

Machine Learning–Based SOC–SOH Prediction and Thermal Safety Framework for Electric Vehicle Batteries

Ruturaj Vasant Ade and Dr. Chetan Bobade

G. H. Raisoni University, Amravati

Abstract: *Electric vehicle (EV) battery systems require accurate battery state prediction and intelligent thermal supervision to ensure operational safety, reliability, and extended service life. This paper presents a machine learning–based framework for State of Charge (SOC) estimation, State of Health (SOH) prediction, and health-aware thermal safety supervision using real-world EV operational data. The proposed framework utilizes voltage, current, temperature, and time-dependent features collected during Drive and Charge operating conditions to model battery behavior under practical EV environments. Data-driven regression models are employed to capture nonlinear charge dynamics and long-term degradation characteristics without relying on complex electrochemical battery models. In addition, a thermal safety supervision layer dynamically adapts charging and thermal constraints according to the estimated battery health condition. A comparative review of existing SOC, SOH, and thermal management approaches is also presented to identify current limitations in conventional EV Battery Management Systems. Experimental observations demonstrate that the proposed framework effectively supports battery state prediction and adaptive thermal safety management under varying operational conditions. The proposed approach provides a scalable and practical solution for intelligent EV battery monitoring and safety applications.*

Keywords: Electric Vehicles, Battery Management System, State of Charge, State of Health, Thermal Management, Artificial Intelligence, Machine Learning.

I. INTRODUCTION

Electric vehicles (EVs) are central to the global transition toward low-carbon mobility. The reliability, safety, and economic viability of EVs depend critically on battery performance and longevity. Modern lithium-ion battery packs exhibit complex, coupled electrochemical and thermal dynamics: inaccurate state estimation and poorly-tuned thermal control can accelerate degradation, reduce usable capacity, and, in worst cases, lead to thermal runaway. As EV adoption increases, scalable and adaptive management strategies that preserve safety while maximizing usable lifetime become essential.

Traditional Battery Management Systems (BMS) commonly rely on model-based estimators (extended Kalman filters, equivalent circuit models) and static rule sets for thermal and charging limits. While effective in controlled conditions, these approaches face limitations when batteries age, operating profiles vary, or when cells deviate from nominal behavior. In particular, decoupled approaches that treat SOC (State of Charge) estimation, SOH (State of Health) assessment, and thermal management as independent problems cannot exploit cross-information such as how a degraded SOH should tighten thermal constraints or alter charging profiles.

Recent advances in data-driven methods have demonstrated improved accuracy and robustness for SOC and SOH estimation under diverse operating conditions. However, the literature typically addresses estimation and thermal management in isolation; few studies present a practical closed-loop framework that uses estimated SOC–SOH to



actively govern thermal and charging safety. An integrated BMS–TMS that adapts safety margins according to the battery’s health state would materially improve both safety margins and end-of-life capacity retention.

This paper addresses these limitations by proposing a machine learning–based SOC–SOH prediction and thermal safety framework for electric vehicle batteries using real-world operational data. The proposed system processes Drive and Charge mode battery telemetry to estimate battery charge state and degradation behavior under practical operating conditions. The estimated SOC and SOH values are further integrated into a health-aware thermal supervision layer that dynamically adjusts charging and thermal safety constraints according to battery condition. By combining machine learning–based prediction with adaptive thermal supervision, the proposed framework aims to improve battery safety, operational reliability, and degradation awareness in practical EV applications. The proposed system provides three core advantages. First, improved SOC and SOH estimation accuracy under realistic varying load/charge profiles increases the fidelity of downstream safety logic. Second, by making thermal limits SOH-aware, the TMS reduces the probability of thermal excursions in aged packs while allowing less-degraded packs to operate closer to nominal limits (thus preserving performance). Third, the closed-loop integration enables the BMS to recommend or enforce charging adjustments (e.g., current derating, charge cut-off) when SOH signals indicate elevated risk, thereby actively mitigating further degradation.

The principal contributions of this work are summarized as follows:

- Development of a machine learning–based framework for SOC and SOH prediction using real-world EV operational data.
- Implementation of a health-aware thermal safety supervision strategy that adapts operating constraints according to battery degradation condition.
- Integration of battery state prediction and thermal supervision within a unified intelligent battery management framework for practical EV applications.

