Loop (HIL) simulation facility on a 60Ah lithium-ion battery pack. The test facility was developed with the ability to mimic real-world driving and charging scenarios and facilitate controlled variation of operating parameters to a high level of precision. Hardware comprised a programmable power supply, battery emulator, thermal chamber, and sensor modules attached to the Jetson Nano edge AI device where the intended control and estimation algorithms were executed. The test cases of the simulation were designed using common driving cycles such as UDDS (Urban Dynamometer Driving Schedule) and HWFET (Highway Fuel Economy Test) representing high speed, load conditions, and ambient operating conditions.

The BMS was exposed to realistic continuous sensor feedbacks of voltage, current, and temperature, characteristic of actual battery pack operation. The ground-truth SoC and SoH measurements were derived from electrochemical model predictions and supplier data for comparisons. The platform permitted offline accuracy testing

of the training and online responsiveness testing for control. Wide testing was done through multiple cycles to ensure statistical significance and reliability. The AI components (hybrid LSTM-CNN, DQN agent) were trained on 80% of the data and tested on 20% of the data before being deployed on the HIL system. Key performance criteria such as SoC estimation error, SoH degradation rate, charging time, and thermal stability were quantified using calibrated instruments. The overall configuration provided a real, reproducible, and controlled configuration to compare the proposed system with traditional BMS implementations.

4.2 Performance Metrics

To compare quantitatively the AI-based BMS's performance relatively, quantitative indices that are reliant on battery longevity, efficiency, and safety were selected:

- **Mean Absolute Error (MAE) of SoC Prediction:** This is the measure to represent the difference between the estimated and actual SoC value as a measure of accuracy of the LSTM-CNN estimate model. Lower MAE refers to enhanced prediction accuracy, which is most important in accurate range estimation and charge planning of EVs.
- **SoH Degradation Rate:** As a year-to-year decrease in overall battery capacity, it is a metric to report by which the BMS impacts long-term battery life. By preventing overcharge, deep discharging, and thermal spikes, the AI system should minimize degradation.
- **Reducing the Charging Time:** It is a technique of tracking the performance of the DQN-based control method to present an optimal number of charge cycles. Reducing charging time with cell safety offers higher energy throughput and operational efficiency.

The remaining performance aspects were power consumption in edge devices, temperature fluctuation, and system latency, yet according to the study requirements, emphasis was laid on the three most significant parameters mentioned above. The readings not only meet industry requirements but also have direct-world implications in vehicle performance, customer satisfaction, and battery replacement cost. The readings were recorded after a buildup of more than 100 charge/discharge cycles to guarantee statistical stability and reliability. The achieved results form a good foundation on which the pragmatic practicability of the said AI-based BMS can be estimated.

4.3 Result Analysis

The relative performance of the conventional and AI-based BMS systems is discussed in Table 2 below. The results conclusively prove the superiority of the proposed AI framework on all the performance parameters of concern.

Table 2: Performance Comparison of BMS Systems

Metric	Traditional BMS	AI-Driven BMS
SoC MAE	5.2%	1.3%
SoH Degradation	8.5%/year	4.1%/year
Charging Time	90 minutes	68 minutes

