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DATA-DRIVEN BATTERY TEMPERATURE PREDICTION FOR SAFE AND EFFICIENT ELECTRIC MOBILITY SYSTEMS

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ABSTRACT

The rapid adoption of electric mobility has increased the importance of reliable battery thermal monitoring and predictive temperature management because battery temperature directly influences safety, charging performance, energy efficiency, degradation rate, driving range, and operational life. Lithium-ion battery packs operate under highly dynamic conditions involving rapid acceleration, regenerative braking, high-rate charging, variable ambient temperature, traffic congestion, changing state of charge, cell imbalance, and repeated electrochemical cycling. Conventional battery thermal management systems generally depend on measured temperature values, fixed protection thresholds, predefined cooling strategies, and reactive control mechanisms. Such approaches may identify thermal abnormalities only after significant temperature increase has already occurred and may not adequately anticipate future thermal behavior under changing vehicle loads. This paper proposes a data-driven battery temperature prediction framework for safe and efficient electric mobility systems. The proposed methodology integrates distributed battery sensing, Internet of Things connectivity, edge preprocessing, historical thermal data management, multi-sensor data fusion, contextual feature engineering, machine-learning-based temperature forecasting, Digital Twin-assisted battery representation, predictive thermal risk classification, adaptive cooling decision support, secure API interoperability, MLOps lifecycle management, and sustainability-aware cloud processing. Real-time observations involving cell voltage, pack voltage, charging and discharging current, battery temperature, ambient temperature, state of charge, estimated state of health, vehicle speed, acceleration behavior, charging mode, cooling activity, energy consumption, and historical thermal exposure are continuously collected and analyzed. The framework predicts near-future battery temperature trends and identifies emerging overheating risk before critical thresholds are reached. Edge intelligence enables rapid processing of safety-relevant observations, while centralized analytics supports long-term model training and fleet-level battery intelligence. A representative evaluation demonstrates improvements in temperature prediction accuracy, thermal anomaly anticipation, early warning time, false alarm reduction, excessive heat exposure, cooling efficiency, energy utilization, battery availability, and predictive maintenance effectiveness compared with conventional threshold-based and reactive thermal monitoring approaches. The results indicate that data-driven temperature prediction can transform battery thermal management from a reactive protection function into a proactive intelligence mechanism supporting safer, more efficient, and more sustainable electric mobility.

Keywords: Battery Temperature Prediction, Electric Mobility, Lithium-Ion Battery, Machine Learning, Battery Thermal Management, Electric Vehicles, Predictive Analytics, Internet of Things, Digital Twin, State of Health, Edge Computing, Sustainable Transportation.

I. INTRODUCTION

The rapid expansion of electric mobility has accelerated the development of intelligent

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Battery Management Systems (BMS) capable of ensuring safe, reliable, and energy-efficient operation of lithium-ion battery packs. Battery temperature is one of the most critical parameters affecting battery performance because it directly influences charging efficiency, power capability, degradation rate, cycle life, safety, and overall driving range. During vehicle operation, batteries experience continuously changing thermal conditions resulting from rapid acceleration, regenerative braking, fast charging, varying ambient temperatures, traffic congestion, and fluctuating electrical loads. Conventional Battery Management Systems primarily depend on real-time temperature measurements and predefined protection thresholds, which often respond only after excessive heat has already accumulated. Therefore, data-driven battery temperature prediction has become an essential technology for proactive thermal management in modern electric mobility systems **[1], [2]**.

Battery temperature evolution is governed by multiple interacting factors including charging current, discharge rate, state of charge, state of health, internal resistance, cooling effectiveness, environmental temperature, and battery aging. Because these variables exhibit highly nonlinear relationships, conventional mathematical models often struggle to accurately estimate future thermal behavior under diverse operating conditions. Recent advances in machine learning enable predictive models to learn complex thermal characteristics directly from historical operational data, allowing battery systems to anticipate temperature changes before critical safety thresholds are reached. Such predictive intelligence improves battery reliability while reducing unnecessary cooling actions and energy consumption **[3], [4]**.

Modern electric vehicles increasingly integrate Internet of Things (IoT) connectivity, distributed sensing, edge computing, Digital Twins, and cloud analytics to continuously monitor battery health and thermal behavior. Multi-sensor observations involving voltage, current, temperature, vehicle speed, ambient conditions, charging mode, cooling activity, and battery health are continuously analyzed to identify hidden thermal patterns and predict future overheating risks. Intelligent battery temperature prediction enables adaptive cooling, optimized charging strategies, early fault detection, and predictive maintenance, thereby improving operational safety and extending battery service life **[5], [6]**.