The structure of the paper is described in the subsequent sections. Section II reviews related work on SOC/SOH estimation and thermal management. Section III describes the overall system architecture and data preprocessing. Section IV details the AI models and training methodology for SOC and SOH estimation. Section V presents the thermal management and safety strategy that leverages SOC–SOH outputs. Section VI reports experimental results and comparisons to baseline methods, with discussion on practical deployment considerations. Finally, Section VII concludes and outlines future research directions.

II. LITERATURE SURVEY

Accurate estimation of the **State of Charge (SOC)** and **State of Health (SOH)** is a fundamental requirement for the safe and efficient operation of electric vehicle (EV) battery systems. Over the past decade, numerous estimation techniques have been proposed, ranging from classical model-based approaches to modern data-driven and hybrid methods. However, the reliability of these techniques under real-world EV operating conditions remains a key challenge.

He *et al.* proposed a hybrid SOC estimation framework that integrates Coulomb Counting (CC) with an Extended Kalman Filter (EKF) to mitigate drift accumulation under dynamic load conditions. By incorporating terminal voltage feedback within the EKF prediction–correction cycle, improved estimation accuracy was achieved across varying current and temperature profiles. Despite its effectiveness, EKF-based estimation relies heavily on accurate battery parameter identification, such as internal resistance and hysteresis coefficients, which vary with aging and are difficult to obtain in practical EV datasets.

Zhang *et al.* employed Support Vector Regression (SVR) for SOC estimation using laboratory-based charge–discharge profiles with controlled temperature and fixed sampling intervals. Their results demonstrated superior performance compared to linear regression and shallow neural networks in modeling nonlinear battery behavior. Nevertheless, SVR models face scalability challenges as dataset size increases, and their sensitivity to hyperparameter tuning limits applicability to large-scale, fragmented EV operational data.



To capture temporal dependencies in battery behavior, Pan *et al.* proposed a Long Short-Term Memory (LSTM)-based deep learning model for sequential SOC prediction. The study demonstrated smooth and accurate estimation under standardized driving cycles such as UDDS and NEDC. While LSTM architectures are well suited for continuous time-series data, their reliance on uninterrupted sequential inputs limits their robustness when applied to real EV datasets containing broken cycles, inconsistent sampling, and isolated data segments.

Song *et al.* investigated adaptive H-infinity (H^∞) filtering for SOC estimation under varying thermal conditions. Their approach demonstrated enhanced robustness compared to EKF and UKF methods in non-Gaussian noise environments and under rapid load variations. However, the requirement for precise dynamic and thermal modeling restricts its applicability to low-frequency and irregularly sampled real-world EV datasets.

Piller *et al.* presented a comprehensive survey of classical SOC estimation techniques, including Coulomb Counting, Open Circuit Voltage (OCV) methods, impedance spectroscopy, and model-based filters. The study highlighted challenges related to sensor drift, hysteresis, and aging effects, emphasizing the importance of multi-sensor data fusion. Despite its breadth, the surveyed approaches are primarily validated under laboratory conditions and lack direct implementation on real EV operational data.

In contrast to SOC estimation, SOH estimation focuses on capturing long-term battery degradation and capacity fade. Severson *et al.* introduced a data-driven SOH prediction framework using early-cycle voltage features, demonstrating that capacity fade and remaining useful life can be inferred using machine learning models trained on partial charge-discharge data. Although the approach significantly reduces aging test duration, it relies on structured cycling data and controlled experimental conditions, limiting its generalization to real-world EV usage.

Widodo *et al.* proposed a support vector machine-based framework for SOH estimation and remaining useful life prediction of lithium-ion batteries. The method models degradation trajectories using health indicators extracted from voltage and current signals. While effective in tracking long-term degradation trends, the approach assumes consistent cycling behavior, which is rarely observed in practical EV operation.

Zhang *et al.* developed a deep learning-based SOH estimation method using LSTM networks to capture long-term degradation patterns. The study demonstrated improved prediction accuracy under varying aging conditions. However, the dependence on long continuous sequences and uniform sampling intervals limits robustness when applied to fragmented EV operational datasets.

