Survey on ML-based Battery Management System for Solar Batteries

Gorde V. S[1], Abhale B.A[2], Mr. Ansari Tanveer Ahmed Nisar Ahmed[3], Mr. Desale[4], Lalit Ravindra[5], Mr. Bramhane Sanket Sanjay[6], Mr. Koli Diptesh Rajkumar[7]
[1,2,3,4,5,6,7]S.N. D College of engineering and research center, yeola Savitribai Phule Pune University

***Abstract*—A Battery Management System (BMS) is essential for maintaining the safety, reliability, and performance of rechargeable batteries by tracking key operational factors like the State of Charge (SOC) and State of Health (SOH). Traditional estimation techniques often struggle with nonlinear battery behaviour, sensor noise, and environmental variations. Machine learning (ML) techniques have recently enhanced SOC and SOH prediction by identifying patterns in both historical and real-time battery data, leading to more precise and adaptable estimation models. This enhancement is particularly impactful in solar battery storage systems, where precise energy management is essential for optimizing charge/discharge cycles, extending battery lifespan, and ensuring operational safety. Integrating ML into BMS platforms enhances reliability and enables predictive maintenance, while also supporting monitoring across systems of various sizes and capacities. Applications span from residential solar systems and electric vehicles to grid-scale energy storage and second- life battery integration. By leveraging data-driven models, ML-enhanced BMS technologies represent a transformative step toward more intelligent, sustainable, and efficient energy storage solutions.**

***Index Terms*—Safe, Efficient, Rechargeable Batteries, Machine Learning, Sensor Noise, Solar Battery Storage, Battery Management System (BMS), State of Charge (SOC), Charge/Discharge Cycles, Battery Lifespan, State of Health (SOH).**

I. INTRODUCTION

As the demand for renewable energy grows, solar photovoltaic (PV) systems paired with battery storage are becoming increasingly common in both residential and industrial applications. At the core of these energy storage systems lies the Battery Management System (BMS), a critical component responsible for maintaining battery safety, performance, and longevity. A BMS tracks vital parameters such as the battery's charge status (SOC) and overall health condition (SOH), which together indicate performance and aging trends. Accurate estimation of these parameters is vital for efficient energy utilization, system reliability, and user safety.

Conventional BMS methods struggle to accurately capture the nonlinear and dynamic characteristics of batteries, particularly under fluctuating environmental and load conditions, inconsistent usage patterns, and aging effects. These limitations are particularly concerning in solar battery storage applications, where batteries are exposed to fluctuating charge/discharge cycles and elevated thermal conditions. Overheating remains a significant safety hazard, potentially leading to thermal runaway, fires, or even explosions if not detected early.

Machine learning introduces an innovative approach that allows the development of data-driven, adaptive models for monitoring and managing battery systems with improved accuracy. ML-based approaches can learn intricate relationships from historical and real-time sensor data, enabling more precise SOC/SOH estimation and early detection of abnormal behaviours. Incorporating predictive analytics enables a BMS to anticipate overheating, recognize early signs of malfunction, and initiate preventive actions before severe failures happen.

This paper presents an ML-based Battery Management System specifically designed for solar battery applications, with a focus on predictive overheating and blast prevention. By leveraging advanced learning algorithms and real-time monitoring, the proposed system aims to enhance safety, extend battery life, and improve overall system resilience. Such innovations are essential for ensuring the long-term viability and safety of solar- powered energy storage, especially in residential, commercial, and utility-scale deployments.

II. LITERATURE SURVEY

Sr. No.	Paper Title	Author Name	Year
1	Hybrid Machine Learning Model for EV Battery SoC and SoH Prediction	Amrutha Varshini, C. R., A. Jha, A.Tiwari, and K. Deepa	2024
2	State of Health Estimation for Lithium-Ion Batteries with an Attention-Integrated BiLSTM-MLP Hybrid Model	Yang, M., Y. Liu, B. Li, and C. Yang	2025
3	Data-driven Thermal Anomaly Detection for Batteries using Unsupervised Shape Clustering	Xiaojun Li, Jianwei Li, Ali Abdollahi,Trevor Jones	2021
4	Data-Driven Thermal Anomaly Detection in Large Battery Packs	Kiran Bhaskar	2022
5	Case Study of an Electric Vehicle	Wei Gao,Xiaoyu Li,	2021

