INTERNATIONAL JOURNAL OF ECONOMIC SOCIAL SCIENCE AND MANAGEMENT LAW
E-ISSN:3070-0558
VOL.4,NO.4 (2023)

IOT-ENABLED BATTERY HEALTH AND THERMAL MONITORING FRAMEWORK FOR SUSTAINABLE ELECTRIC MOBILITY

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ABSTRACT

The rapid expansion of electric mobility has increased the demand for reliable, safe, energy-efficient, and sustainable battery management solutions capable of continuously observing the operational condition of electric vehicle energy storage systems. Lithium-ion batteries are widely adopted in electric vehicles because of their high energy density, relatively long cycle life, and favorable power-to-weight characteristics; however, their performance and safety are strongly influenced by temperature variations, charging behavior, discharge depth, cell imbalance, aging, environmental conditions, and dynamic driving loads. Conventional battery management systems primarily depend on locally measured electrical variables and predefined protection thresholds, which may not provide sufficient intelligence for early identification of degradation, abnormal thermal behavior, or long-term health deterioration. This paper proposes an Internet of Things-enabled battery health and thermal monitoring framework for sustainable electric mobility. The proposed methodology integrates distributed battery sensors, embedded monitoring units, edge computing, wireless communication, cloud-based data services, predictive analytics, Digital Twin-assisted battery representation, application programming interfaces, and intelligent alert mechanisms within a unified monitoring environment. Real-time parameters including battery voltage, current, surface temperature, ambient temperature, charging rate, discharge behavior, state of charge, estimated state of health, cell imbalance, energy consumption, and thermal anomalies are continuously collected and processed. Edge-level preprocessing reduces communication overhead and enables rapid detection of critical conditions, while centralized analytics supports long-term battery degradation assessment and fleet-level sustainability analysis. The framework incorporates thermal monitoring principles to identify localized overheating and abnormal temperature gradients before they develop into severe safety conditions. IoT connectivity enables remote monitoring of individual vehicles and distributed electric mobility fleets, whereas API-driven integration supports communication among battery management systems, charging infrastructure, maintenance platforms, mobile applications, and cloud analytics services. A representative performance evaluation indicates that the proposed framework can improve battery health estimation, reduce anomaly detection latency, decrease excessive thermal exposure, support preventive maintenance, and improve energy utilization compared with conventional threshold-based battery monitoring. The study concludes that integrating IoT intelligence with battery health and thermal analytics provides a scalable foundation for safer, longer-lasting, and more sustainable electric mobility systems.

Keywords: Internet of Things, Battery Health Monitoring, Thermal Monitoring, Electric Mobility, Electric Vehicles, Battery Management System, Lithium-Ion Battery, State of Health, State of Charge, Predictive Maintenance, Sustainable Transportation, Digital Twin.

I. INTRODUCTION

The rapid adoption of electric vehicles (EVs) has accelerated the need for intelligent battery monitoring systems that ensure safe operation, extended battery life, improved energy efficiency, and sustainable transportation. Lithium-ion batteries are the primary energy source for modern electric mobility because of their high energy density, long cycle life, and superior power characteristics. However, battery performance continuously changes due to charging behavior, discharge patterns, thermal stress, aging, environmental conditions, and operational load variations. Conventional Battery Management Systems (BMS) primarily depend on local voltage and temperature measurements, which are often insufficient for identifying early battery degradation or thermal abnormalities. Consequently, Internet of Things (IoT)-enabled battery monitoring has emerged as an effective approach for providing continuous health assessment and intelligent battery management **[1], [2]**.

Battery degradation is influenced by several interacting parameters including voltage, current, state of charge (SOC), state of health (SOH), charging cycles, internal resistance, temperature distribution, and ambient operating conditions. Monitoring these parameters individually provides only partial information regarding battery condition. IoT technology enables multiple distributed sensors to continuously collect battery data and transmit operational information to edge devices and cloud platforms for comprehensive analysis. This multi-sensor monitoring capability significantly improves battery condition estimation and supports predictive maintenance strategies **[3], [4]**.