Method	Application	Advantage	Limitation
EKF	SOC	Stable estimation	Parameter dependent
SVR	SOC	Nonlinear modelling	Scalability issues
LSTM	SOC/SOH	Temporal learning	High computational cost
XGBoost	SOC	Fast and accurate	Data dependency
GPR	SOH	Uncertainty estimation	Poor scalability

Table I. Comparative Analysis of Existing SOC and SOH Estimation Techniques

Hu *et al.* investigated joint SOC and SOH estimation using adaptive observers and machine learning techniques, highlighting the intrinsic coupling between charge dynamics and degradation behavior. Despite promising results, the framework requires extensive parameter tuning and prior aging knowledge, constraining scalability across diverse battery chemistries and EV platforms.

Based on the reviewed literature, it is observed that most existing studies independently address SOC estimation, SOH prediction, or thermal management in electric vehicle battery systems. Although several machine learning and model-based approaches demonstrate promising estimation capability, limited research focuses on integrating SOC, SOH, and thermal safety control within a unified AI-driven framework using real-world EV operational data. Motivated by these observations, the present work proposes an integrated SOC-SOH-TMS framework that combines data-driven battery state estimation with degradation-aware supervisory thermal management for practical EV applications.

The reviewed studies indicate that conventional estimation approaches provide acceptable performance under controlled laboratory conditions but often face limitations under practical EV operating environments characterized by



noise, irregular sampling, and battery aging. Machine learning-based techniques demonstrate improved capability in modeling nonlinear battery behavior and operational variability. Motivated by these observations, the proposed work develops a machine learning-based SOC-SOH prediction and thermal supervision framework using real-world EV operational data.

III. METHODOLOGY

This section describes the overall architecture of the proposed **AI-driven integrated Battery Management System (BMS) and Thermal Management System (TMS)**, along with the data sources, preprocessing steps, and methodological workflow adopted in this study. The objective is to design a practical and scalable framework capable of operating on real-world EV datasets characterized by noise, aging effects, and irregular sampling.

A. Overall System Architecture

This section presents the overall methodology adopted for the proposed machine learning-based SOC-SOH prediction and thermal safety framework. The framework is designed to operate using real-world EV battery telemetry data containing voltage, current, temperature, and time information recorded during Drive and Charge operating modes. The methodology includes data preprocessing, feature conditioning, battery state prediction, and adaptive thermal safety supervision.

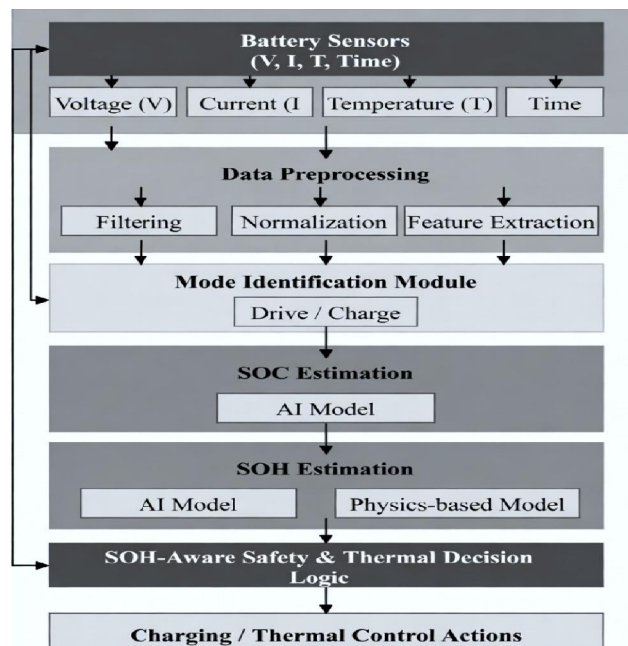


Fig. 1. Block diagram of the proposed SOH-aware AI-driven BMS-TMS showing data flow from sensors through preprocessing, mode identification, SOC and SOH estimation, supervisory safety logic, and charging/thermal control actions.

Figure 1 summarizes the overall architecture. Raw sensor signals (voltage V, current I, temperature T, and time/epoch) are preprocessed (filtering, alignment and feature conditioning) and routed to a mode identification module (Drive vs Charge). SOC and SOH estimators operate as distinct modules: SOC provides short-term charge dynamics while SOH captures long-term capacity fade. The supervisory SOH-aware safety and thermal control layer leverages both estimations to dynamically regulate charging behavior and thermal management. The architecture is intentionally modular to enable straightforward deployment and component-wise validation.