III. METHODOLOGY

This research introduces a Machine Learning (ML)-driven Battery Management System (BMS) tailored for solar battery setups. Its primary goal is to improve safety and efficiency by offering accurate estimations of State of Charge (SOC) and State of Health (SOH), as well as forecasting potential overheating or failure events. The proposed framework is structured into six sequential phases: collecting raw data, pre-processing and feature engineering, building SOC/SOH estimation models, detecting temperature anomalies, validating performance, and final deployment.

- System Architecture Overview

The proposed ML-based BMS follows a multi- layered system architecture designed for real-time monitoring and predictive control of solar battery units.

Sensor Interface Layer: acquires live data, including voltage, current, and temperature from both battery modules and ambient sensors.

Pre-processing Layer: cleans and normalizes data, removing noise and filling missing values using interpolation.

Estimation Module: utilizes hybrid models such as BiLSTM and MLP for SOC/SOH prediction, trained on time-series battery data.

Anomaly Detection Module: applies unsupervised techniques (autoencoders, clustering, isolation forests) to identify abnormal thermal patterns.

Decision Layer: issues alerts and safety actions such as cooling or controlled shutdown when anomalies exceed threshold limits.

- Data Acquisition

Data was obtained from solar battery systems operating under various charge/discharge cycles and environmental conditions. Key parameters collected include:

Voltage and current, Internal and ambient temperature, Battery cycle count, State transitions and operational status.

To enhance model reliability, historical data with documented overheating and thermal runaway incidents were used during training and validation phases.

- Preprocessing and Feature Engineering

Preprocessing steps include noise filtering, data normalization (e.g., z-score), and interpolation for missing values. Feature extraction focused on identifying meaningful behavioural indicators like voltage fluctuation rates, current response signals, heat rise patterns, discharge curve shapes, and long- term degradation metrics.

These features enable the ML models to learn temporal dependencies and degradation behaviour.

- SOC and SOH Estimation Models

For estimating SOC and SOH, a hybrid deep learning model was developed using a combination of Bidirectional LSTM (BiLSTM) and Multilayer Perceptron (MLP) layers. The BiLSTM captures temporal dependencies in charge–discharge cycles, while the MLP performs final regression output for precise numerical estimation. Model training minimized Mean Absolute Error (MAE) and Root Mean Square Error (RMS), ensuring accurate convergence. Attention mechanisms were incorporated to emphasize critical time steps during learning.

- Predictive Overheating and Blast Prevention

Thermal anomaly detection was achieved through unsupervised learning models trained exclusively on normal operational data. Any deviation in temperature or voltage patterns triggered anomaly alerts. Shape-based clustering helped detect temperature curve irregularities, while autoencoders and isolation forests enhanced recognition of unseen fault patterns. To prevent hazardous events like thermal runaway, a multi-layer classification system assessed risk levels low, medium, and high using input from multiple sensors (temperature, voltage, and gas). Based on classification outcomes, the system could automatically initiate preventive measures such as cooling, current derating, or isolation of battery modules

- Model Validation and Deployment:

Model evaluation employed both real-world and simulated datasets. SOC/SOH accuracy was validated against lab-measured ground-truth data using MAE and RMSE metrics. For anomaly detection, metrics such as precision, recall, and F1- score were recorded, with particular focus on early detectionlead time. The deployment phase integrated the trained models into embedded edge devices, enabling low-latency, real-time decision-making. Cloud dashboards supported long-term trend visualization, model updates, and remote diagnostics.

IV. OBJECTIVE

- Develop an ML-based Battery Management System (ML-BMS) specifically optimized for solar battery storage applications to improve monitoring, safety, and performance.
- Enhance accuracy of State of Charge (SOC) and State of Health (SOH) estimation using advanced machine learning models such as BiLSTM, MLP, and attention-based deep learning architectures.
- Analyze real-time and historical battery data (temperature, voltage, current, and charge/discharge cycles) to support precise battery condition assessment in dynamic solar environments.
- Implement predictive safety mechanisms by detecting early thermal anomalies, overheating, and potential thermal runaway using unsupervised learning, clustering, and real-time classification techniques.
- Enable proactive battery control and protection by integrating predictive analytics into a real-time decision-making framework to prevent failures and extend battery lifespan.
- Improve energy management efficiency in solar systems for residential, commercial, and utility-scale installations through intelligent battery monitoring and predictive maintenance.
- Advance sustainable energy technology by enhancing battery safety, reliability, and performance in renewable energy storage systems.

