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AI-BASED EARLY BATTERY THERMAL PREDICTION SYSTEM

[1]Ms.M. Roshni — Assistant Professor

[2]Ms. K. Nivettha Sri — Final Year Student

[3]Ms.R. Rama Jeevitha — Final Year Student

Department Of Computer Science And Engineering,
Vivekanandha College Of Engineering For Women, Tiruchengode, India

Abstract: Lithium-ion batteries are widely used in renewable energy systems, electric vehicles, and portable devices, but they are highly sensitive to temperature variations and operational stress, which can lead to thermal runaway and safety hazards. Early detection of such conditions is essential to prevent failures, extend battery life, and ensure system reliability. This project proposes an AI-based Battery Management System (BMS) for early prediction of thermal runaway and accurate estimation of battery State-of-Health (SOH). The system utilizes multiple sensors such as voltage, current, and temperature to continuously monitor battery parameters in real time. The collected data is processed using machine learning algorithms to identify abnormal patterns and predict potential faults at an early stage. The integration of renewable solar charging with an MPPT controller ensures efficient and sustainable energy utilization. Additionally, the system supports real-time monitoring and intelligent decision-making, enabling preventive actions and self-healing mechanisms. The proposed solution is scalable, cost-effective, and suitable for deployment in rural and off-grid microgrid applications, improving battery safety, performance, and overall energy management efficiency.

Index Terms: Battery Management System (BMS), Lithium-Ion Battery, Thermal Runaway Prediction, State of Health (SOH), Artificial Intelligence, Machine Learning, IoT, Real-Time Monitoring, Renewable Energy, Solar Microgrid, Temperature Monitoring, Fault Detection, Predictive Maintenance, Embedded Systems, Energy Storage Systems.

I. INTRODUCTION

Lithium-ion batteries have become a crucial component in modern energy storage systems, widely used in renewable energy applications, electric vehicles, and portable electronic devices. Despite their high energy density and efficiency, these batteries are highly sensitive to operating conditions such as temperature, voltage, and current. Improper management or extreme conditions can lead to thermal runaway, a critical failure that may cause overheating, fire hazards, and even explosions. In recent years, the increasing deployment of battery systems in solar microgrids and off-grid environments has raised significant concerns regarding safety, reliability, and long-term performance. Therefore, early detection of battery faults and accurate health monitoring are essential to prevent failures and ensure safe operation.

Conventional Battery Management Systems (BMS) rely on rule-based methods and predefined thresholds to monitor battery parameters. Techniques such as Coulomb counting and Kalman filtering are commonly used for estimating battery state, but they often lack accuracy under dynamic operating conditions. These systems are generally limited in their ability to predict future failures and cannot effectively detect early signs of degradation or thermal instability. Moreover, traditional approaches require frequent calibration and are often dependent on specific battery chemistry, making them less flexible and inefficient for real-time applications in renewable energy systems.

To overcome these limitations, this project proposes an AI-based Battery Management System for early prediction of thermal runaway and accurate estimation of battery State-of-Health (SOH). The system utilizes multiple sensors to continuously monitor parameters such as voltage, current, and temperature. The collected data is processed using machine learning algorithms to identify patterns, detect anomalies, and predict potential failures at an early stage. The integration of solar energy with an MPPT-based charging system ensures efficient and sustainable energy utilization. Additionally, the system supports real-time monitoring and intelligent decision-making, enabling preventive actions and improving battery lifespan. Overall, the proposed solution provides a reliable, scalable, and cost-effective approach for enhancing battery safety and performance in modern energy storage systems.

II.RELATED WORKS

With the rapid advancement of energy storage technologies and renewable energy systems, significant research has been carried out in the field of lithium-ion battery monitoring and management. Researchers have focused on developing Battery Management Systems (BMS) that monitor critical parameters such as voltage, current, temperature, and charge cycles. These systems continuously collect real-time data and use it to estimate battery performance and safety conditions. The use of multiple sensors improves monitoring accuracy by capturing dynamic variations in battery behavior. Many existing systems are designed to operate automatically, reducing the need for manual supervision. However, most traditional approaches rely on fixed threshold values and simple estimation techniques, which limit their ability to detect early-stage faults and predict future failures.