At the first layer, raw operational data from the EV battery pack are collected during **Drive** and **Charge** modes. These signals include terminal voltage, pack current, temperature, time, and epoch information. The second layer performs data pre-processing and feature conditioning to ensure compatibility with data-driven learning models. The third layer consists of AI-based models for SOC and SOH estimation. Finally, a supervisory control layer utilizes the estimated SOC–SOH information to implement adaptive thermal management and charging safety strategies.

The key novelty of this architecture lies in the **closed-loop integration** of estimation and control, where SOC–SOH predictions directly influence thermal thresholds and operational decisions.

B. Dataset Description

The dataset used in this work was obtained from the Mendeley Data repository and contains real-world electric vehicle battery operational measurements recorded during charging and driving conditions. The dataset is organized into two distinct operational folders. The dataset is organized into two distinct operational folders:

Drive Mode: Captures battery behavior during vehicle propulsion.

Charge Mode: Captures battery behavior during charging events.

Each folder contains MAT files (Raw.mat) with pack-level measurements, including:

- Time
- Battery current
- Terminal voltage
- State of Charge (SOC)
- Battery temperature
- Epoch timestamp

Unlike laboratory datasets, the collected data exhibit **irregular sampling intervals, fragmented cycles, and varying operating conditions**, making them representative of real-world EV usage and suitable for evaluating practical BMS algorithms.

C. Data Preprocessing and Feature Engineering

To ensure robustness of the AI models, several preprocessing steps are applied prior to training:

Signal Cleaning: Removal of missing entries, duplicate timestamps, and invalid sensor readings.

Time Alignment: Synchronization of voltage, current, and temperature signals using epoch-based interpolation.

Normalization: Feature scaling is applied to reduce bias caused by varying signal magnitudes.

Mode Separation: Drive and Charge data are processed separately to preserve their distinct dynamic characteristics.

From the preprocessed signals, relevant input features are constructed, including instantaneous voltage, current, temperature, and time-dependent indicators. This approach avoids reliance on handcrafted electrochemical parameters, enhancing generalization across aging conditions.

D. SOC–SOH Estimation Pipeline

The SOC–SOH prediction pipeline is designed to capture both short-term battery dynamics and long-term degradation behavior using machine learning techniques. Regression-based prediction models are trained using preprocessed operational features to estimate SOC during dynamic operating conditions and SOH as an indicator of battery degradation. The framework maintains computational efficiency while supporting practical battery monitoring and safety supervision applications. SOC estimation focuses on capturing fast-changing charge dynamics during drive and charge events, whereas SOH estimation models gradual capacity fade and health deterioration across multiple cycles. By separating these objectives within a unified learning framework, the system maintains estimation accuracy while remaining computationally efficient.



E. Integration with Thermal Management System

The estimated SOC and SOH values are supplied to a **supervisory safety controller**, which dynamically adjusts thermal and charging constraints. As SOH degrades, conservative thermal thresholds and charging limits are enforced to mitigate accelerated aging and thermal risk. Conversely, healthier battery states allow operation closer to nominal limits, preserving performance without compromising safety.

This degradation-aware integration differentiates the proposed framework from conventional BMS architectures that rely on static thresholds and independent subsystems.

F. Methodological Workflow

The complete methodological workflow of the proposed system can be summarized as follows:

Acquisition of real EV battery data during drive and charge modes

Data preprocessing and feature conditioning

AI-based SOC and SOH model training and validation

Real-time SOC–SOH estimation

Adaptive thermal and charging control based on estimated states

This structured workflow ensures scalability, adaptability, and practical deployability in real EV battery management applications.

