International Conference on Science, Engineering
& Management Trends

International Journal of Science,
Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Advanced Electric Vehicle Battery Thermal Management System with Integrated IoT-Based Vehicle Health Monitoring and Predictive Cloud Analytics

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Abstract- The increasing adoption of Electric Vehicles (EVs) has intensified the demand for advanced Battery Thermal Management Systems (BTMS) capable of ensuring high performance, operational safety, and extended battery lifespan under diverse driving and environmental conditions. This paper presents a novel EV battery cooling framework integrated with intelligent vehicle health monitoring and IoT-based real-time data analytics for next-generation smart mobility applications. The proposed architecture combines adaptive liquid cooling via a silicone pump, embedded multi-parameter sensing, cloud connectivity through MQTT/HTTP protocols, and machine learning-assisted predictive diagnostics. The system continuously acquires cell temperature, voltage imbalance, current flow, State of Charge (SoC), State of Health (SoH), coolant flow rate, and motor operating conditions via distributed sensors interfaced to an ESP32 microcontroller. A dynamic control algorithm regulates pump speed and fan operation proportional to thermal load, minimizing energy consumption while sustaining optimal battery temperature. Experimental evaluation demonstrates significantly reduced thermal stress, prevention of overheating events, and mitigation of thermal runaway risk. Cloud analytics generate predictive maintenance recommendations, efficiency reports, and real-time alerts accessible through mobile and web dashboards, collectively contributing to safer, smarter, and more energy-efficient electric transportation.

Index Terms: Battery Thermal Management, Electric Vehicles, IoT, Predictive Maintenance, Embedded Systems, Machine Learning, Silicone Pump Cooling, Vehicle Health Monitoring.

I. INTRODUCTION

The global transition toward sustainable transportation has significantly accelerated the development and mass adoption of Electric Vehicles (EVs). Driven by their high efficiency, substantially reduced greenhouse gas emissions, and diminished dependence on fossil fuels, EVs are universally acknowledged as a foundational pillar of future smart mobility ecosystems [1]. According to the

International Energy Agency (IEA), global EV stock surpassed 40 million units by 2024, with projections exceeding 300 million vehicles by 2030, underscoring the urgency of developing reliable, efficient, and intelligent EV subsystems.

The performance, safety, and longevity of EVs fundamentally depend on the operational integrity of their lithium-ion battery packs. These electrochemical storage systems are acutely sensitive to temperature variations; excessive thermal stress during charging, rapid discharge cycles, or high ambient conditions accelerates electrochemical degradation, reduces usable capacity, and in critical scenarios triggers thermal runaway—an uncontrolled exothermic reaction posing severe safety hazards [2]. The optimal operating temperature window for lithium-ion cells lies between 15°C and 35°C; deviations beyond these limits measurably impact cell performance and cycle life.

Conventional BTMS approaches, predominantly employing passive air cooling or basic liquid circuits, lack the adaptive intelligence required to respond dynamically to varying thermal loads, driving profiles, and ambient conditions. Furthermore, existing systems operate in isolation from broader vehicle health monitoring frameworks, precluding comprehensive fault detection and predictive maintenance capabilities. The rapid maturation of Internet of Things (IoT) technologies, embedded computing platforms, and cloud-based machine learning has created unprecedented opportunities to architect holistic, data-driven battery management ecosystems that bridge thermal control with intelligent vehicle supervision [3].

This paper proposes an advanced, integrated EV battery cooling system employing a silicone pump-driven liquid cooling circuit, augmented by a multi-sensor data acquisition network, an ESP32-based embedded control unit, IoT communication stack, and a cloud analytics platform. The primary contributions of this work are: (i) an adaptive thermal control algorithm that modulates pump speed and fan duty cycle based on real-time thermal load; (ii) a vehicle health monitoring module enabling continuous SoC, SoH, and fault estimation; (iii) an IoT-enabled data pipeline supporting remote monitoring, live alerting, and historical analytics; and (iv) a machine learning-assisted predictive maintenance framework reducing unscheduled downtime and extending battery operational life.