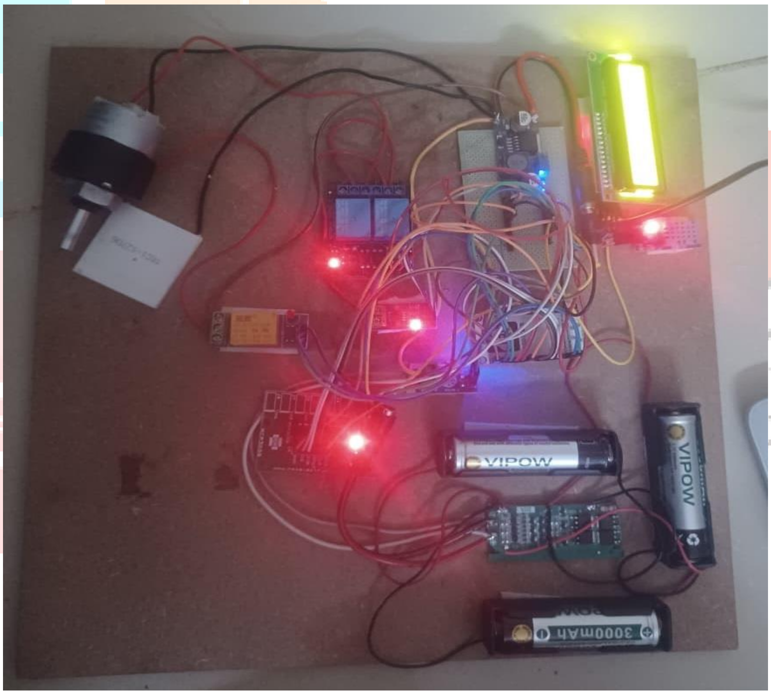
Many conventional BMS implementations are based on embedded platforms such as microcontrollers and utilize techniques like Coulomb counting, equivalent circuit models, and Kalman filtering for estimating battery parameters such as State of Charge (SOC) and State of Health (SOH). These systems are widely used due to their simplicity and low computational requirements. However, they often suffer from inaccuracies under varying operating conditions, battery aging, and environmental changes. In addition, these methods require frequent calibration and are highly dependent on battery chemistry, making them less adaptable for real-time and large-scale applications. The lack of intelligent decision-making capabilities further limits their effectiveness in predicting thermal runaway and other critical failures.

Wireless communication technologies such as GSM, Wi-Fi, and Bluetooth have been used in earlier battery monitoring systems to enable remote data transmission and monitoring. While these technologies allow basic connectivity, they suffer from limitations such as high power consumption, limited coverage range, and network dependency. In remote or off-grid environments, especially in solar microgrid applications, these communication methods may not provide reliable and continuous monitoring. As a result, ensuring real-time data availability and system reliability becomes challenging in such scenarios.

Recent research has introduced advanced data-driven approaches using Artificial Intelligence (AI) and Machine Learning (ML) techniques for battery health prediction and fault detection. These models analyze both real-time and historical battery data to identify complex patterns, predict degradation trends, and detect abnormal behavior at an early stage. Techniques such as Random Forest, Support Vector Machines, and Long Short-Term Memory (LSTM) networks have shown promising results in improving prediction accuracy. AI-based systems significantly reduce false alarms and enhance early warning capabilities compared to traditional threshold-based methods. However, many of these models are implemented in isolation and are not fully integrated with real-time embedded BMS frameworks. Additionally, some AI models require high computational resources and cloud-based processing, which may introduce latency and limit real-time decision-making.

Energy efficiency and intelligent data processing have become key focus areas in modern battery management research. Researchers are exploring multi-parameter data fusion techniques, where inputs such as voltage, current, temperature, and internal resistance are combined to improve prediction accuracy. Low-power system design and efficient charging strategies are also being developed to extend battery lifespan and ensure safe operation. Techniques such as adaptive charging, thermal management, and predictive maintenance are gaining importance in advanced BMS designs. However, achieving a balance between computational efficiency, real-time performance, and prediction accuracy remains a major challenge. Therefore, there is a strong need for integrated systems that combine IoT-based monitoring, AI-driven analysis, and energy-efficient design to provide reliable, scalable, and intelligent battery management solutions.

SAMPLE OUTPUT IMAGE



III.METHODOLOGY

The methodology of the proposed system focuses on designing and implementing an intelligent Battery Management System (BMS) that ensures early detection of thermal runaway and accurate prediction of battery State-of-Health (SOH) through real-time monitoring, data-driven analysis, and reliable system integration. The system combines multiple sensors, a microcontroller, machine learning algorithms, and a renewable energy-based charging system to continuously monitor battery conditions and detect potential faults. The development process includes data acquisition, preprocessing, intelligent analysis, prediction, decision-making, and real-time monitoring.

3.1 Power Supply and Charging System

This module provides a stable and regulated power supply to all components of the system. Since the system is designed for solar microgrid and off-grid applications, it utilizes renewable solar energy as the primary power source. An MPPT (Maximum Power Point Tracking) controller is used to optimize energy harvesting and ensure efficient battery charging. A voltage regulator maintains stable voltage levels for sensors, microcontroller, and other electronic components. This module ensures uninterrupted system operation and improves overall energy efficiency.