V. PROBLEM DEFINATIONS

As renewable energy adoption accelerates, solar PV systems combined with energy-storage batteries have become a key component across household, industrial, and grid-level applications. Such installations depend largely on lithium-ion batteries because of their superior energy density and conversion efficiency compared with other chemistries. However, their performance, safety, and longevity are deeply influenced by several dynamic factors, including fluctuating solar input, variable loads, ambient temperature, and usage cycles. A core component in managing these batteries is the Battery Management System (BMS), which is responsible for monitoring and controlling key parameters such as State of Charge (SOC) and State of Health (SOH). Accurate estimation of these parameters is essential for ensuring optimal energy usage, charging control, and safe operation.

Despite their importance, traditional BMS frameworks face significant limitations. Traditional estimation techniques such as Coulomb counting or Kalman-filter-based models generally assume stable conditions and thus fail to represent the nonlinear, time-dependent behavior of real batteries. These methods are prone to cumulative errors, especially under the irregular charge/discharge patterns typical of solar storage systems. As a result, SOC and SOH estimations become increasingly unreliable over time, leading to poor energy management decisions, premature battery degradation, and system inefficiencies.

More critically, battery safety is at risk due to inadequate predictive capabilities in existing BMS designs. Thermal anomalies, such as overheating, internal short circuits, and overcharging, are often detected too late only after critical thresholds are exceeded. This reactive approach fails to prevent dangerous events such as thermal runaway, which can result in fires or explosions, causing damage to property and posing significant safety hazards. In high-temperature environments or poorly ventilated installations (common in solar applications), this risk is further magnified. Additionally, conventional systems do not analyse complex sensor interactions or environmental data to identify subtle patterns that could indicate early signs of failure.

Given these challenges, there is a pressing need for a more intelligent and proactive BMS that can adapt to real-time operating conditions, learn from historical performance data, and detect faults or dangerous thermal behaviour before they escalate. Machine Learning (ML) presents a powerful solution by enabling models that can learn complex, nonlinear relationships from multidimensional sensor data. ML-based approaches can enhance the accuracy of SOC and SOH predictions, enable anomaly detection, and support early warning systems for overheating or battery abuse. Furthermore, such systems offer the flexibility to scale across various battery types and installation sizes, from household solar setups to large grid- connected battery arrays.

In summary, conventional BMS methods produce inaccurate SOC and SOH estimates under irregular charging patterns and environmental variation. Moreover, limited predictive capability means many systems detect overheating only after thresholds are crossed, increasing the likelihood of thermal runaway. These shortcomings emphasize the need for an adaptive, intelligent BMS that can learn from data to anticipate and mitigate risk in real time.

