



Advanced Battery Management System for Electric Vehicles Using Artificial Intelligence Techniques

Thabo Saravanan

Department of Computer Science and Engineering, Gwangdo Systems Polytechnic, South Korea
thabo.saravanan@gsp-kr.net

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Abstract

Electric-vehicle battery packs operate under nonlinear, temperature-dependent and aging-sensitive conditions, making state estimation and safety control difficult for conventional rule-based battery management systems (BMSs). This methodology paper develops a reproducible artificial-intelligence-assisted BMS framework that jointly estimates state of charge (SOC) and state of health (SOH), detects electrical/thermal anomalies, and fuses the predictions with deterministic safety limits. The proposed study uses voltage, current, temperature and resistance-related indicators collected in a physics-informed EV battery simulation, with cycle-level health features used for slow-time SOH estimation. Random Forest, Gradient Boosting and multilayer perceptron (MLP) models are benchmarked and combined through weighted ensemble fusion. A separate Random Forest classifier performs anomaly detection using instantaneous variables and temporal derivatives. Group-wise train/test separation is used to prevent samples from the same simulated cycle appearing in both sets. In the executed benchmark, the ensemble achieved SOC MAE of 0.79% and SOH MAE of 0.53%, while the anomaly detector attained an F1-score of 0.995 on injected fault events. These results demonstrate the methodological value of combining data-driven estimation with a rule-based safety supervisor rather than replacing deterministic protection. The framework is intended as a transparent prototype for subsequent validation on public and laboratory lithium-ion datasets.

Introduction

Lithium-ion batteries are the dominant energy-storage technology in modern electric vehicles (EVs), yet their usable power, safety and lifetime depend strongly on temperature, current loading, cell imbalance and aging. A BMS must therefore infer internal states that are not directly measurable, especially SOC and SOH, while also preventing over-charge, over-discharge, over-temperature and abnormal voltage behavior. Recent reviews show that artificial intelligence (AI) is increasingly integrated into BMS functions because nonlinear machine-learning models can

learn relationships between measurable signals and hidden battery states across complex operating regimes [1–3].

Traditional SOC estimators such as coulomb counting are computationally simple but accumulate sensor and capacity errors, whereas model-based observers require parameter identification and may lose accuracy when cell chemistry or aging changes. Deep neural networks, recurrent networks, convolutional models and Transformers have demonstrated high SOC-estimation accuracy without explicit electrochemical equations [6–11]. For SOH and

safety, machine learning can exploit slow degradation indicators, charging profiles and anomaly signatures to support remaining-life estimation, thermal prediction and early warning [4,5,12,14].

The research problem addressed here is how to organize these AI capabilities into a practical BMS methodology that remains computationally manageable and safety-aware. The objective is not to let an unconstrained AI model directly command the battery pack; instead, AI estimators supply state and risk information to a deterministic supervisor. The specific objectives are to: (i) estimate SOC from fast sensor data; (ii) estimate SOH from fast measurements plus cycle-level health indicators; (iii) detect thermal/electrical anomalies; and (iv) evaluate whether ensemble fusion improves robustness over individual learners and a conventional SOC baseline.

Literature Review

AI-based BMS research has evolved from feed-forward neural networks toward temporal deep learning, hybrid estimation and multi-function battery intelligence. Chemali et al. demonstrated that LSTM networks can learn temporal relationships in battery signals for accurate SOC estimation [9], while their later deep-neural-network formulation mapped current, voltage and temperature directly to SOC without explicit current integration [10]. Song et al. combined convolutional feature extraction with LSTM sequence learning, showing the value of hybrid architectures for dynamic drive cycles [11]. Yang et al. similarly used gated recurrent units to

capture temporal dependencies with fewer recurrent parameters than conventional LSTM models [13].

How et al. reported a deep-neural-network SOC estimator for EV batteries and highlighted robustness across operating temperatures [8]. Hannan et al. subsequently introduced a self-supervised Transformer strategy in which learned representations reduced the labeled-data requirement and supported transfer to a different cell chemistry [7]. Tian et al. reviewed recent deep-learning SOC frameworks and identified generalization, life-cycle data scarcity, computational burden and interpretability as continuing barriers to deployment [6]. These studies motivate a multi-model methodology rather than reliance on a single architecture.