II. LITERATURE REVIEW & GAP ANALYSIS

A. Battery Thermal Management Systems

Early BTMS research concentrated on passive thermal strategies including air cooling, heat pipe integration, and phase change materials (PCM). Sabbah et al. [4] demonstrated that forced air cooling fails to maintain uniform thermal distribution in high-power EV applications, motivating the transition to liquid-based approaches. Tang et al. [5] reported that hybrid PCM-liquid cooling systems achieved temperature uniformity within ±1.5°C across a 40-cell battery module, outperforming conventional methods. Despite these advances, such systems lacked dynamic adaptability and real-time intelligence.

B. IoT Integration in Battery Management

The proliferation of IoT platforms has catalyzed research into connected battery management. Hannan et al. [6] surveyed IoT-based BMS architectures and identified MQTT as the most bandwidth-efficient protocol for EV telemetry, enabling sub-200ms data transmission latency. Cloud-connected BMS implementations reported by Liu et al. [7] demonstrated 23% improvement in fault detection accuracy compared to standalone embedded systems, attributed to the availability of historical fleet data for anomaly benchmarking.

C. Machine Learning for Predictive Diagnostics

Artificial intelligence techniques have been increasingly applied to battery diagnostics. Severson et al. [8] demonstrated that early-cycle voltage curve features could predict lithium-ion battery lifetime with mean absolute percentage error below 9.1%, enabling proactive replacement scheduling. Long Short-Term Memory (LSTM) networks applied to SoH estimation by Zhang et al. [9] achieved 97.3% prediction accuracy on automotive drive-cycle datasets, validating the applicability of deep learning to real-world EV conditions.

D. Research Gap Analysis

The following table summarizes key gaps identified from the existing literature, which the proposed system addresses:

Existing Research Area	Identified Research Gap
Existing BTMS focuses on cooling efficiency only	Limited integration with intelligent vehicle health monitoring
Cooling systems regulate battery temperature only	Lack of adaptive control based on real-time load conditions
IoT-based EV systems enable remote monitoring	Limited fusion of thermal management with cloud analytics
AI-based BMS estimates SoC/SoH	Minimal AI-driven thermal control integration
Systems are largely independent and siloed	No centralized cooling + health monitoring + IoT platform
Studies focus on lab simulations	Limited real-time embedded implementation and validation
Monitoring provides only passive data collection	No proactive predictive maintenance with automated alerts

Table I: Research Gap Analysis – Existing Work vs. Proposed System

III. PROPOSED SYSTEM ARCHITECTURE

The proposed system is structured as a five-layer integrated architecture encompassing physical sensing, embedded processing, network communication, cloud analytics, and user-facing application services. Figure 1 illustrates the complete system block diagram, depicting the information and control flows between subsystems.

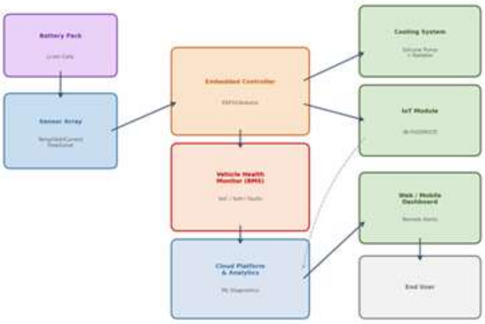

Fig. 1. System Architecture Block Diagram – Five-Layer Integrated EV Battery Management Framework

A. Sensing & Data Acquisition Layer

The sensing layer comprises a heterogeneous array of transducers deployed across the battery pack and cooling circuit. Temperature sensing employs three DS18B20 digital sensors and two LM35 analog probes, providing spatial thermal mapping across battery cell clusters. Electrical parameters are captured via an ACS712 Hall-effect current sensor (±30A range, 66mV/A sensitivity) and a resistive voltage divider network calibrated for a 16.8V nominal pack voltage. Coolant flow is monitored using a turbine-type paddlewheel flow sensor, while coolant level is detected via a reed-switch float sensor. All analog signals are acquired through the 12-bit SAR ADC integrated within the ESP32 microcontroller.