VI. ARCHITECTURE DIAGRAM

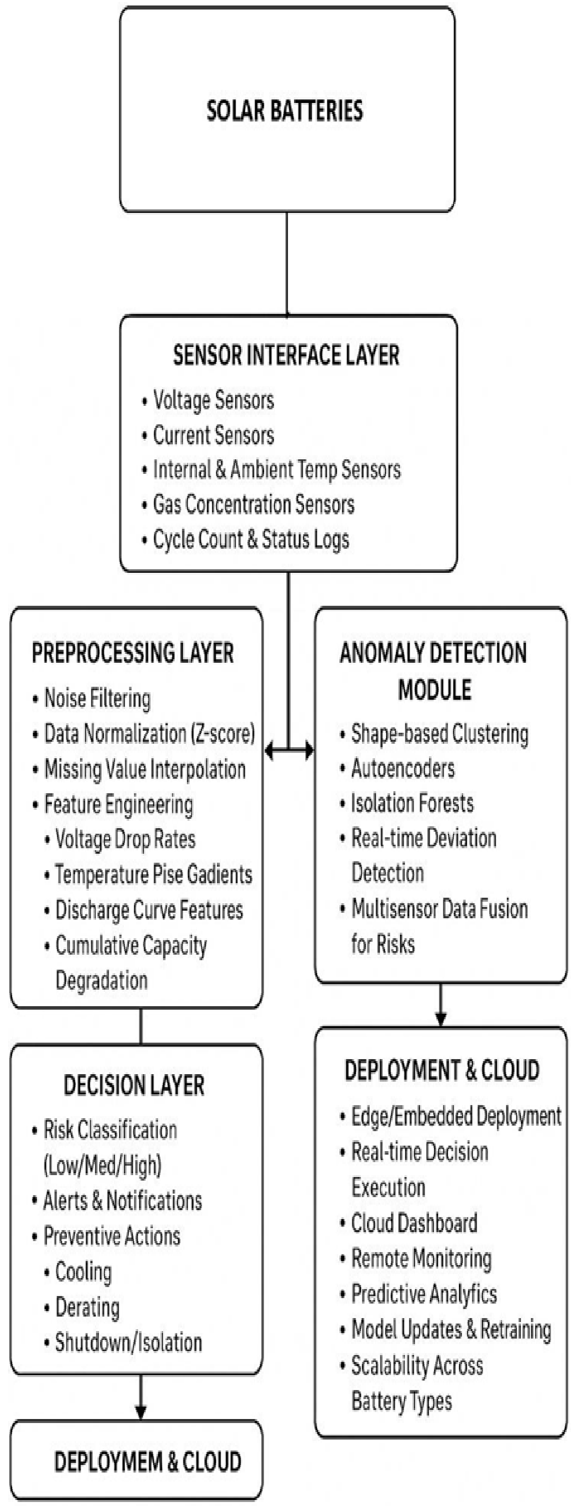

Figure 1: Architecture for ML-based BMS for Solar Batteries.

VII. DFD DIAGRAM

DFD Level 0

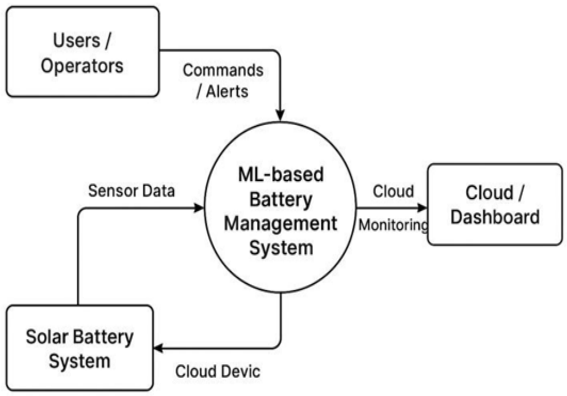

Figure 2: DFD Level 0 for ML-based BMS for Solar Batteries.

DFD Level 1

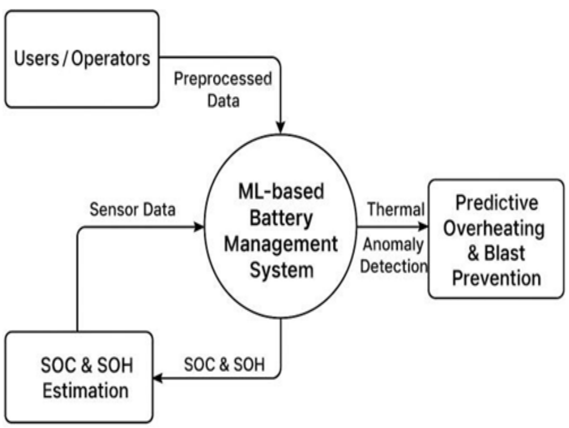

Figure 3: DFD Level 1 for ML-based BMS for Solar Batteries.