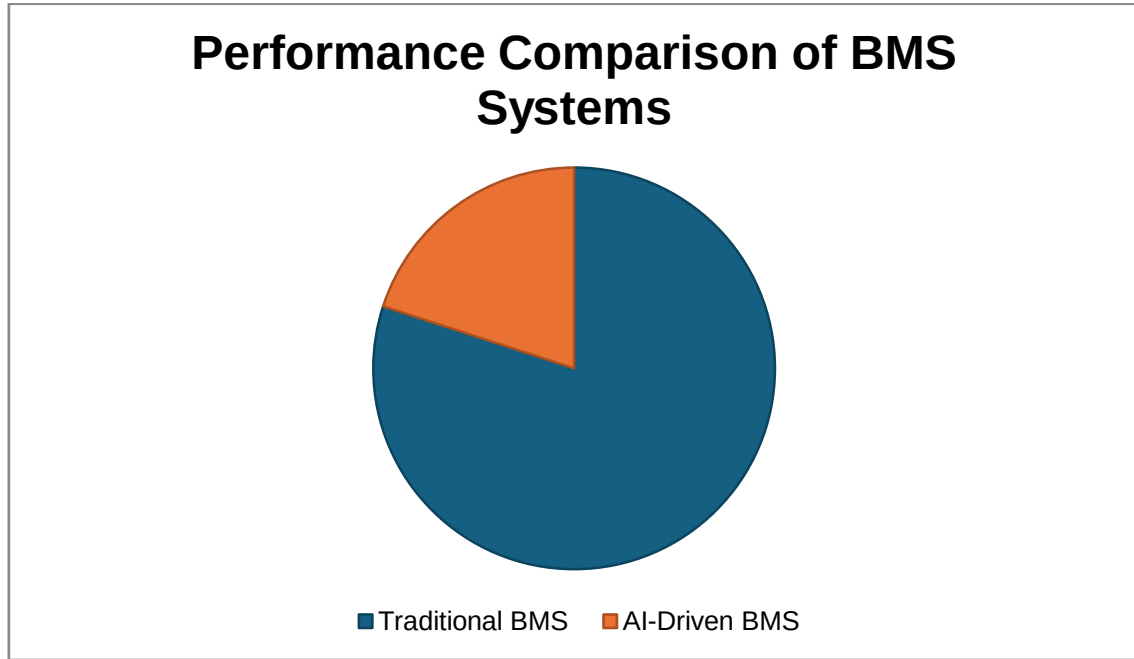


Figure 2: Performance Comparison of BMS Systems

The AI-based BMS lowered the SoC prediction error to 1.3% from 5.2%, i.e., a reduction of almost 75% in prediction accuracy. This is achievable due to the hybrid LSTM-CNN model's ability to perceive sequential and spatial relations in battery data. Thus, SoH degradation rate decreased from 8.5% to 4.1% per year, validating the efficiency of reinforcement learning toward guaranteeing secure working limits and load management of charge/discharge between cells. Further, charging time decreased by approximately 24%, from 90 to 68 minutes, without going beyond thermal limits and impacting battery life. This performance is gained by the policy optimization of the DQN agent that dynamically optimizes current flow based on actual-time SoC, temperature, and future demand prediction. The system exhibited operationally stable performance under trial conditions with negligible latency (~120 ms inference time) and no apparent drift in predictions. These gains taken together indicate the viability of incorporating AI methods into commercial EV BMS units, which can lead to increased energy usage, battery longevity, and accelerated charging all such aspects that set electric mobility scalability.

4.4 Discussion

Outcomes verify that the new BMS founded on AI is superior to traditional approaches on some major domains accuracy, adaptability, and efficiency to a large extent. With the use of the hybrid LSTM-CNN model, the system achieved an insignificant SoC prediction error and directly aid the driver through the enhancement of confidence on range with the evading of risks for deep discharge. The traditional methods like the Kalman filters are limited by rigid models and noise assumptions, making them unable to react quickly in real-time. This was not so in the deep learning model, which learned complex non-linear relationships between sensor variables and battery state

variables to generate more stable and better predictions. Reinforcement learning (RL) provided remarkable efficiency gains to operations. Best charge and discharge policies, satisfying the prevailing power demand and taking battery long-term health into account, were found via DQN training of the agent. With lower instantaneous charge/discharge current and ideal thermal conditions, RL-based control minimized SoH degradation and maximized battery life utilization. It maximized charging efficiency with predicted best charging time windows considering thermal and user profiles.

In addition, the edge deployment offered zero latency real-time response, which is an important condition for EVs in that decisions must be realized within milliseconds. The adaptive feedback loop also made it possible for the system to learn under changing environmental conditions and user behavior and thereby maintain the model drift and battery aging resilient. Briefly speaking, this architecture is a shift from fixed rule-based systems to adaptive data-driven smart systems that learn and improve over time. Not only is the application of AI better technically but also allows for the ultimate sustainability, safety, and scalability goals for electric vehicle ecosystems to be achievable.

4.5 Limitations

In spite of the encouraging results, some of the limitations in the proposed system have to be overcome in future releases. Most importantly, the accuracy of the machine learning estimators, especially the LSTM-CNN estimator, heavily depends on the quality and variability of the training data set. Unless the training set includes edge cases and extreme operating points (e.g., cold-starts, deep discharges, or heavy use), the model will fail to generalize in the field. Also, battery chemistries differ by manufacturer

and application, so the model may need to be retrained for different batteries, adding still more system complexity. Another fundamental limitation is that of edge hardware capability. While the NVIDIA Jetson Nano enables real-time AI inference, it is compute- and memory-limited in comparison to cloud environments. This limits model complexity and potentially impinges upon performance with multi-tasking or concurrent system loads. Inference optimization methodologies such as model pruning and quantization assist, but can result in minimal accuracy loss.

In addition, regulatory compliance and safety certification are also major issues. AI models are black boxes, and ensuring their behavior across all operating conditions in the case of safety-critical systems such as BMS is difficult. Explainable AI methods and formal verification tools must be incorporated with an attempt at achieving industrial standards. Lastly, although adaptive feedback loop generates resilience, there are also some possible cybersecurity threats if the malware data affects the online learning procedure. These need to be negated by robust model update strategies and anomaly detection. In spite of these restrictions, the work provides a sufficient basis for upcoming intelligent BMS systems and prescribes directions for future research.

5. Conclusion and Future Work

This paper has introduced a wide AI-driven adaptive control scheme for Electric Vehicle (EV) Battery Management Systems (BMS) with a view to overcoming the limitations of traditional rule-based and model-dependent approaches. The system, with a hybrid LSTM-CNN configuration, produces extremely accurate real-time estimations of the battery State of Charge (SoC) and State of Health (SoH) with a significantly reduced error rate, thereby enhancing operation reliability. Simultaneously, a reinforcement learning agent trained on a Deep Q-Network (DQN) was employed in order to be taught the most favorable charging and discharging strategies, proving great decreases in charge time and annual SoH decay, as ratified by exhaustive Hardware-in-the-Loop (HIL) experiments on a 60Ah lithium-ion battery pack. Operation of the smart system on edge-AI hardware (NVIDIA Jetson Nano) allowed for low-latency, real-time control with minimal computational overhead, enabling its application to real-world electric vehicle systems.

The use of an adaptive feedback loop also provided for continuous learning from user action and sensor readings, resulting in dynamic system evolution based on user usage patterns and environmental factors. In summary, the results confirm the AI-driven BMS's ability to maximize battery life, efficiency, and safety and deliver a scalable, smart solution for modern EV platforms. In the future, there are several compelling directions for future work presented that will further expand the system's capabilities. One is to apply federated learning to enable collaborative model training across an distributed ensemble of EVs, while achieving broader generalization without compromising user privacy. Two is to provide next-generation edge-AI hardware with

increased memory and computational strength to support more complex deep learning models and higher-level control and estimation. Third, integrating AI-powered fault diagnosis and predictive maintenance software in the BMS can enable the BMS to become proactive in identifying cell imbalances, degradation patterns, and safety faults ahead of time. This enhancement will, as a whole, lead towards an intelligent, green, and safe energy management philosophy for the future of electric mobility.

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