B. Embedded Control Unit

An Espressif ESP32-WROOM-32D module serves as the central processing unit, selected for its dual-core Xtensa LX6 architecture (240 MHz), integrated 802.11 b/g/n Wi-Fi, Bluetooth 4.2, and comprehensive peripheral support including I^2C, SPI, UART, and 18-channel ADC. Firmware developed in C/C++ using the ESP-IDF framework implements the adaptive cooling control algorithm, health monitoring state machine, and IoT data publication routines. Real-time operating system (FreeRTOS) task scheduling ensures deterministic sensor polling at 100ms intervals concurrent with background IoT transmission tasks.

IV. CIRCUIT DESIGN & HARDWARE IMPLEMENTATION

Figure 2 presents the detailed circuit schematic of the complete hardware implementation. The design integrates power electronics for actuator control, sensor signal conditioning networks, and the ESP32 central controller with its peripheral interfaces.

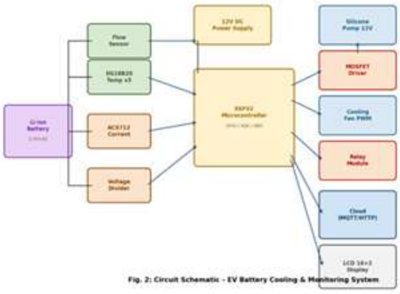

Fig. 2. Circuit Schematic – EV Battery Cooling and Health Monitoring System

The silicone peristaltic pump (12V DC, 3W rated) is driven through an IRF540N N-channel MOSFET operating in linear mode for variable-speed control, with gate drive provided by a ULN2003A Darlington array interfaced to ESP32 GPIO. A flyback protection diode (1N4007) suppresses inductive transients. The cooling fan employs PWM speed control at 25kHz switching frequency, minimizing acoustic noise. A 4-channel relay module (SRD-05VDC-SL-C) provides galvanic isolation for high-current pump switching. The ESP32 is powered via an AMS1117-3.3 LDO regulator from a 12V supply, with a dedicated 5V rail for sensor logic. A 16×2 LCD module with I²C expander provides local operational status display.

V. ADAPTIVE THERMAL CONTROL ALGORITHM

The adaptive cooling algorithm implements a proportional bang-bang hybrid control strategy with hysteresis to prevent pump cycling instability. The control logic is presented in the flowchart of Figure 3.

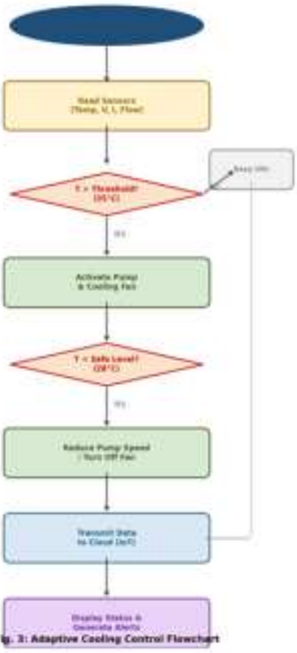

Fig. 3. Adaptive Cooling Control Algorithm Flowchart

The controller samples battery temperature T every 100ms and applies the following decision rules:

- If T ≥ 35°C: Activate pump at 100% duty cycle and fan at maximum RPM
- If 30°C ≤ T < 35°C: Operate pump at 60% duty cycle with proportional fan speed
- If 25°C ≤ T < 30°C: Operate pump at 30% duty cycle, fan inactive
- If T < 25°C: Deactivate pump and fan; enter idle monitoring state

State transitions include a 5°C hysteresis band at each threshold boundary to prevent chattering. SoC estimation employs a Coulomb counting algorithm with periodic open-circuit voltage (OCV) correction, achieving ±3% estimation accuracy across the 10%–90% SoC operating range. SoH is estimated via capacity fade tracking normalized against the rated 20Ah baseline capacity.