VIII. UML DIAGRAM

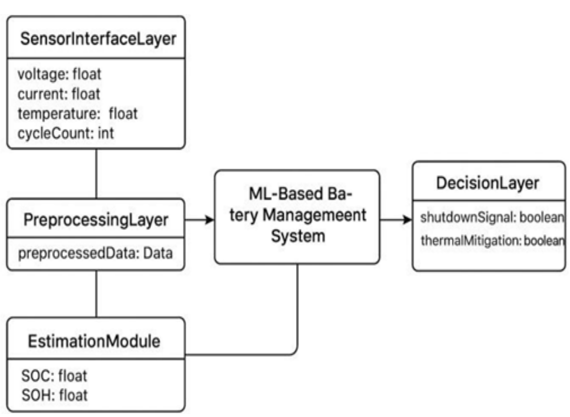

Figure 4: UML Diagram for ML-based BMS for Solar Batteries.

IX. FLOW CHART

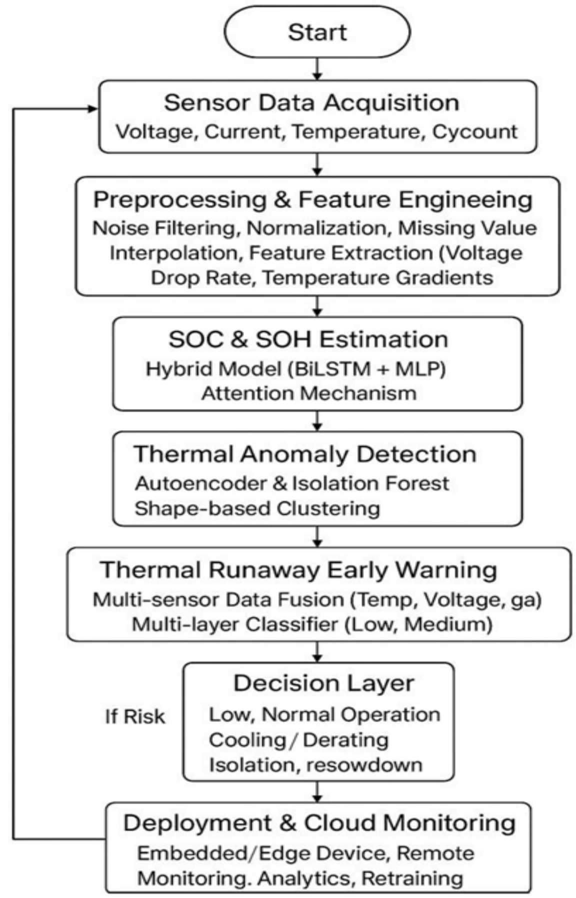

Figure 5: Flowchart for ML-based BMS for Solar Batteries.

X. FUCTIONAL REQUIREMENTS

The functional requirements define the core capabilities of the proposed Machine Learning- based Battery Management System (ML-BMS) for solar battery storage with predictive overheating and blast prevention features. These requirements are derived from the system methodology and aim to ensure accurate monitoring, real-time anomaly detection, and predictive safety control.

- Feature Extraction: Derived indicators such as voltage gradients, thermal rise rates, and degradation markers will be computed to support model learning.
- Real-Time SOC Estimation: A hybrid BiLSTM-MLP model will estimate SOC with sub-second latency using live sensor streams.
- SOH Prediction: Deep-learning models with

attention layers will assess long-term battery health and remaining useful life.

- Thermal-Anomaly Detection: Unsupervised models (autoencoders, isolation forests) will flag temperature or voltage deviations and classify them as normal, warning, or critical.
- Predictive Safety Response: When a high-risk condition is detected, the system will automatically initiate alerts, reduce charge/discharge rate, or disconnect the affected module.
- Performance Evaluation: Accuracy metrics such as MAE, RMSE, and F1-score will be logged for ongoing validation and retraining.
- Edge Implementation: All inference tasks will run locally on embedded hardware to guarantee real- time response even without cloud access.
- Cloud Interface – Periodic uploads to a secure dashboard will enable visualization, analytics, and remote updates.

XI. NON FUCTIONAL REQUIREMENTS

The non-functional requirements ensure that the proposed ML-enhanced Battery Management System operates reliably, securely, efficiently, and is maintainable and scalable for long-term solar energy storage applications.