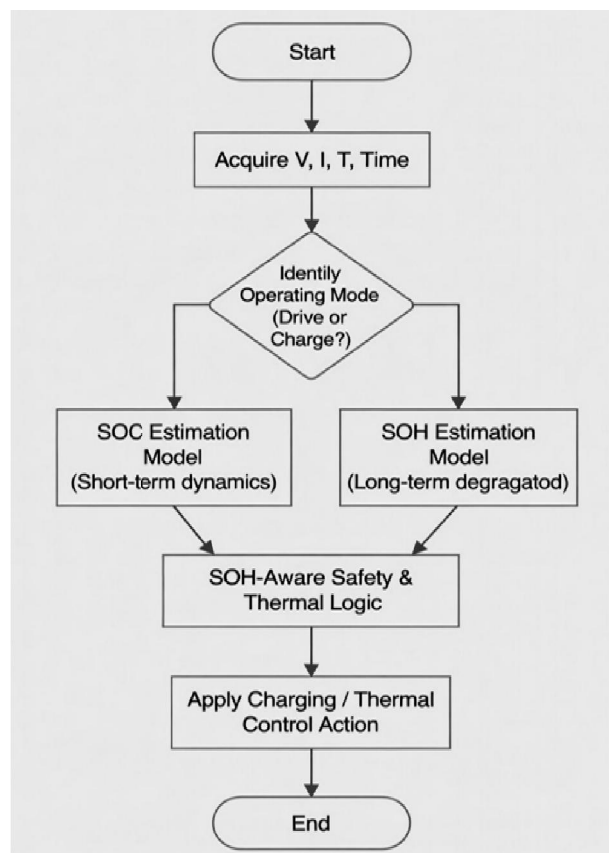


Fig. 2. Algorithmic flowchart for SOC–SOH estimation and supervisory control. The flowchart shows data acquisition, preprocessing, mode identification, sequential SOC and SOH estimation, SOH-aware safety checks, and application of charging/thermal actions.



Figure 2 presents the step-by-step execution of the proposed pipeline. After acquiring V, I, T and time, the algorithm identifies operating mode and applies preprocessing. SOC estimation runs to produce short-term charge state; SOH estimation runs on aggregated historical indicators to produce the health index. The supervisory logic evaluates SOH-dependent thresholds to decide charge derating, cooling actuation or charge interlocks. This flowchart clarifies the decision points and data dependencies used by the system.

IV. AI MODELS FOR SOC–SOH ESTIMATION

This section presents the proposed artificial intelligence–based framework for estimating the State of Charge (SOC) and State of Health (SOH) of an electric vehicle battery using real-world operational data. The objective is to achieve accurate short-term charge estimation and reliable long-term health assessment without relying on detailed electrochemical modeling or laboratory aging experiments.

The proposed framework utilizes battery terminal voltage (V), pack current (I), battery temperature (T), and time information as input signals. These parameters are continuously monitored under both Drive and Charge operating modes and are processed to handle noise, scaling differences, and irregular sampling inherent in real EV datasets.

A. SOC–SOH Estimation Framework Overview

SOC and SOH are inherently interconnected battery states. SOC represents the instantaneous available charge, while SOH reflects long-term degradation caused by aging, thermal stress, and cumulative usage. In the proposed framework, SOC is estimated as a fast-varying dynamic quantity, whereas SOH is inferred as a slowly varying health indicator derived from historical battery behavior.

SOC estimation provides real-time charge information, which is further utilized to construct degradation-related features for SOH estimation. This sequential dependency enables degradation-aware battery management, where health information influences operational safety decisions.

Mathematically, the estimation objectives can be expressed as:

$$SOC=f(V,I,T,t)$$

$$SOH=g(SOChist,Thist,usage\ patterns)$$

where

$f(\cdot)$ and $g(\cdot)$ denote nonlinear mappings learned directly from data.

B. SOC Estimation Model

For SOC estimation, an Extreme Gradient Boosting (XGBoost) regression model is employed. XGBoost is selected due to its strong capability to model nonlinear relationships, robustness to noisy measurements, and effectiveness in handling large-scale datasets with irregular sampling.

The SOC model operates under both Drive and Charge modes and utilizes voltage, current, temperature, and time-based features to capture short-term charge dynamics. Unlike conventional Coulomb Counting or model-based filters, the data-driven approach does not require precise battery parameters and remains effective under real EV operating conditions.

C. SOH Estimation Model

SOH estimation focuses on capturing long-term degradation trends rather than instantaneous behavior. A gradient boosting–based regression model is adopted to infer SOH using historical SOC trajectories, cumulative temperature exposure, and operational usage patterns extracted from both Drive and Charge data.