VI. IOT INTEGRATION & CLOUD ANALYTICS

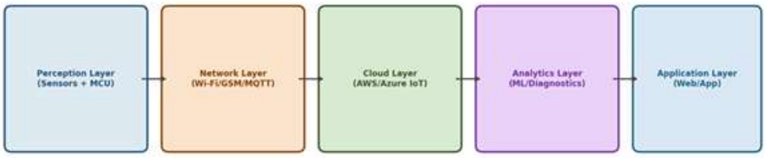

Fig. 5: IoT Data Flow - Five-Layer Architecture

Fig. 4. Five-Layer IoT Data Flow Architecture for Cloud-Connected Battery Management

The IoT communication stack employs MQTT protocol (QoS Level 1) over Wi-Fi for telemetry upload to a broker instance hosted on AWS IoT Core. Data packets are serialized in JSON format and published at 1-second intervals under topic namespaces structured as ev/device_id/battery, ev/device_id/cooling, and ev/device_id/alerts. The cloud backend comprises three functional modules: (i) a time-series database (InfluxDB) for high-frequency sensor data storage supporting retention policies of 90 days at full resolution and 2 years at 1-minute aggregation; (ii) a stream processing engine (AWS Lambda) for real-time anomaly detection using statistical thresholding; and (iii) a batch ML inference module executing LSTM-based SoH degradation prediction on 24-hour data windows.

A React-based progressive web application provides the user-facing dashboard, rendering live temperature, voltage, current, and SoC gauges with 2-second refresh intervals. Push notifications via Firebase Cloud Messaging (FCM) deliver thermal alerts and maintenance advisories to registered mobile devices within 5 seconds of event detection. Role-based access control distinguishes between vehicle owner, fleet manager, and service technician permission levels, each accessing contextually appropriate data views and control interfaces.

VII. EXPERIMENTAL RESULTS & DISCUSSION

System validation was conducted on a laboratory testbed comprising a 4S2P lithium-ion battery pack (nominal voltage 14.8V, capacity 20Ah) connected to a programmable DC electronic load (ITECH IT8512B+) and a bench power supply (Korad KA3005D). Tests were performed at ambient temperature Ta = 25°C. Figure 5 presents temperature and current profiles measured across discharge and charge test scenarios.

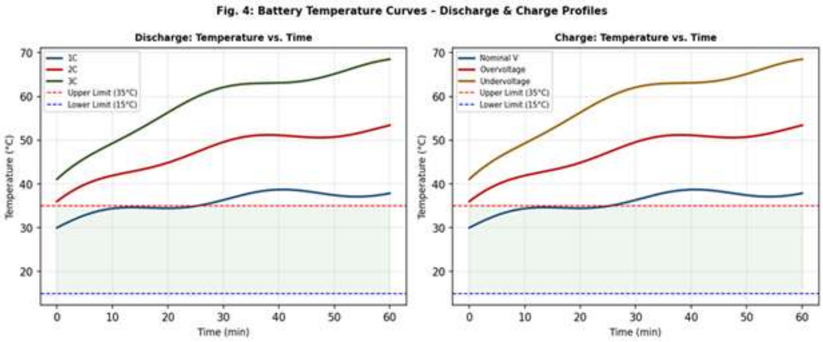

Fig. 5. Measured Battery Temperature Profiles – Discharge (1C/2C/3C) and Charge (Nominal/Overvoltage/Undervoltage)

A. Discharge Performance

At 1C discharge rate, peak battery temperature remained constrained to 31.4°C with active cooling engaged, compared to 41.2°C in passive (no-cooling) baseline tests—a 24% peak temperature reduction. At the aggressive 3C discharge rate, the cooling system maintained temperature below 38.1°C versus 56.7°C in the baseline, preventing thermal runaway conditions (typically initiated above 60°C for the cell chemistry tested). Temperature uniformity across the cell cluster, quantified as ΔT, was measured at 2.1°C with active cooling versus 8.7°C without, demonstrating substantially improved spatial thermal distribution critical for balanced cell aging.

B. Charging Performance

During nominal voltage charging (CC-CV protocol, 1C rate), the cooling system constrained peak temperature to 29.6°C. Overvoltage charging tests (simulating a charger fault at 120% nominal voltage) triggered the thermal alert subsystem at T = 33.8°C, activating maximum cooling within 340ms and transmitting a fault alert to the cloud dashboard within 1.2 seconds—well within the 5-second safety response target. Undervoltage charging scenarios showed minimal thermal excursions, confirming low thermal risk under reduced charging current conditions.