The deployment of intelligent battery monitoring platforms further requires secure communication among Battery Management Systems, charging infrastructure, cloud analytics platforms, Digital Twins, and fleet management services. Standardized APIs, secure authentication, enterprise integration, and scalable cloud-native deployment ensure reliable exchange of battery telemetry while protecting sensitive operational information from unauthorized access. Secure software architectures therefore play an important role in enabling trustworthy battery temperature prediction within connected electric mobility ecosystems **[7], [8]**.

Although previous studies have independently investigated battery thermal management, lithium-ion batteries, predictive analytics, machine learning, Digital Twins, and cloud-based Battery Management Systems, relatively few studies integrate distributed sensing, predictive temperature forecasting, secure API communication, Digital Twin-assisted battery representation, MLOps lifecycle management, and sustainability-aware computation into a unified framework. Therefore, this research proposes a **Data-Driven Battery Temperature Prediction Framework for Safe and Efficient Electric Mobility Systems** by integrating multi-sensor data fusion, machine learning, Digital

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Twin technology, IoT connectivity, predictive thermal intelligence, secure enterprise communication, and adaptive cooling decision support to improve battery safety, charging efficiency, operational reliability, energy utilization, and sustainable electric mobility **[9], [10]**.

II. LITERATURE SURVEY

Gummadi (2021) proposed a secure API lifecycle management framework integrating MuleSoft Secrets Manager for enterprise data protection. The study demonstrated that secure API governance improves authentication, authorization, credential management, and protected communication among distributed enterprise services. These capabilities are highly applicable to cloud-connected Battery Management Systems that continuously exchange battery telemetry with Digital Twins and predictive analytics platforms **[11]**.

Pokala (2023) proposed a production-ready Retrieval-Augmented Generation and Agentic AI framework supporting enterprise-scale intelligent automation and lifecycle management. The research demonstrated that cloud-native machine learning deployment improves scalability, model governance, and predictive intelligence. These concepts support real-time battery temperature prediction systems requiring continuous model updates and operational monitoring **[12]**.

Vetter et al. (2005) reviewed lithium-ion battery aging mechanisms and analyzed electrochemical degradation processes affecting long-term battery performance. Their work demonstrated that battery aging significantly influences internal resistance, heat generation, and thermal behavior, emphasizing the importance of incorporating battery aging information into predictive temperature estimation models **[13]**.

Kumar (2018) investigated machine learning-based optimization techniques for complex engineering systems and demonstrated that predictive algorithms effectively model nonlinear relationships among operational variables. These findings support the development of intelligent battery temperature prediction models capable of learning complex thermal behavior under varying operating conditions **[14]**.

Berecibar et al. (2016) reviewed state-of-health estimation methods for lithium-ion batteries and highlighted the importance of integrating battery health information into intelligent battery management systems. Their study demonstrated that battery degradation directly influences thermal characteristics, making health estimation an important input for accurate temperature prediction **[15]**.

Srikanth Kavuri (2023) investigated machine learning approaches for software security vulnerability detection and demonstrated that intelligent predictive analytics improve software reliability and automated decision-making. Although focused on software engineering, the concepts of continuous monitoring and intelligent prediction support cloud-connected Battery Management Systems and secure vehicle analytics **[16]**.

Gummadi (2023) proposed a MuleSoft batch-processing architecture supporting scalable enterprise data integration. The study demonstrated efficient processing of high-volume operational data through standardized integration mechanisms. These concepts support battery fleet monitoring systems that continuously process large volumes of battery telemetry for predictive temperature analytics **[17]**.

Kumar Adabala (2021) proposed a smart ERP modernization framework emphasizing structured data migration, enterprise integration, and lifecycle governance. The research demonstrated that reliable information management improves large-scale enterprise systems. Similar concepts support battery Digital

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Twin platforms that maintain long-term battery histories and predictive maintenance information **[18]**.

Severson et al. (2019) demonstrated that early operational battery data contain sufficient information to accurately predict long-term battery cycle life using machine learning. Their findings provide strong evidence that data-driven analytical models can successfully identify hidden relationships within battery operational data, supporting predictive battery temperature forecasting using similar learning principles **[19]**.

Maturi (2022) investigated vulnerabilities in IEEE 802.11 wireless client selection mechanisms and emphasized secure communication, trustworthy connectivity, and reliable distributed system operation. These principles are highly relevant for connected Battery Management Systems where secure wireless communication is essential for transmitting battery telemetry, predictive temperature information, and cloud-based monitoring services **[20]**.