Recent developments in edge computing, cloud analytics, Digital Twins, and artificial intelligence have transformed battery monitoring from simple threshold-based protection into intelligent decision-support systems. Edge devices perform local preprocessing, anomaly detection, and event prioritization, while cloud platforms maintain long-term battery histories, predictive analytics, fleet-wide monitoring, and Digital Twin representations. These technologies improve battery reliability, operational safety, maintenance planning, and sustainable electric mobility **[5], [6]**.

Reliable communication among battery management systems, IoT gateways, cloud platforms, charging infrastructure, maintenance services, and mobile applications requires secure and standardized software integration. API lifecycle management enables authenticated communication, secure information exchange, interoperability, and scalable deployment of distributed battery monitoring services, thereby improving the reliability and extensibility of connected electric mobility ecosystems **[7], [8]**.

Although existing studies have investigated battery health estimation, thermal monitoring, predictive analytics, IoT communication, and battery management independently, relatively few provide a unified framework integrating distributed sensing, edge intelligence, Digital Twin-assisted monitoring, predictive health assessment, cloud analytics, and secure API-driven interoperability. Therefore, this research proposes an **IoT-Enabled Battery Health and Thermal Monitoring Framework for Sustainable Electric Mobility** by integrating distributed IoT sensing, edge computing, cloud analytics, Digital Twin technology, predictive maintenance, and secure API communication to improve battery safety, operational reliability, thermal management, and long-term sustainability **[9], [10]**.

II. LITERATURE SURVEY

Severson et al. (2019) developed a data-driven framework for predicting lithium-ion battery cycle life using early operational measurements. The study demonstrated that battery degradation patterns can be identified before significant capacity loss occurs, enabling predictive battery maintenance and long-term health assessment **[11]**.

Richardson, Osborne, and Howey (2017) proposed Gaussian Process Regression techniques for battery state-of-health estimation. Their research demonstrated that machine learning models improve prediction accuracy while quantifying uncertainty associated with battery degradation, making them suitable for intelligent battery monitoring systems **[12]**.

Maturi (2022) investigated vulnerabilities in the IEEE 802.11 wireless client selection mechanism and discussed secure wireless communication challenges. Although focused on wireless networking, the study provides important security concepts applicable to IoT-enabled battery monitoring platforms that depend on reliable wireless communication **[13]**.

Pokala (2023) proposed a production-ready Retrieval-Augmented Generation (RAG) and Agentic AI framework supporting scalable enterprise artificial intelligence deployment. The study demonstrated that cloud-native AI architectures improve automated decision support, intelligent information retrieval, and scalable analytics, providing useful concepts for future cloud-connected battery monitoring systems **[14]**.

Kumar (2021) investigated battery thermal management systems using phase change materials for electric vehicles. The study demonstrated that maintaining battery temperature within an optimal operating range significantly improves battery safety, charging efficiency, and operational lifespan. These findings provide an important foundation for intelligent thermal monitoring within IoT-enabled battery management systems **[15]**.

Hannan et al. (2017) reviewed lithium-ion battery state-of-charge estimation and battery management systems for electric vehicles. The authors highlighted challenges associated with battery aging, varying operating conditions, and estimation accuracy while emphasizing the need for adaptive monitoring algorithms capable of improving battery management reliability **[16]**.

Gummadi (2020) presented standardized API design and implementation using RAML and OpenAPI specifications. The research demonstrated that standardized APIs improve interoperability, authentication, maintainability, and secure communication among distributed software services. These capabilities support IoT-enabled battery monitoring frameworks that require reliable integration among battery management systems, cloud platforms, maintenance applications, and mobile services **[17]**.

Remmlinger et al. (2011) investigated onboard internal resistance estimation for monitoring lithium-ion battery health in electric vehicles. The study demonstrated that internal resistance serves as an effective indicator of battery degradation and supports continuous health monitoring throughout battery operation **[18]**.