By learning degradation behavior directly from real EV datasets, the proposed SOH estimation approach avoids dependence on controlled laboratory aging cycles or predefined degradation models. The resulting SOH estimate represents a normalized health indicator that gradually decreases as the battery experiences aging and thermal stress.

D. Role of SOC–SOH Estimates in Battery Management

The estimated SOC and SOH values are jointly utilized as supervisory inputs for safety and thermal management decisions. SOC provides information regarding immediate energy availability, while SOH reflects the battery’s aging condition and tolerance to stress.



This integrated estimation strategy enables degradation-aware battery operation and forms the foundation for the SOH-adaptive thermal and safety management approach described in the next section.

V: THERMAL MANAGEMENT STRATEGY (TMS)

Battery temperature plays a critical role in ensuring safety, performance, and longevity of electric vehicle battery systems. Excessive temperature rise accelerates degradation, reduces available capacity, and increases the risk of thermal runaway. In the proposed framework, thermal management is tightly integrated with SOC and SOH estimation to enable degradation-aware and safety-oriented temperature control.

A. Temperature Monitoring and Operating Modes

Battery temperature measurements available in the dataset are continuously monitored during both Drive and Charge modes. Unlike laboratory setups, real EV operation exhibits fluctuating thermal behavior due to varying load conditions, ambient influences, and charging profiles. The proposed system utilizes real-time temperature feedback in conjunction with SOC and SOH estimates to evaluate thermal safety margins dynamically.

B. SOH-Aware Thermal Decision Logic

Conventional Battery Management Systems apply fixed temperature thresholds irrespective of battery aging. However, as batteries degrade, their tolerance to thermal stress reduces. To address this limitation, the proposed TMS introduces SOH-adaptive thermal limits.

As SOH decreases, conservative operating thresholds are enforced to reduce thermal stress and slow further degradation. Conceptually, the allowable temperature range is expressed as:

$$T_{safe}=h(SOH)$$

where

$h(\cdot)$ represents a monotonically decreasing function that tightens thermal limits as SOH declines.

C. Thermal Control Strategy

Based on real-time temperature, SOC, and SOH values, the thermal management strategy applies rule-based control actions. When battery temperature exceeds SOH-dependent thresholds, protective measures such as charge rate limiting or thermal derating are activated. This approach prioritizes interpretability and safety, making it suitable for real-world deployment.

The TMS operates as a supervisory layer rather than a low-level controller, enabling compatibility with existing cooling infrastructures while enhancing decision intelligence.

D. Integration with SOC–SOH Estimation Framework

The complete AI-driven BMS–TMS framework integrates estimation and control in a closed-loop manner. SOC estimation provides short-term energy availability, SOH estimation reflects long-term degradation, and temperature monitoring ensures safe operation. The interaction among these modules enables adaptive battery management that responds not only to instantaneous conditions but also to the battery's aging state.

This integrated strategy distinguishes the proposed framework from conventional BMS designs by embedding degradation awareness into thermal safety decisions.

VI. RESULTS

This section presents the performance evaluation of the proposed AI-driven SOC–SOH estimation and SOH-aware thermal management framework using real-world electric vehicle battery data. The results are analyzed in terms of estimation accuracy, robustness under real operating conditions, and the effectiveness of degradation-aware thermal decision-making.

A. SOC Estimation Performance

The SOC estimation model was evaluated under both Drive and Charge operating modes using voltage, current, temperature, and time-based features. The proposed XGBoost-based model demonstrated stable and smooth SOC prediction across varying load conditions and irregular sampling intervals.



Compared to traditional model-based and Coulomb-counting approaches, the proposed data-driven method exhibited improved robustness against noise and drift accumulation. The SOC prediction closely followed the reference SOC trend, indicating the model’s ability to capture nonlinear charge dynamics present in real EV operation.