3.2 Data Acquisition and Monitoring

In this module, multiple sensors are used to continuously monitor battery parameters such as voltage, current, and temperature. These parameters are critical indicators of battery health and performance. The sensor data is collected in real time and transmitted to the microcontroller for further processing. Continuous monitoring helps in identifying variations in battery behavior under different operating conditions and provides the foundation for accurate analysis and prediction.

3.3 Data Processing and Decision Making

The microcontroller acts as the central processing unit of the system. It receives real-time sensor data and performs initial processing, including filtering and normalization. The processed data is compared with predefined safety thresholds to identify abnormal conditions such as overheating, overcharging, or excessive current flow. If any parameter exceeds the safe limits, the system identifies it as a potential risk. This module enables quick decision-making and ensures immediate response to critical situations.

3.4 AI-Based Analysis and Prediction

This module enhances the system by incorporating Artificial Intelligence and Machine Learning techniques for intelligent battery monitoring. The collected data is analyzed using machine learning algorithms such as Random Forest or LSTM to predict battery State-of-Health (SOH) and detect early signs of thermal runaway. The AI model is trained using historical and real-time data to identify patterns and anomalies. This approach improves prediction accuracy, enables early fault detection, and reduces false alarms. It also supports predictive maintenance and extends battery lifespan.

3.5 Communication and Monitoring

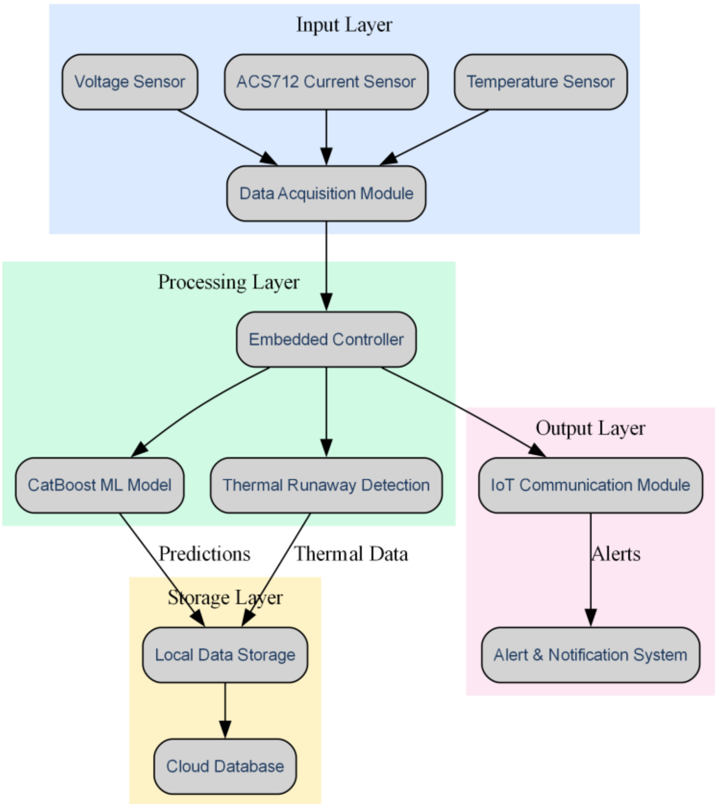
The system includes a communication module to enable real-time monitoring and data transmission. The processed data and prediction results can be transmitted to a remote monitoring system or cloud platform using suitable communication technologies. This allows users to monitor battery performance remotely through web or mobile interfaces. The communication system ensures continuous data availability and enhances system reliability, especially in remote or off-grid environments.

IV SYSTEM ARCHITECTURE

The proposed AI-Based Early Battery Thermal Runaway Prediction System is designed to provide real-time monitoring, intelligent analysis, and early detection of potential battery failures in lithium-ion battery systems. The architecture consists of multiple integrated components, including sensor modules, a data acquisition unit, a preprocessing module, a machine learning-based prediction system, a communication module, and an alert mechanism. These components work together to ensure accurate prediction and reliable operation, especially in renewable energy-based microgrid environments. The system is designed for continuous monitoring, enabling uninterrupted tracking of battery health. It also supports scalability, allowing multiple battery units to be monitored simultaneously. The integration of AI and IoT technologies enhances prediction accuracy, reduces risk, and improves overall system efficiency.