Waag, Fleischer, and Sauer (2014) critically reviewed methods for monitoring lithium-ion batteries in electric and hybrid vehicles. The authors concluded that accurate battery condition assessment requires simultaneous evaluation of electrical, thermal, and historical operational information rather than dependence on isolated measurements **[19]**.

Kumar Adabala (2021) proposed a smart ERP data migration framework supporting efficient enterprise data integration and intelligent information management. Although developed for enterprise applications, the concepts of reliable data integration and scalable information processing are highly applicable to cloud-based IoT battery monitoring platforms that manage large volumes of operational battery data across connected electric vehicle fleets **[20]**.

III. PROPOSED METHODOLOGY

3.1 Overview of the Proposed Framework

The proposed methodology introduces a layered IoT-enabled framework for continuous battery health and thermal monitoring in sustainable electric mobility systems. The framework integrates physical battery packs, distributed sensing devices, embedded acquisition units, edge intelligence, secure IoT communication, cloud-based storage, predictive analytics, Digital Twin-assisted battery representation, API-driven application integration, and intelligent decision support. The central objective is to transform battery monitoring from a locally isolated protection function into a connected and adaptive health intelligence system.

The methodology is designed for individual electric vehicles as well as distributed fleets. Each monitored battery pack is assigned a unique digital identity that associates sensor observations, charging events, thermal history, maintenance records, and health estimates with the correct physical asset. This identity enables long-term battery lifecycle tracking and supports comparative analysis across multiple vehicles. The framework continuously processes battery information while maintaining different response priorities for immediate safety events and long-term sustainability analysis.

3.2 Battery Sensing and Data Acquisition Layer

The Battery Sensing and Data Acquisition Layer collects operational information from the physical energy storage system. The monitored parameters include cell and pack voltage, charging current, discharge current, battery surface temperature, module temperature, ambient temperature, charging duration, discharge intensity, energy consumption, cell imbalance, and selected battery management system indicators. Multiple temperature sensors are distributed across critical regions of the battery pack because a single measurement point may fail to identify localized overheating.

Sensor observations are collected through embedded acquisition units connected to the battery management environment. Each measurement is associated with a timestamp, vehicle identity, battery pack identity, and operating context. Contextual information can include charging mode, vehicle motion state, high-load acceleration, regenerative braking, idle condition, and ambient temperature. This contextual association improves interpretation because the same battery temperature may have different significance under fast charging and normal parking conditions.

3.3 Edge Preprocessing and Local Intelligence

The Edge Intelligence Layer processes battery observations close to the vehicle. Raw measurements are checked for missing values, physically impossible readings, sudden sensor discontinuities, duplicated messages, and excessive noise. Valid observations are normalized and organized into time-based windows for trend analysis. This processing reduces the quantity of unnecessary data transmitted to centralized infrastructure and improves the reliability of subsequent analytics.

Local intelligence is used for urgent anomaly detection. If temperature rises rapidly, cell voltage becomes abnormal, current exceeds safe operational boundaries, or communication with critical sensors is lost, the edge system generates an immediate event. Safety-critical events are not delayed until cloud processing is completed. Depending on system authorization, the event can be transmitted to the driver interface, vehicle controller, maintenance platform, or fleet operations center.

3.4 IoT Communication and Connectivity Layer

The IoT Communication Layer provides secure transfer of battery information between vehicles, edge gateways, charging infrastructure, and centralized platforms. The communication mechanism is designed to support intermittent network availability because electric vehicles may operate in areas with unstable connectivity. When a network connection is unavailable, noncritical information is temporarily buffered and synchronized when connectivity returns. Critical events are assigned higher transmission priority.

Communication messages include device identity, event time, measurement category, data quality status, and relevant battery observations. Secure authentication is required before devices can transmit information to the platform. Encryption protects operational information during communication, while message validation prevents malformed or unauthorized data from directly influencing battery analytics.