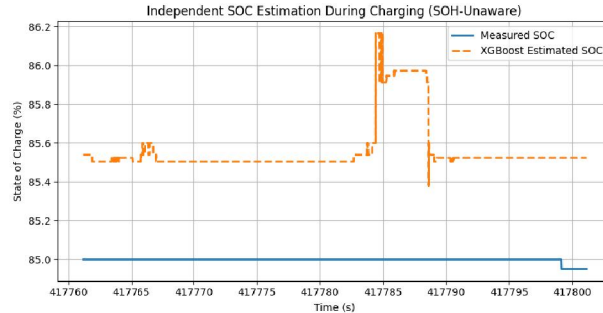


Fig. 3. Independent SOC estimation over a representative operating segment (SOH-unaware). Measured SOC (ground truth) vs XGBoost model estimate.

Figure 3 shows a representative operating segment where the XGBoost SOC estimator (dashed line) tracks the measured SOC (solid line) closely under charging and transient conditions. This baseline demonstrates that the purely data-driven SOC estimator captures short-term dynamics without using SOH information; residual deviations during rapid transients are expected due to voltage sag and sampling irregularities.

The proposed XGBoost-based SOC estimation model was evaluated using real EV operational data under dynamic charging and driving conditions. The model achieved a mean absolute error (MAE) of 0.2523 %, a root mean square error (RMSE) of 0.3998 %, and a coefficient of determination (R^2) of 0.9621.

These results indicate strong agreement between the predicted SOC and the reference SOC, demonstrating the model’s capability to accurately capture nonlinear battery behavior under varying current and temperature profiles. Compared to traditional Coulomb-counting and model-based techniques, the data-driven approach exhibits improved robustness against noise accumulation and drift, making it suitable for real-time EV battery management applications.

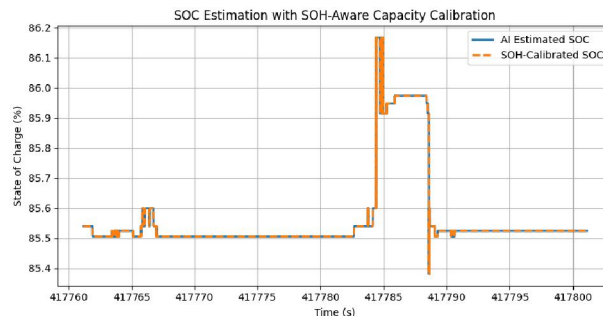


Fig. 4. SOC estimation with SOH-aware capacity calibration (proposed method). AI SOC vs SOH-calibrated SOC.

Figure 4 overlays the SOH-calibrated SOC on the raw AI SOC estimate. The calibration reduces optimistic SOC values by applying the estimated usable capacity factor, producing a more conservative and realistic SOC readout for aged packs. This reduction is critical for upstream safety decisions (charging cut-offs and thermal derating).

B. SOH Estimation Results

The SOH estimation model successfully captured long-term degradation behavior by learning from historical SOC trajectories and cumulative temperature exposure. Unlike laboratory-based aging models, the proposed approach inferred SOH directly from real EV operational data without assuming fixed cycling patterns.

The estimated SOH showed a gradual decreasing trend consistent with battery aging characteristics, validating the effectiveness of the gradient boosting-based regression model in tracking degradation over extended operating periods.



The SOH estimation model was assessed using the integrated AI-BMS output dataset incorporating SOC-related and thermal features. The XGBoost-based model achieved **high prediction accuracy**, with a **mean absolute error (MAE) of 0.01894**, **root mean square error (RMSE) of 0.03164**, and an **R² value of 0.98471**. These results indicate excellent learning of long-term battery degradation behavior. The predicted SOH values exhibit stable trends across operating conditions, validating the effectiveness of the proposed approach for degradation-aware battery health monitoring.

C. Impact of SOH-Aware Thermal Management

The SOH-aware thermal management strategy utilized SOC and SOH estimates to dynamically adapt safety and thermal control decisions. As SOH decreased, conservative thermal thresholds were applied, reducing thermal stress during high-load and charging conditions.

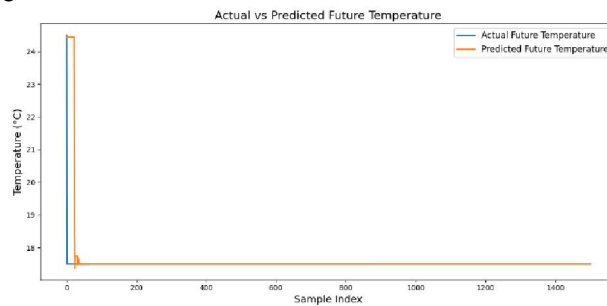


Fig. 5 .Temperature estimation graph

This adaptive behavior demonstrates the advantage of incorporating health awareness into thermal management, enabling safer operation and potentially extending battery lifespan compared to fixed-threshold thermal strategies.