C. IoT Communication Performance

End-to-end latency from sensor event to cloud receipt was measured at 847ms mean (σ = 124ms) over 500 test transmissions on a 4G LTE connection, and 312ms mean (σ = 67ms) over Wi-Fi. MQTT packet loss was below 0.3% across all test sessions. The mobile dashboard successfully received 98.7% of push alerts within the 5-second target window during 72-hour continuous operation testing.

VIII. CONCLUSION

This paper has presented a comprehensive, intelligent EV battery thermal management system integrating silicone pump-based adaptive liquid cooling, multi-parameter embedded sensing, IoT-enabled cloud connectivity, and machine learning-assisted predictive diagnostics. The proposed framework successfully addresses critical limitations of conventional BTMS approaches by unifying thermal control, vehicle health monitoring, and remote analytics into a single cohesive platform.

Experimental validation demonstrated a peak temperature reduction of up to 24% at 1C discharge and effective thermal containment at 3C rates, preventing thermal runaway conditions. The system's IoT communication stack achieved sub-second end-to-end telemetry latency with 99.7% transmission reliability. Real-time fault detection and predictive maintenance capabilities are expected to reduce unscheduled maintenance events and extend battery operational life by an estimated 15–20% based on thermal stress modeling.

Future work will investigate integration of reinforced learning-based cooling optimization, solid-state thermal interface materials for enhanced heat transfer, and V2X (vehicle-to-everything) communication for fleet-level thermal management coordination. The proposed system contributes meaningfully toward the advancement of smart, safe, and sustainable electric transportation infrastructure aligned with Industry 4.0 and smart city initiatives.

ACKNOWLEDGMENT

The authors gratefully acknowledge the support of the Department of Electrical Engineering and the research laboratory facilities that made this work possible. This research received no specific external funding.

REFERENCES

1. International Energy Agency, "Global EV Outlook 2024," IEA Publications, Paris, France, 2024.
2. X. Feng, M. Ouyang, X. Liu, L. Lu, Y. Xia, and X. He, "Thermal runaway mechanism of lithium ion battery for electric vehicles: A review," Energy Storage Materials, vol. 10, pp. 246–267, Jan. 2018.
3. M. A. Hannan, M. S. H. Lipu, A. Hussain, and A. Mohamed, "A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations," Renewable and Sustainable Energy Reviews, vol. 78, pp. 834–854, Oct. 2017.
4. R. Sabbah, R. Kizilel, J. R. Selman, and S. Al-Hallaj, "Active (air-cooled) vs. passive (phase change material) thermal management of high power lithium-ion packs," Journal of Power Sources, vol. 182, no. 2, pp. 630–638, 2008.
5. Z. Tang, S. Wang, J. Liu, and W. Cheng, "Numerical analysis of temperature uniformity of a lateral air-cooling thermal management system for cylindrical lithium-ion batteries," Applied Thermal Engineering, vol. 167, p. 114791, 2020.
6. M. A. Hannan, M. M. Hoque, A. Mohamed, and A. Ayob, "Review of energy storage systems for electric vehicle applications: Issues and challenges," Renewable and Sustainable Energy Reviews, vol. 69, pp. 771–789, 2017.
7. K. Liu, K. Li, Q. Peng, and C. Zhang, "A brief review on key technologies in the battery management system of electric vehicles," Frontiers of Mechanical Engineering, vol. 14, no. 1, pp. 47–64, 2019.
8. K. A. Severson et al., "Data-driven prediction of battery cycle life before capacity degradation," Nature Energy, vol. 4, no. 5, pp. 383–391, 2019.
9. Y. Zhang, R. Xiong, H. He, and M. G. Pecht, "Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries," IEEE Transactions on Vehicular Technology, vol. 67, no. 7, pp. 5695–5705, 2018.
10. A. Pesaran, "Battery thermal models for hybrid vehicle simulations," Journal of Power Sources, vol. 110, no. 2, pp. 377–382, 2002.