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Smart IoT Based Battery Management System for EV Battery

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ABSTRACT

Advanced battery management is now essential for lifetime and safety due to the quick spread of lithium-ion batteries in electric cars and renewable energy systems. Static hardware thresholds are usually used by traditional battery management systems (BMS) to guard against overvoltage, undervoltage, and overcurrent. Although these static methods work well for simple defects, they frequently fail to anticipate compounding stress elements that cause thermal runaway or cell deterioration. The design and implementation of a sophisticated, Internet of Things-enabled BMS for a 3S (11.1V) Lithium-ion battery pack is shown in this study. It integrates real-time telemetry with an edge-computed Machine Learning (ML) algorithm. The system accomplishes high-fidelity sensing by using a 16-bit ADS1115 Analogue-to-Digital Converter and an ESP8266 microprocessor dynamic "Risk Score" is continually computed by a Logistic Regression model using voltage, current, temperature, State of Charge (SoC), and State of Health (SoH). The system has a multi-tiered protection procedure that includes a physical relay cutoff during critical stages and a nonblocking audio warning during medium-risk conditions. Additionally, the BMS transmits telemetry to the ThingSpeak cloud platform in its capacity as a smart-grid edge device. The dependability and remote observability of energy storage systems are greatly improved by this predictive method, as demonstrated by experimental data.

Keywords: *Internet of Things (IoT), Machine Learning, Logistic Regression, Lithium-Ion, Edge Computing, Battery Management System (BMS).*

1. INTRODUCTION

The global transition toward sustainable energy and electric mobility is heavily reliant on the efficiency and safety of Lithium-ion (Li-ion) batteries. However, Li-ion chemistry is highly sensitive to operational extremes, necessitating robust Battery Management Systems (BMS) to prevent catastrophic failures such as thermal runaway [1]. Conventional low-cost BMS architectures employ static threshold protection. While these systems successfully isolate batteries when predefined, hard limits are crossed (e.g., maximum voltage), they do not account for the dynamic, multi-variable stress a battery experiences under load [2]. For instance, a moderate current draw may be safe at 25°C but critically dangerous at 50°C. This paper proposes a novel BMS architecture that bridges traditional power electronics with modern computing paradigms. By embedding a Machine Learning (ML) Logistic Regression model directly onto an edge microcontroller (ESP8266), the system evaluates the real-time interplay between multiple electrical and thermal parameters. Coupled with IoT cloud telemetry, this predictive BMS identifies fault trajectories before absolute physical limits are breached, thereby extending battery lifespan and enhancing user safety.

2. SYSTEM ARCHITECTURE

The proposed BMS operates on mixed-voltage logic architecture (12.6V, 5V, 3.3V) to safely interface high-power battery lines with sensitive microelectronics.

2.1 Hardware Design: The core processing unit is the ESP8266 NodeMCU. To overcome the resolution limits of the microcontroller's internal 10-bit ADC, a dedicated ADS1115 16-bit ADC is utilized over the I2C bus. This provides a resolution of 0.187mV, enabling highly accurate Coulomb counting.

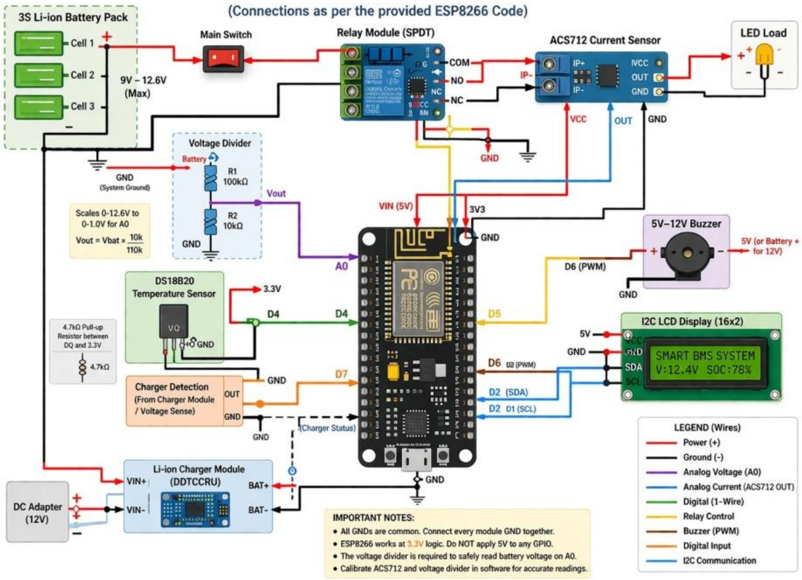

Fig-1: System Circuit Diagram

i. **Voltage Sensing:** A 5:1 passive resistor potential divider drops the 12.6V maximum pack voltage to a safe ~2.5V logic level.
ii. **Current Sensing:** An Allegro ACS712 Hall-effect sensor is placed in series with the load. An automated zero-point calibration routine is executed at boot to filter ambient electromagnetic noise.
iii. **Thermal Sensing:** A DS18B20 digital thermometer is thermally coupled to the battery cells to monitor ambient pack temperature.
iv. **Safety Interlock:** A 5V Active-Low relay acts as the primary digital circuit breaker, isolating the load during fault conditions.