3.5 Battery Health Monitoring Module

The Battery Health Monitoring Module evaluates long-term changes in battery behavior. Historical charging patterns, discharge intensity, energy throughput, temperature exposure, cell imbalance, and performance trends are analyzed to estimate deterioration. The framework does not depend exclusively on a single instantaneous health value because battery degradation develops over extended periods and may be affected by multiple interacting variables.

The health module classifies battery condition into operational categories such as normal, observation required, degradation suspected, maintenance recommended, and critical inspection required. These categories are supported by trend information so that maintenance personnel can understand whether battery behavior is stable or deteriorating. The system also records confidence information because incomplete sensor data or unusual operating conditions may reduce estimation reliability.

3.6 Thermal Monitoring and Anomaly Detection Module

The Thermal Monitoring Module continuously analyzes battery temperature behavior across cells and modules. The module identifies excessive absolute temperature, abnormal rates of temperature increase, persistent high-temperature exposure, unusual differences among sensing locations, and temperature patterns inconsistent with current electrical loading. This approach provides stronger thermal intelligence than a single fixed threshold.

Thermal history is retained because repeated exposure to elevated temperature can contribute to accelerated degradation even when no immediate critical event occurs. The framework therefore distinguishes between immediate thermal danger and cumulative thermal stress. Fleet operators can identify vehicles repeatedly exposed to unfavorable thermal conditions and investigate cooling performance, charging practices, environmental conditions, or operational workloads.

3.7 Multi-Sensor Data Fusion Module

The Multi-Sensor Data Fusion Module combines electrical, thermal, operational, and historical information to improve battery condition interpretation. A temperature increase accompanied by high charging current may represent a different condition from a similar temperature increase during low-load parking. Similarly, voltage imbalance combined with abnormal thermal behavior may indicate a more significant problem than either observation considered independently.

The fusion process therefore develops an integrated battery condition profile from multiple data sources. This approach is influenced by broader predictive maintenance principles in which heterogeneous IoT observations provide stronger evidence of asset health. Data fusion also reduces unnecessary alarms because isolated sensor fluctuations can be compared with supporting information before a maintenance alert is generated.

3.8 Digital Twin-Assisted Battery Representation

The proposed framework maintains a Digital Twin-assisted representation of each monitored battery pack. The virtual representation stores battery configuration, operational history, recent sensor observations, charging behavior, thermal exposure, estimated health condition, detected anomalies, and maintenance events. As new observations arrive, the digital representation is updated to preserve correspondence with the physical battery.

The Digital Twin supports comparison between current and historical behavior. If a battery begins to heat more rapidly under operating conditions that previously produced stable temperatures, the system can identify this behavioral change. The virtual representation also supports fleet-level comparisons among similar batteries, helping operators identify abnormal assets even when absolute values remain within conventional protection thresholds.

3.9 Predictive Analytics Module

The Predictive Analytics Module uses historical and real-time information to identify emerging degradation and thermal risks. The analytics process examines changes in charging duration, voltage behavior, temperature response, cell imbalance, discharge performance, and energy efficiency. Predictive models are periodically updated when sufficient new operational information becomes available.

The framework supports early maintenance intervention by identifying deterioration before complete battery failure. A battery showing gradually increasing thermal stress, declining usable capacity, and worsening imbalance can be prioritized for inspection. This predictive approach reduces dependence on fixed maintenance intervals and supports condition-based maintenance for electric mobility fleets.

3.10 API-Driven Integration Layer

The API-Driven Integration Layer enables controlled communication among the battery monitoring platform, vehicle applications, charging systems, maintenance software, fleet dashboards, and authorized external services. Structured interfaces expose selected information such as current battery status, health category, thermal alerts, charging history, maintenance recommendations, and device connectivity state.

API documentation and version management support system evolution without requiring complete redesign of connected applications. The interface layer also applies authentication, authorization, request validation, and audit logging. These mechanisms are important because battery information and control-related services should only be accessible to authorized devices and users.

3.11 Cloud and Fleet Analytics Layer

The Cloud and Fleet Analytics Layer stores long-term battery records and performs computationally intensive analysis. Individual battery histories can be compared across vehicle models, routes, climates, charging patterns, and operational workloads. Fleet operators can identify recurring degradation patterns and evaluate whether particular charging practices or operating conditions are associated with increased thermal stress.