III. PROPOSED METHODOLOGY

3.1 Overview of the Proposed Framework

The proposed methodology introduces a layered data-driven architecture for predicting battery temperature and supporting proactive thermal management in electric mobility systems. The framework is based on the principle that battery temperature should not be treated exclusively as a currently measured protection variable. Instead, present electrical, thermal, environmental, operational, and historical information is continuously analyzed to estimate likely near-future temperature behavior.

The architecture consists of a Physical Battery and Vehicle Layer, Distributed Sensing Layer, IoT Connectivity Layer, Edge Intelligence Layer, Data Quality and Synchronization Layer, Historical Thermal Data Layer, Multi-Sensor Fusion Layer, Contextual Feature Engineering Layer, Machine-Learning Temperature Prediction Layer, Digital Twin-Assisted Battery Layer, Predictive Thermal Risk Layer, Adaptive Thermal Decision-Support Layer, Secure API Integration Layer, MLOps Governance Layer, and Sustainability Management Layer.

3.2 Physical Battery and Vehicle Layer

The Physical Battery and Vehicle Layer contains the lithium-ion battery pack, battery modules, individual cells where monitoring is available, battery management system, cooling equipment, vehicle propulsion components, charging interface, and associated control systems. Each monitored battery pack is assigned a unique digital identity linking operational observations with historical records.

Vehicle operating context is retained because thermal behavior depends on how the battery is being used. Rapid acceleration, sustained high-speed travel, stop-and-go traffic, regenerative braking, hill climbing, heavy loading, fast charging, and prolonged parking under high ambient temperature can create different thermal patterns.

The framework records whether the battery is charging, discharging, idle, cooling, or operating under unusual load. This context strengthens prediction because identical current temperature values may evolve differently under different vehicle states.

3.3 Distributed Battery Sensing Layer

The sensing layer continuously collects battery and vehicle information. Temperature sensors are distributed across critical battery locations to identify localized heating and temperature differences. Pack and module voltage observations provide electrical state information, while current sensors capture charging and discharging intensity.

Ambient temperature is measured because environmental conditions influence heat rejection. State-of-charge information provides

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battery operating context, while estimated state of health indicates long-term degradation. Vehicle speed and acceleration behavior provide indirect evidence of propulsion demand.

Cooling system activity is also monitored. Pump state, fan activity, coolant-related indicators, and thermal control commands can help the prediction model understand whether temperature is likely to stabilize or continue increasing.

Each observation is associated with timestamp, battery identity, sensor identity, measurement unit, and data quality status.

3.4 IoT Connectivity and Data Transfer

The IoT Connectivity Layer transfers selected battery observations among vehicle gateways, edge services, charging infrastructure, fleet platforms, and centralized analytics. The framework supports intermittent connectivity because vehicles cannot be assumed to maintain continuous network access.

Safety-critical analysis remains available locally. When connectivity is unavailable, noncritical observations are buffered and synchronized later. Thermal events and high-risk predictions receive greater communication priority.

The communication architecture validates device identity before accepting data. Messages include timestamps and source information to support traceability.

3.5 Edge Preprocessing and Local Intelligence

The Edge Intelligence Layer validates and preprocesses battery observations near the vehicle. Missing values, duplicated records, impossible measurements, abrupt sensor discontinuities, and communication errors are identified before data enter the prediction pipeline.

Noise reduction is performed according to sensor characteristics. Short-lived fluctuations are distinguished from persistent thermal changes. Recent time windows are maintained locally because temperature prediction depends on trend direction and not only on the latest measurement.

The edge layer also performs immediate protection analysis. If current measured temperature already indicates a critical condition, the system does not wait for predictive modeling before generating an alert. Prediction complements existing protection mechanisms rather than replacing them.

3.6 Temporal Synchronization and Data Quality Assessment

Battery variables are generated at different frequencies. Current can change rapidly, while health estimates may update slowly. The synchronization mechanism aligns observations within consistent analytical windows.

Data quality assessment evaluates completeness, freshness, consistency, and plausibility. A temperature sensor producing unstable readings receives reduced confidence. Missing ambient information is recorded explicitly rather than silently replaced without traceability.

Cross-sensor consistency checks identify possible sensor faults. If one temperature sensor reports extreme heating while nearby sensors and electrical behavior remain stable, the system investigates whether the condition represents localized heating or sensor malfunction.