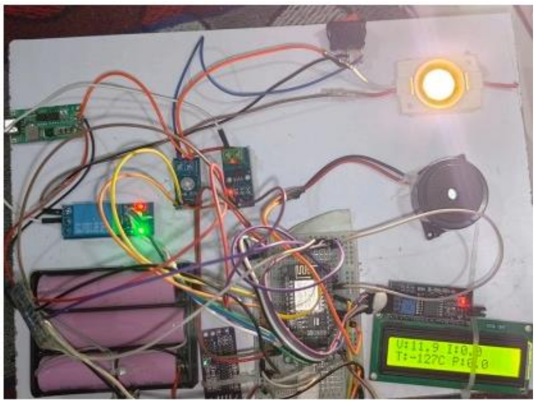

Fig-2: System connections and analysis

2.2 IoT Telemetry: The ESP8266 acts as a smart-grid edge device, utilizing its integrated Wi-Fi stack to publish serialized HTTP POST requests to the MathWorks ThingSpeak platform. Telemetry data including Voltage, Current, Power, Temperature, SoC, SoH, and the ML Risk Score is updated every 20 seconds, ensuring compliance with API rate limits while providing high-fidelity remote monitoring.

3. PREDICTIVE MACHINE LEARNING MODEL

The primary innovation of this BMS is the shift from reactive to predictive protection using Edge ML. A Logistic Regression algorithm was trained heuristically to evaluate battery stress.

3.1 Risk Score Calculation:

The algorithm calculates a dynamic Risk Score (Z) using the following equation:

Z = b0 + b1*V + b2*I + b3*T + b4*SoC + b5*SoH

Where the coefficients are optimized for a Panasonic 18650 cell profile: Bias (b0 = -3.5), Voltage (b1=0.25), Current (b2 = 0.40), Temperature (b3 = 0.05), State of Charge (b4 =-0.015), and State of Health (b5 = -0.03). The output is passed through a sigmoid activation function to generate a probability between 0 and1.

Risk Score = $(1/1+e^{-z})$

3.2 Multi-Tiered Protection Protocol:

Based on the Risk Score, the system executes a multi-tiered response utilizing a non blocking timing loop (millis()), allowing continuous data acquisition even during alarm states:

i. **Safe (< 0.60):** Normal operation; relay remains closed.
ii. **Warning (0.60 - 0.85):** Relay remains closed to prevent nuisance tripping, but a localized 5-beep audible alarm and visual LCD warning (! WARN) are triggered.
iii. **Critical/Fault (> 0.85):** Immediate isolation. The relay snaps open, cutting power to the load, accompanied by a continuous alarm.

4. RESULTS AND DISCUSSION

The prototype was subjected to rigorous bench testing using a 3S (11.1V, 5.0Ah) Li-ion pack. The performance of the static hardware limits and the dynamic ML model were evaluated independently.

4.1 Static Hardware Limit Validation: As shown below in Table 1, the system successfully triggered the safety interlock under forced extreme conditions, effectively replicating the reliability of standard commercial BMS units.

Table 1: Static Hardware Protection Validation.

Fault Condition	Programmed Limit	Observed Sensor Value	Interlock Action
Deep Discharge	<9.0V	8.92V	Cutoff (Pass)
Over Charge	>12.7V	12.75V	Cutoff (Pass)
Thermal Runway	>59.0 ºC	60.5ºC	Cutoff (Pass)

4.2 ML Predictive Algorithm Performance: The predictive capability of the system was tested by applying a heavy continuous load, generating a compounding stress scenario(voltage sag + rising temperature). As detailed in Table II, the system successfully entered the Warning phase at a calculated Risk Score of 0.74, alerting the user without immediately cutting power. As thermal limits continued to rise alongside dropping SoC, the system pre-emptively cut power at a Risk Score of 0.90, before absolute static limits were reached.

Table 2: Dynamic ML Risk Observations

Phase	Volts(V)	Amps(I)	Temp(ºC)	Calculated Risk Score	System State
Idle	12.0	0.00	25	0.02	Safe
Std Load	11.5	2.00	30	0.08	Safe
Heavy Load	10.0	6.00	50	0.74	Warning
Pre-Fault	9.5	8.00	55	0.90	Fault (Cutoff)

CONCLUSION

This project successfully demonstrates the integration of edge-computed machine learning and IoT telemetry into battery management systems. By utilizing high resolution ADCs and a Logistic Regression predictive model, the system successfully identifies compounding battery stress factors before absolute failure limits are reached. The implementation of a multi-tiered warning protocol significantly reduces nuisance tripping while maintaining strict safety interlocks. Future development will focus on integrating bi-directional MQTT cloud control and upgrading the prediction algorithm to Long Short-Term Memory (LSTM) neural networks for precise Remaining Useful Life (RUL) estimation.

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