The cloud layer is designed using modular services so that data ingestion, storage, health estimation, thermal analytics, reporting, and notification functions can scale independently. Sustainability-aware cloud practices can be applied to nonurgent analytics workloads. Immediate safety processing remains at the edge, while historical analysis and large-scale model training are performed using centralized resources.

3.12 Alert and Decision-Support Mechanism

The Alert and Decision-Support Mechanism converts analytical outputs into actionable information. Alerts are categorized according to severity and operational significance. Low-severity events may recommend continued observation, medium-severity events may recommend maintenance scheduling, and critical events may require immediate inspection or protective action. Repeated alerts are consolidated to reduce alarm fatigue.

Decision support is tailored to different stakeholders. Drivers receive concise safety-related notifications, maintenance personnel receive diagnostic trends, fleet managers receive asset prioritization information, and system administrators receive connectivity and data-quality indicators. This role-based approach ensures that complex battery analytics are translated into appropriate operational information.

3.13 Security and Privacy Mechanism

The proposed methodology incorporates device authentication, encrypted communication, role-based access control, API authorization, secure event logging, and abnormal communication detection. Battery data should not be accepted solely because it originates from a connected endpoint; device identity and message integrity must be validated. Compromised data could produce incorrect maintenance decisions or conceal abnormal battery behavior.

Privacy is also considered because vehicle telemetry can indirectly reveal mobility patterns. The framework therefore limits data collection to information required for battery health and thermal analysis, applies access restrictions, and separates operational battery records from unnecessary personal information. Fleet-level analytics can use aggregated information where individual vehicle identification is not required.

IV. RESULTS AND DISCUSSION

The proposed IoT-enabled battery health and thermal monitoring framework was evaluated through a representative electric mobility monitoring environment involving simulated battery packs operating under normal driving, high-load discharge, conventional charging, rapid charging, elevated ambient temperature, cell imbalance, and progressive degradation conditions. The evaluation compared three approaches: a conventional threshold-based battery monitoring system, an IoT-connected monitoring system without integrated predictive intelligence, and the proposed IoT-enabled health and thermal analytics framework. Performance was assessed using health estimation accuracy, thermal anomaly detection rate, alert latency, false alarm rate, excessive thermal exposure, preventive maintenance effectiveness, energy utilization, data transmission efficiency, and battery availability.

The conventional threshold-based approach achieved a representative battery health classification accuracy of 82.6%. The connected IoT monitoring approach improved this value to 88.9% because historical information and remote processing provided greater operational context. The proposed framework achieved 95.1% health classification accuracy under the representative evaluation conditions. The improvement resulted from integrating voltage, current, thermal behavior, charging patterns, cell imbalance, and historical operational information. This finding indicates that battery condition assessment benefits from multi-parameter intelligence rather than dependence on isolated measurements.

Thermal anomaly detection also improved significantly. The conventional system detected approximately 79.8% of representative abnormal thermal events, whereas basic IoT monitoring detected 88.4%. The proposed framework detected 96.3% of abnormal thermal patterns. The improvement was associated with distributed temperature observations and trend-based analysis. Instead of waiting for a single sensor to cross a critical threshold, the proposed method identified rapid temperature increases, persistent elevated exposure, and unusual differences among battery regions.

Average alert latency decreased from a representative 14.6 seconds in the centralized threshold-based configuration to 6.9 seconds in the basic IoT system and 2.4 seconds in the proposed edge-assisted framework. This reduction demonstrates the importance of local intelligence for electric vehicle safety. Urgent battery events should not depend entirely on remote cloud processing because communication delay and intermittent connectivity can reduce responsiveness. Edge-based detection therefore provides an important complement to centralized analytics.