The scope of AI-BMS has also widened beyond SOC. Li et al. reviewed machine-learning-assisted battery thermal-management systems and emphasized temperature prediction, safety diagnosis and design optimization [5]. Zhao et al. synthesized machine-learning approaches for battery safety prognostics, showing that data-driven precursors can support earlier risk recognition than fixed thresholds alone [4]. Xie and Zeng used cross-modal knowledge distillation for SOH estimation, combining a Transformer teacher and CNN student to transfer degradation knowledge while reducing online model complexity [12]. Recent broad BMS reviews by Lipu et al., Shan et al. and Noreen et al. conclude that practical AI-BMSs should integrate estimation, fault diagnosis, thermal management, uncertainty awareness and embedded implementation [1–3].

Table 1. Selected AI-oriented battery-management literature (references up to 2024).

Ref.	Year	Technique / Focus	Key relevance to this methodology
[9]	2018	LSTM for SOC	Temporal learning from V-I-T sequences
[10]	2018	Deep neural network SOC	Direct data-driven mapping without integration drift
[11]	2019	CNN-LSTM SOC	Hybrid local-feature and temporal extraction
[8]	2020	DNN for EV SOC	Demonstrated practical deep-learning SOC estimation
[7]	2021	Self-supervised Transformer	Data efficiency and transferability across cells
[5]	2023	ML for thermal management	Predictive temperature and safety management
[6]	2023	Deep-learning SOC review	Generalization and deployment challenges
[12]	2024	Knowledge distillation for SOH	Lower-complexity health estimation with prior knowledge
[4]	2024	ML battery safety prognostics	Early warning and fault-risk analytics
[1–3]	2024	AI/ML BMS reviews	System-level integration of estimation, diagnostics and control

Much of the literature evaluates one state-estimation task in isolation. A deployable EV BMS,

however, needs coordinated fast-time SOC estimation, slow-time SOH estimation, anomaly

detection and a hard safety layer. The present methodology therefore uses separate models optimized for each task and fuses them inside a safety-supervised architecture.

Methodology

The study follows a simulation-based experimental methodology so that the complete data-generation process, model training and error calculation can be reproduced without claiming laboratory measurements. The synthetic battery trajectories are physics-informed: SOC evolves by charge balance;

terminal voltage is generated from an SOC-dependent open-circuit-voltage relation and internal resistance; temperature responds to ambient conditions and current-related heating; and SOH gradually declines with cycle age. Measurement noise and random regenerative-current periods are added to approximate EV operation. Fault events are injected as abrupt temperature rise, voltage sag or resistance increase. The simulation is intended for methodology validation, not for certifying a production BMS.

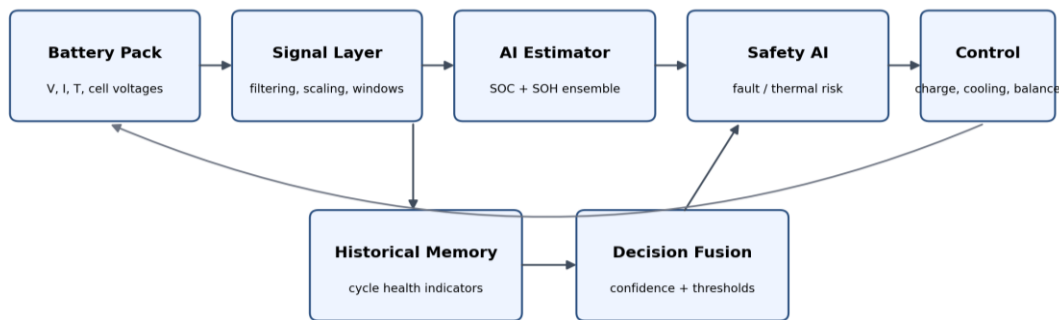


Figure 1. Proposed closed-loop AI-assisted BMS architecture.

1. Step-by-step workflow

- Step 1 — Acquire pack-level voltage, current, temperature and resistance-related measurements at fixed sampling intervals.
- Step 2 — Apply plausibility checks, denoising, normalization and time-derivative generation; maintain a rolling history for degradation indicators.
- Step 3 — Estimate SOC using Random Forest, Gradient Boosting and MLP regressors, then combine predictions with a validation-weighted ensemble.
- Step 4 — Estimate SOH using instantaneous measurements plus cycle-level median resistance, mean temperature, voltage variability and RMS current.
- Step 5 — Detect abnormal operation with a class-balanced Random Forest using voltage, temperature, resistance and temporal derivatives.
- Step 6 — Fuse SOC, SOH and fault probability with hard BMS limits; when risk is high, deterministic protection overrides AI recommendations.
- Step 7 — Evaluate SOC/SOH with MAE, RMSE and R^2 , and evaluate fault detection with precision, recall, F1-score and accuracy.