- Performance: SOC/SOH estimation error shall remain within 2–3 %; anomaly detection must issue alerts at least 10 minutes before critical temperature is reached.
- Reliability: The system should achieve ≥99.5 % uptime and default to safe-shutdown mode upon any model or sensor failure.
- Scalability: Architecture must support multiple battery packs and allow new sensors to be added with minimal configuration.
- Security: All communications must be encrypted (TLS 1.2 or higher); only authenticated users may access configuration or logs.
- Maintainability: Remote diagnostics, firmware, and model updates shall be supported through modular design.
- Usability: Dashboards should clearly display SOC/SOH, temperature trends, and alerts with multi-channel notifications.
- Portability: Software must run on various embedded platforms (e.g., Raspberry Pi, Jetson, STM32).
- Data Logging: Sensor and model data must be stored for at least six months locally and optionally mirrored to the cloud.
- Accuracy: Predictive models should achieve ≥95% accuracy and F1 ≥ 0.9 on benchmark datasets.
- Compliance: The design shall adhere to IEC 62619, IEEE 1725/1625, and relevant data-protection standards.

XII. CONCLUSION

Growing dependence on solar energy has highlighted the necessity for advanced, reliable, and secure energy-storage management. Traditional BMS technologies face challenges in accurately assessing parameters like SOC and SOH and in identifying safety-critical conditions such as overheating or runaway reactions. These limitations pose significant risks to both battery performance and operational safety, especially in solar applications where environmental and load conditions vary unpredictably.

This work tackles these limitations by developing a Machine-Learning-based BMS aimed at enhancing safety and predictive control for solar battery installations. The system leverages real-time sensor data, deep learning models (e.g., BiLSTM and MLP), and unsupervised anomaly detection techniques to deliver precise SOC/SOH estimation, predictive thermal monitoring, and early fault prevention. Through careful integration of edge deployment and cloud-based dashboards, the system ensures low-latency response, scalability, and user accessibility.

By meeting both functional and non-functional requirements—such as performance accuracy, reliability, maintainability, and security,the proposed ML-BMS represents a significant step forward in energy storage technology. It not only enhances the lifespan and efficiency of batteries but also introduces proactive safety mechanisms that are essential for preventing hazardous incidents such as thermal runaway and battery explosions.

In conclusion, the implementation of this ML-enhanced BMS paves the way for a new generation of intelligent, self-learning, and safety-aware energy storage systems. This innovation supports the broader goal of achieving sustainable and resilient renewable energy infrastructure, where data-driven decision-making ensures both performance and protection in real-time.

REFERENCES

[1] Amrutha Varshini, C. R., Jha, A., Tiwari, A., & Deepa, K. (2024). Hybrid Machine Learning Model for EV Battery SoC and SoH Prediction.

[2] Yang, M., Liu, Y., Li, B., & Yang, C. (2025). State of Health Estimation for Lithium-Ion Batteries with an Attention-Integrated BiLSTM–MLP Hybrid Model.

[3] Li, X., Li, J., Abdollahi, A., & Jones, T. (2021). Data-Driven Thermal Anomaly Detection for Batteries Using Unsupervised Shape Clustering.

[4] Bhaskar, K. (2022). Data-Driven Thermal Anomaly Detection in Large Battery Packs.

[5] Gao, W., Li, X., Ma, M., Fu, Y., Jiang, J., & Mi, C. (2021). Case Study of an Electric Vehicle Battery Thermal Runaway and Online Internal Short Circuit Detection.

[6] Choi, Y., & Park, P. (2024). Thermal Runaway Diagnosis of Lithium-Ion Cells Using Data-Driven Methods.

[7] Pu, Z. (2024). Thermal Runaway Warning of Lithium Batteries Based on Electronic Nose and Machine Learning Algorithms.

[8] Nam, K., & Ahn, C. (2025). Energy-Efficient Battery Thermal Management in Electric Vehicles Using Artificial Neural Network-Based Model Predictive Control (ANN-MPC).

[9] Fang, X., Fang, K., Zheng, L., Zhu, H., Zhuo, Q., & Li, J. (2023). SOH Prediction in Li-Ion Battery Energy Storage Systems in Power Energy Networks.

[10] Zhou, K. Q., Qin, Y., & Yuen, C. (2024). Graph Neural Network-Based Lithium-Ion Battery State of Health Estimation Using Partial Discharging Curve.