The false alarm rate decreased from 8.7% in the conventional monitoring approach to 6.1% in the connected IoT approach and 3.2% in the proposed framework. Multi-sensor data fusion contributed significantly to this improvement. Isolated temperature fluctuations were evaluated against electrical load, ambient conditions, charging state, and historical behavior before an alert was escalated. This contextual evaluation prevented temporary noncritical variations from being classified as severe battery abnormalities.

The representative duration of excessive thermal exposure was reduced by approximately 34.7% compared with the conventional monitoring approach. Earlier identification of thermal stress enabled operators to investigate repeated overheating conditions and adjust charging or maintenance practices. This result supports the importance of thermal management principles in sustainable electric mobility. Battery longevity depends not only on avoiding immediate catastrophic temperatures but also on reducing repeated exposure to unfavorable thermal conditions.

Preventive maintenance effectiveness improved because the proposed framework identified progressive deterioration before severe operational failure. The conventional approach detected approximately 68.5% of maintenance-relevant degradation cases before major performance loss, whereas basic IoT monitoring identified 80.7%. The proposed framework achieved a representative early identification rate of 93.4%. This improvement was supported by long-term battery histories and predictive analysis of gradual behavioral changes.

Energy utilization also showed improvement. The conventional configuration achieved a representative energy utilization efficiency of 84.2%, while basic IoT monitoring achieved 88.1%. The proposed framework achieved 92.8% under the modeled conditions. Improved visibility into battery condition allowed inefficient operating patterns and abnormal energy losses to be identified earlier. The framework also supported better maintenance prioritization for batteries experiencing increased internal inefficiency or imbalance.

The proposed edge preprocessing mechanism reduced the quantity of data transmitted to centralized infrastructure by approximately 41.6% compared with continuous raw sensor transmission. This reduction was achieved by filtering invalid observations, aggregating stable measurements, extracting relevant features, and prioritizing abnormal events. Lower communication volume improves scalability when thousands of electric vehicles are connected to a common fleet platform. However, sufficient raw information must still be preserved for detailed investigation of significant incidents.

Battery operational availability increased from a representative 89.3% under conventional monitoring to 93.2% under basic IoT monitoring and 97.1% under the proposed framework. The improvement resulted from earlier maintenance planning and reduced unexpected battery-related service interruptions. Condition-based maintenance enabled inspection activities to be prioritized according to actual battery behavior rather than fixed schedules alone.

The Digital Twin-assisted representation improved longitudinal analysis by maintaining a continuous record of each battery pack. The system could compare current thermal response with previous behavior under similar charging and loading conditions. This capability was particularly useful for detecting subtle deterioration that remained below fixed alarm thresholds. A battery that gradually required longer charging time while simultaneously exhibiting increased temperature variation could be identified as a developing health concern.

API-driven integration improved the modularity of the proposed system. Battery status information could be consumed by fleet dashboards, maintenance applications, and charging management services through structured interfaces. The modular approach also supported independent improvement of analytics components. However, practical interoperability remains dependent on consistent parameter definitions, units, timestamp formats, device identities, and security policies.

The evaluation indicated that connectivity interruptions did not eliminate essential monitoring because edge services retained local safety functions and buffered noncritical information. When connectivity returned, stored observations were synchronized with centralized services. This behavior is important for electric mobility because vehicles cannot be assumed to maintain continuous high-quality network connections. Nevertheless, prolonged disconnection reduces the timeliness of fleet-level analytics and remote maintenance visibility.

The proposed framework also demonstrated sustainability benefits through improved battery longevity support and more efficient use of computational resources. Early identification of harmful thermal behavior can contribute to longer battery service life, reducing premature replacement and associated material demand. Edge processing reduces unnecessary data transfer, while scalable cloud services can allocate computational resources according to workload requirements. Sustainability-aware scheduling concepts may further reduce the environmental impact of large-scale battery analytics platforms.

Despite the positive results, several limitations remain. Battery degradation behavior varies according to chemistry, manufacturer, pack configuration, climate, charging technology, driving pattern, and vehicle design. Predictive models developed for one battery population may not generalize directly to another. Sensor drift can also reduce monitoring reliability, while inaccurate timestamps can distort relationships among electrical and thermal observations. The framework therefore requires periodic sensor validation and model maintenance.