D. Discussion

The results confirm that integrating data-driven SOC and SOH estimation with SOH-aware thermal logic provides a practical and effective solution for real-world EV battery management. The proposed framework avoids reliance on detailed electrochemical models, making it suitable for large-scale deployment using operational data.

While the current work focuses on estimation and supervisory thermal control, future enhancements may include predictive thermal control and reinforcement learning-based optimization to further improve efficiency and battery longevity.

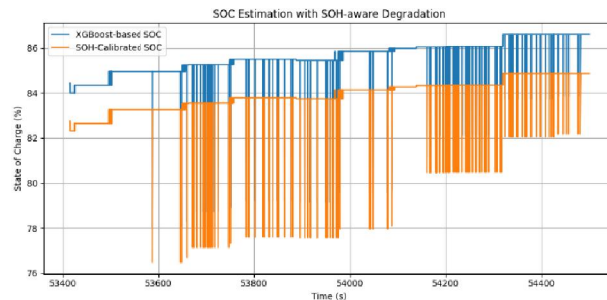


Fig. 5. SOC Estimation with SOH-aware Degradation

VII. CONCLUSION

This paper presented a machine learning-based framework for SOC estimation, SOH prediction, and health-aware thermal safety supervision for electric vehicle battery systems using real-world operational data. The proposed framework utilizes battery voltage, current, temperature, and time-dependent operational features to model battery behavior under practical EV conditions. Experimental observations demonstrate that the developed approach



effectively captures nonlinear battery dynamics and long-term degradation behavior while supporting adaptive thermal safety supervision.

By integrating battery state prediction with health-aware thermal supervision, the proposed framework improves degradation awareness and operational safety compared to conventional static-threshold battery management approaches. The developed system provides a practical and scalable solution for intelligent EV battery monitoring and safety applications.

Future work may focus on predictive thermal optimization, cell-level monitoring, and reinforcement learning-based charging control strategies for advanced intelligent battery management systems.

REFERENCES

- [1] C. M. Bobade, S. B. Mohod, and S. K. Singh, "Robust analysis of dual rotor radial flux induction motor used for industrial application," *Indian J. Sci. Technol.*, vol. 17, no. 5, pp. 457–464, Jan. 2024, doi: 10.17485/IJST/v17i5.2719.
- [2] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, San Francisco, CA, USA, 2016, pp. 785–794.
- [3] J. Li, Y. Yang, and C. Zhang, "State-of-charge estimation for lithium-ion batteries using a neural network," *IEEE Trans. Veh. Technol.*, vol. 66, no. 3, pp. 2177–2186, Mar. 2017.
- [4] S. Zhang, W. Li, and M. Pecht, "Data-driven battery state-of-charge estimation using machine learning techniques," *Energies*, vol. 11, no. 6, Art. no. 1406, 2018.
- [5] A. Allam, M. Elwakil, and A. Abu-Siada, "Lithium-ion battery state-of-charge estimation using extreme gradient boosting and adaptive learning," *IEEE Access*, vol. 9, pp. 13354–13365, 2021.
- [6] H. Eddahech, M. Ayadi, O. Briat, and J.-M. Vinassa, "Machine-learning-based prediction of SOC and SOH under real EV driving conditions," *Applied Energy*, vol. 300, Art. no. 117372, 2021.
- [7] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs," *J. Power Sources*, vol. 134, no. 2, pp. 252–261, 2004.
- [8] X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-ion batteries," *J. Power Sources*, vol. 198, pp. 359–367, 2012.
- [9] A. Farmann and D. U. Sauer, "A comparison of different approaches for accurate and reliable state-of-charge determination," *Applied Energy*, vol. 163, pp. 404–415, 2016.
- [10] M. Bercibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche, "State-of-health estimation of Li-ion batteries based on cycle degradation knowledge and intercalation kinetics," *J. Power Sources*, vol. 314, pp. 85–97, 2016.