The system begins with sensor data acquisition, where sensors continuously measure critical battery parameters such as voltage, current, and temperature. These parameters act as key health indicators for detecting abnormal battery behavior. The collected data is transmitted to the NodeMCU (ESP8266), which acts as the central controller. It gathers real-time data from all sensors and forwards it to the processing system through serial or Wi-Fi communication.

In the data preprocessing stage, the raw sensor data is cleaned and normalized to remove noise and inconsistencies. This step improves data quality and ensures accurate input for the machine learning model. The processed data is then fed into the K-Nearest Neighbors (KNN) algorithm, which serves as the core prediction module. The algorithm analyzes the input data by comparing it with previously trained data and classifies the battery condition based on similarity patterns.



During the prediction and decision-making stage, the system categorizes battery status into three conditions: Normal, Pre-runaway, and Critical fault. If the battery operates within safe limits, the system continues monitoring. If early warning signs are detected, it identifies a pre-runaway condition and generates alerts. In case of critical abnormalities, the system flags a fault condition, enabling immediate preventive action. This stage ensures early fault detection and reduces the risk of thermal runaway.

Finally, the system includes a communication and alert mechanism, where the predicted results are transmitted to a monitoring interface or user system. Alerts can be generated in real time to notify users of potential risks. This enables quick response and preventive maintenance. The overall architecture ensures a smart, reliable, and efficient battery management system suitable for modern energy applications.

V RESULTS AND DISCUSSION

The proposed AI-Based Battery Thermal Runaway Prediction System was tested under various operating conditions to evaluate its performance in monitoring battery health and predicting potential failures. The system continuously monitored key parameters such as voltage, current, and temperature using sensors. These parameters were analyzed in real time using the KNN-based machine learning model to classify battery conditions. When the sensor values deviated from normal operating ranges, the system successfully identified abnormal patterns and predicted potential thermal runaway conditions. Immediate alerts were generated to notify users, enabling preventive actions. The results demonstrate that the system provides accurate prediction, early fault detection, and improved safety compared to traditional methods.

The performance of the system under different conditions is summarized in Table 1.

Table 1: System Performance Analysis

S.No	Parameter Monitored	Normal Range	Observed Condition	System Response	Result
1	Temperature	20°C – 40°C	Above 50°C	Immediate Alert	Thermal risk detected
2	Voltage	3.0V – 4.2V	Above 4.3V / Below 2.8V	Warnin Generated	Overcharge/ Deep discharge
3	Current	Safe operating limit	Excess current	Alert Generated	Overcurrent detected
4	Battery State (KNN Output)	Normal	Pre-runaway detected	Early Warning	Fault predicted
5	Critical Condition	Safe	Critical fault	Immediate Action	Thermal runaway prevention
6	Communication (NodeMCU)	Stable	Data transmitted	Real-time update	Reliable monitoring
7	System Response Time	< 3 sec	Immediate	Automatic alert	Fast response

From the observed results, it is evident that the proposed system effectively identifies different battery states, including Normal, Pre-runaway, and Critical conditions. The integration of AI enables intelligent decision-making by analyzing real-time sensor data and detecting hidden patterns. The system responds quickly to abnormal conditions, reducing the risk of battery failure and thermal hazards. Additionally, the use of NodeMCU ensures reliable data transmission and continuous monitoring. The system shows high accuracy, fast response time, and efficient performance in ensuring battery safety and reliability. Overall, the proposed solution demonstrates significant improvement in predictive capability, making it suitable for modern energy storage and renewable energy applications.

VI CONCLUSION

The proposed AI-Based Battery Thermal Runaway Prediction System provides an efficient and reliable solution for monitoring lithium-ion battery health in real-time. The system continuously tracks critical parameters such as voltage, current, and temperature using sensors. By utilizing NodeMCU (ESP8266) and IoT communication, the collected data is transmitted effectively for analysis. This real-time monitoring enables early detection of abnormal battery conditions, helping to prevent thermal runaway and ensuring system safety.

The integration of Artificial Intelligence enhances the system's capability to perform accurate and intelligent predictions. Sensor data is analyzed using the KNN machine learning algorithm to classify battery conditions into normal, pre-runaway, and critical states. This predictive approach minimizes false alarms and enables early warning generation. The system responds quickly to hazardous conditions by providing real-time alerts, allowing timely preventive actions and improving battery lifespan.

Overall, the system demonstrates high accuracy, fast response time, and reliable performance. The use of low-cost hardware and scalable architecture makes it suitable for applications in renewable energy systems, electric vehicles, and smart energy storage. Furthermore, the system can be enhanced by integrating advanced machine learning models, cloud-based monitoring, and mobile alert systems. This makes it a promising solution for future intelligent battery management and safety systems.

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