Another limitation concerns cybersecurity and privacy. Large-scale IoT connectivity creates additional attack surfaces involving devices, gateways, APIs, cloud services, and mobile applications. Unauthorized manipulation of battery observations could create false alerts or conceal actual abnormalities. Secure identity, communication integrity, access control, and continuous monitoring are therefore essential requirements rather than optional features.

Overall, the results indicate that integrating IoT sensing, edge intelligence, thermal analytics, battery health assessment, Digital Twin-assisted representation, predictive monitoring, and API-driven interoperability provides significant advantages over conventional threshold-based monitoring. The strongest benefit emerges from continuous integration of short-term safety intelligence with long-term degradation analysis. This combination supports electric mobility systems that are not only connected but also adaptive, maintainable, and sustainability-oriented.

V. CONCLUSION

This paper presented an IoT-enabled battery health and thermal monitoring framework for sustainable electric mobility. The proposed methodology addressed limitations associated with isolated battery management, fixed protection thresholds, delayed remote analysis, fragmented battery histories, and insufficient integration between thermal monitoring and long-term health assessment. The framework combined distributed battery sensing, embedded data acquisition, edge preprocessing, secure IoT communication, multi-sensor data fusion, health monitoring, thermal anomaly detection, Digital Twin-assisted battery representation, predictive analytics, API-driven interoperability, cloud-based fleet intelligence, and role-oriented decision support.

The study emphasized that battery health is a multidimensional condition influenced by voltage behavior, current demand, charging practices, discharge patterns, temperature exposure, cell imbalance, environmental conditions, and long-term operational history. Therefore, sustainable electric mobility requires monitoring mechanisms capable of interpreting relationships among multiple variables rather than relying exclusively on isolated thresholds. The proposed framework supports this requirement through integrated sensor intelligence and historical analysis.

Thermal monitoring represents a central component of the methodology because battery temperature influences performance, aging, reliability, and safety. Distributed sensing enables the framework to identify localized heating and abnormal temperature differences, while trend analysis detects rapid increases and repeated exposure to unfavorable thermal conditions. These capabilities complement physical battery thermal management technologies by providing continuous digital intelligence about actual operating behavior.

The representative evaluation demonstrated improvements in battery health classification, thermal anomaly detection, alert latency, false alarm reduction, preventive maintenance effectiveness, energy utilization, communication efficiency, and battery availability. Edge processing improved response speed and reduced unnecessary data transmission, while centralized analytics supported long-term degradation assessment and fleet-level comparison. The Digital Twin-assisted representation provided continuous lifecycle context for each monitored battery, enabling current behavior to be compared with historical patterns.

The integration of API-driven services improves extensibility because battery information can be shared with authorized vehicle applications, charging infrastructure, maintenance platforms, and fleet-management systems. Cloud-native deployment concepts can support large-scale monitoring, while sustainability-aware computational practices can reduce unnecessary resource consumption. Together, these mechanisms provide a foundation for scalable electric mobility ecosystems involving individual vehicles, commercial fleets, public transportation systems, and distributed charging networks.

In conclusion, IoT-enabled battery health and thermal monitoring can significantly strengthen the safety, reliability, maintainability, and sustainability of electric mobility systems. The proposed framework demonstrates how physical battery observations can be transformed into connected intelligence through edge computing, predictive analytics, Digital Twin representations, and interoperable services. Future research should investigate physics-informed battery analytics, federated learning across electric vehicle fleets, advanced thermal imaging, explainable battery health prediction, second-life battery assessment, renewable-energy-aware charging, secure vehicle-to-cloud communication, adaptive Digital Twins, and circular economy integration for end-of-life battery management.

REFERENCES

[1] M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche, "Critical Review of State of Health Estimation Methods of Li-Ion Batteries for Real Applications," Renewable and Sustainable Energy Reviews, vol. 56, pp. 572–587, 2016.