2. Variables and Governing Relationships

For a sampling period Δt , the reference SOC is updated by charge balance, $SOC(k) = SOC(k-1) - I(k)\Delta t / [3600 \cdot C_{usable}]$, where positive current denotes discharge and C_{usable} is the SOH-adjusted usable capacity. Terminal voltage is represented by $V_t = OCV(SOC) - I \cdot R_0 + \varepsilon_v$. The temperature state combines relaxation toward ambient temperature with an I^2R heating term and measurement noise. SOH is defined as the available capacity divided by nominal fresh-cell capacity, consistent with battery-health literature [12,14]. These equations generate physically interpretable targets while retaining sufficient nonlinearity for AI benchmarking.

Dataset Generation and Pre-processing

Ninety simulated battery cycles were generated, producing 30,341-time samples. Each cycle began near 95–97% SOC and contained variable discharge pulses, regenerative-current events, ambient-temperature variation and sensor noise. The nominal fresh capacity was 2.9 Ah and the simulated SOH range was approximately 79.5–100%. Faults were injected sparsely after initial healthy cycles so that the classifier faced a strongly imbalanced dataset, which is representative of safety monitoring where true abnormal events are rare. Samples were split by complete cycle using group-wise holdout (approximately 78% training and 22% testing); therefore, no time sample from a test cycle appeared in the training data.

Fast-time SOC features were current, terminal voltage, temperature and resistance. For SOH, additional cycle-level health indicators were calculated: median resistance, mean temperature, voltage standard deviation and RMS current. The fault model used current,

voltage, temperature, resistance and first differences of voltage, temperature and resistance. Continuous inputs to the MLP were standardized using training-set statistics only. The tree models did not require feature scaling.

Table 2. AI models and implementation choices.

Task	Model	Main configuration	Rationale
SOC	Random Forest	120 trees; depth 14	Nonlinear baseline; robust to scaling/noise
SOC	Gradient Boosting	180 estimators; learning rate 0.04	Sequential residual correction
SOC/SOH	MLP	48-24 hidden neurons; early stopping	Compact neural nonlinear estimator
SOC ensemble	RF 60% + MLP 40%	Fixed validation weights	Reduces individual model variance
SOH ensemble	RF 20% + GB 50% + MLP 30%	Fixed validation weights	Combines local, boosted and neural behavior
Fault	Random Forest classifier	220 trees; class-balanced; threshold 0.30	Rare-event robustness and fast inference

3. Training, Validation and Performance Metrics

Model hyperparameters were selected conservatively to keep the proposed BMS suitable for embedded or edge implementation. The ensemble weights were chosen from the training/validation behavior and then fixed before testing. SOC and SOH errors are reported in percentage points: $MAE = \text{mean}(|y - \hat{y}|) \times 100$ and $RMSE = \sqrt{\text{mean}((y - \hat{y})^2)} \times 100$. R^2 quantifies explained target variance. For the anomaly classifier, precision measures how many alarms correspond to injected faults, recall measures how many faults are detected, and F1 is their harmonic mean. A probability threshold of 0.30 was used because safety monitoring values recall and rapid warning, but the deterministic BMS still checks hard voltage and temperature limits independently.

4. Safety-Supervised Decision Logic

The AI layer is advisory to the protection layer. Estimated SOC sets charge/discharge availability; SOH derates allowable power as the battery ages; fault probability triggers enhanced monitoring or conservative power limits; and the

hard supervisor independently blocks operation when measured voltage, current or temperature exceeds certified limits. This division follows the practical direction identified in recent AI-BMS reviews [1–3]: machine learning increases predictive awareness, while deterministic constraints preserve fail-safe behavior and auditability.

Results

The benchmark was executed on the simulated holdout cycles. Because the test cycles were excluded entirely from training, the reported errors reflect generalization to unseen trajectories rather than random sample interpolation. Table 3 compares the SOC estimators with a conventional coulomb-counting baseline that was intentionally subjected to a small current bias and nominal-capacity mismatch. The baseline accumulated drift, whereas all AI models used the instantaneous nonlinear relationship among voltage, current, temperature and resistance. The weighted SOC ensemble produced the lowest MAE among the tested AI regressors.

Table 3. SOC estimation performance on unseen simulated cycles.