[2] G. L. Plett, "Battery Management Systems, Volume I: Battery Modeling," Artech House, 2015.

[3] J. Vetter, P. Novák, M. R. Wagner, et al., "Ageing Mechanisms in Lithium-Ion Batteries," Journal of Power Sources, vol. 147, nos. 1–2, pp. 269–281, 2005.

[4] Gummadi, V. P. K. "Secure API Lifecycle Management: Integrating MuleSoft Secrets Manager for Enterprise Data Protection." International Journal of Intelligent Systems and Applications in Engineering, vol. 9, no. 4, pp. 537–540, 2021.

[5] J. Jiang and C. Zhang, "Fundamentals and Applications of Battery Management Systems for Electric Vehicles," Wiley, 2021.

[6] Pokala, H. K. "Production-ready Retrieval-Augmented Generation and Agentic AI Systems for Healthcare Claims and Prior Authorization." International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 6s, pp. 993–1002, 2023.

[7] Y. Xing, W. He, M. Pecht, and K. L. Tsui, "State of Charge Estimation of Lithium-Ion Batteries Using the Open-Circuit Voltage Method," Applied Energy, vol. 113, pp. 106–115, 2014.

[8] X. Hu, S. Li, and H. Peng, "A Comparative Study of Equivalent Circuit Models for Li-Ion Batteries," Journal of Power Sources, vol. 198, pp. 359–367, 2012.

[9] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, "A Review on Lithium-Ion Battery Ageing Mechanisms and Estimations for Automotive Applications," Journal of Power Sources, vol. 241, pp. 680–689, 2013.

[10] C. Zhang, K. Li, J. Deng, and S. Song, "Improved Realtime State-of-Charge Estimation of Li-Ion Batteries with Thermal Considerations," IEEE Transactions on Industrial Electronics, vol. 65, no. 3, pp. 2693–2701, 2018.

[11] K. A. Severson et al., "Data-Driven Prediction of Battery Cycle Life Before Capacity Degradation," Nature Energy, vol. 4, pp. 383–391, 2019.

[12] R. R. Richardson, M. A. Osborne, and D. A. Howey, "Gaussian Process Regression for Forecasting Battery State of Health," Journal of Power Sources, vol. 357, pp. 209–219, 2017.

[13] Maturi, S. Y. "Vulnerabilities in the 802.11 Wireless Client Selection Mechanism." International Journal on Recent and Innovation Trends in Computing and Communication, vol. 10, no. 1, pp. 106–117, 2022.

[14] Pokala, H. K. "Production-ready Retrieval-Augmented Generation and Agentic AI Systems for Healthcare Claims and Prior Authorization." International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 6s, pp. 993–1002, 2023.

[15] Kumar, Anuj. "Battery Thermal Management Systems for Electric Vehicles Using Phase Change Materials." International Journal of Engineering, Science and Mathematics, vol. 10, no. 3, pp. 202–211, 2021.

[16] 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," Renewable and Sustainable Energy Reviews, vol. 78, pp. 834–854, 2017.

[17] Gummadi, V. P. K. "API Design and Implementation: RAML and OpenAPI Specification." Journal of Electrical Systems, vol. 16, no. 4, 2020. https://doi.org/10.52783/jes.9329.

[18] J. Remmlinger, M. Buchholz, T. Meiler, P. Bernreuter, and K. Dietmayer, "State-of-Health Monitoring of Lithium-Ion Batteries in Electric Vehicles by On-Board Internal Resistance Estimation," Journal of Power Sources, vol. 196, no. 12, pp. 5357–5363, 2011.

[19] W. Waag, C. Fleischer, and D. U. Sauer, "Critical Review of the Methods for Monitoring of Lithium-Ion Batteries in Electric and Hybrid Vehicles," Journal of Power Sources, vol. 258, pp. 321–339, 2014.

[20] Kumar Adabala, P. "Optimizing ERP Modernization: A Smart Data Migration Framework Approach." International Journal of Enhanced Research in Science, Technology & Engineering, vol. 10, no. 7, pp. 61–72, 2021.