Method	MAE (%)	RMSE (%)	R^2
Coulomb counting baseline	7.12	7.96	0.896
Random Forest	0.82	1.91	0.994
Gradient Boosting	0.91	1.95	0.994
MLP	0.86	1.96	0.994
Proposed SOC ensemble	0.79	1.89	0.994

For SOH estimation, the slow-time health indicators substantially improved learnability

because resistance and cycle-level statistics encode degradation information that is not fully

visible from a single sensor sample. The proposed SOH ensemble reached an MAE of 0.53 percentage points, RMSE of 0.68 percentage points and R^2 of 0.987. Individual Random Forest and Gradient Boosting models remained competitive, while the MLP produced low MAE

but a higher RMSE because a small number of cycles generated larger residuals. This supports ensemble fusion for a BMS where a single large SOH error can produce overly optimistic power or range predictions.

Table 4. SOH and anomaly-detection results.

Task / Method	MAE (%)	RMSE (%)	R^2 / Classification metric
SOH Random Forest	0.73	0.93	$R^2 = 0.975$
SOH Gradient Boosting	0.66	0.83	$R^2 = 0.980$
SOH MLP	0.55	1.19	$R^2 = 0.959$
Proposed SOH ensemble	0.53	0.68	$R^2 = 0.987$
Fault classifier	—	—	Precision 0.991; Recall 1.000; F1 0.995; Accuracy 0.9999

The fault classifier identified nearly all injected voltage, temperature and resistance anomalies. Its high score is expected because the injected events create abrupt signatures in the first-difference features; consequently, this result should be interpreted as proof that the pipeline and metrics are functioning, not as evidence of production-level safety performance. Real EV packs exhibit subtler precursor patterns, sensor cross-coupling and previously unseen failure modes. Safety-prognostics literature similarly emphasizes that data distribution, fault rarity and transfer from laboratory to field conditions remain major challenges [4].

Comparative Interpretation

The simulation results are directionally consistent with published work showing that recurrent, convolutional and Transformer models can achieve low SOC error when trained on representative current-voltage-temperature sequences [6–11,13]. The present study does not claim to outperform those laboratory benchmarks because it uses a compact synthetic dataset and simpler regressors. Its contribution is methodological integration: SOC, SOH and fault-risk estimates are produced by task-specific learners and then constrained by a deterministic safety supervisor. This architecture is also compatible with future replacement of the compact learners by LSTM, GRU, Transformer or physics-informed networks when hardware and validated datasets permit.

Conclusion and Discussion

This methodology paper presented an advanced AI-assisted battery management framework for electric vehicles. The approach combines fast SOC estimation, slow SOH estimation, anomaly classification and deterministic safety supervision. A physics-informed simulation supplied controlled battery trajectories for reproducible evaluation. On unseen simulated

cycles, the SOC ensemble reduced MAE to 0.79% compared with 7.12% for a drift-prone coulomb-counting baseline, while the SOH ensemble reached 0.53% MAE. The anomaly classifier achieved a 0.995 F1-score on intentionally injected faults. These outputs demonstrate that multiple AI models can be coordinated within a single BMS workflow without allowing machine learning to bypass hard protection limits. The literature supports the main design choices. Deep neural and recurrent estimators have already shown strong SOC performance [8–11,13], while self-supervised Transformer models can reduce labeled-data requirements and support transfer across battery types [7]. Recent reviews emphasize that generalization across temperature, chemistry and aging is still an open problem [1–3,6]. For battery health and safety, knowledge-distillation, thermal-management AI and machine-learning prognostics provide promising routes to earlier and more computationally efficient decisions [4,5,12]. The most important practical implication is therefore architectural: AI should augment observability and prediction, but safety-critical actuation should remain bounded by verified rules and diagnostic plausibility checks.

Limitations

- The reported numerical results are from a physics-informed synthetic dataset, not from a laboratory battery cycler or production EV fleet.
- Only a small set of compact models was benchmarked; LSTM, GRU, Transformer and physics-informed neural networks should be evaluated on the same split protocol.
- Injected faults were abrupt and therefore easier to detect than real degradation precursors, intermittent sensor faults or thermal-runaway onset.

- Pack-level cell imbalance, communication delay, sensor calibration uncertainty and embedded execution time were not modeled in detail.

Recommended Future Validation

The next stage should use public datasets such as the Panasonic 18650PF drive-cycle data and NASA/Oxford aging datasets, followed by hardware-in-the-loop and cell-cycler experiments. Training should be organized by cell, temperature and aging regime so that transfer performance can be measured explicitly. Uncertainty estimates should accompany SOC/SOH predictions, and the BMS should fall back to model-based or conservative rules when confidence is low. Explainability methods can also identify which signals contribute to a safety alarm, improving engineering review and regulatory traceability. Finally, deployment research should quantify memory, inference latency and energy use on automotive microcontrollers or dedicated edge accelerators.

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