3.7 Historical Thermal Data Management

The Historical Thermal Data Layer preserves recent and long-term battery behavior. Stored information includes temperature trajectories, charging sessions, high-current events, ambient exposure, cooling activity, thermal warnings, maintenance events, and health estimates.

Historical data are organized according to battery identity. This enables the framework to compare current thermal response with previous behavior from the same battery.

Fleet-level datasets can also be created from authorized aggregated information. These

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datasets support model development across diverse operating conditions.

3.8 Multi-Sensor Data Fusion

The Multi-Sensor Fusion Layer combines temperature, current, voltage, state of charge, estimated health, ambient temperature, vehicle dynamics, charging mode, and cooling activity.

The objective is to create an integrated representation of thermal demand. A temperature of 38 degrees Celsius during low-current stable operation may have a different future trajectory from the same temperature during rapid charging under high ambient heat.

Fusion also improves anomaly interpretation. Increasing temperature accompanied by high current and reduced cooling effectiveness provides stronger evidence of future thermal escalation than temperature alone.

3.9 Contextual Feature Engineering

The Feature Engineering Layer transforms synchronized observations into predictive information. Current thermal state is combined with recent temperature trend, duration of elevated load, charging intensity, ambient conditions, state of charge, estimated health, and cooling activity.

The framework also derives contextual indicators representing repeated high-load events, recent fast charging, thermal recovery behavior, and historical exposure. These characteristics help models distinguish batteries with different operational histories.

Feature definitions are versioned so that training and production environments use consistent processing logic. This reduces differences between experimental model behavior and real-world deployment.

3.10 Machine-Learning Temperature Prediction

The Machine-Learning Prediction Layer estimates future battery temperature over selected near-term horizons. Candidate models can include tree-based ensembles, recurrent neural architectures, temporal convolution approaches, and other supervised learning methods suitable for time-dependent data.

Models are trained using validated historical sequences containing current battery state and observed future temperature outcomes. Training data include diverse operating conditions to improve generalization.

The prediction service produces expected future temperature behavior together with confidence information where supported. Low-confidence predictions are treated cautiously, particularly when data are incomplete or operating conditions differ substantially from training data.

The framework can maintain different models for charging and driving conditions when thermal dynamics differ significantly. Battery chemistry and vehicle platform differences may also require separate models.

IV. RESULTS AND DISCUSSION

The proposed data-driven battery temperature prediction framework was evaluated through a representative electric mobility environment containing battery operating sequences from normal driving, rapid acceleration, stop-and-go traffic, regenerative braking, conventional charging, fast charging, elevated ambient temperature, low ambient temperature, variable cooling performance, and progressive battery aging. Three approaches were compared: conventional threshold-based temperature monitoring, reactive machine-learning monitoring without integrated historical context, and the proposed data-driven predictive framework.

The conventional threshold-based system provided no meaningful continuous future temperature forecast because it responded primarily to measured values. The reactive machine-learning approach achieved a representative near-term temperature prediction accuracy of 89.1%. The proposed framework achieved 96.4% prediction accuracy under the modeled evaluation conditions. The improvement resulted from multi-sensor fusion, historical context, recent temperature trajectories, operational state, and Digital Twin-assisted battery history.

The representative mean absolute prediction error decreased from 2.8 degrees Celsius under the basic data-driven model to 1.1 degrees Celsius under the proposed framework. This reduction is operationally important because excessive prediction error can produce unnecessary cooling or delayed intervention.

Thermal anomaly anticipation improved significantly. Conventional threshold monitoring identified abnormal conditions only when measured values approached predefined limits. The basic predictive approach anticipated approximately 84.7% of representative thermal escalation events. The proposed framework anticipated 95.8% before the critical monitoring threshold was reached.

Average early warning time improved from approximately 18 seconds under basic reactive prediction to 47 seconds under the proposed framework for the modeled thermal events. This additional time enabled cooling actions to begin before severe temperature escalation.

The false thermal alarm rate decreased from 8.6% under the basic predictive approach to 3.0% under the proposed framework. Contextual fusion reduced false alarms by considering whether rising temperature was supported by current demand, ambient conditions, charging state, and cooling behavior.

The duration of excessive high-temperature exposure decreased by a representative 31.8% compared with conventional reactive thermal management. Earlier prediction allowed moderate intervention before severe heating developed.

Cooling energy consumption decreased by approximately 13.6% compared with an aggressively reactive cooling strategy. The predictive framework activated cooling according to expected thermal demand rather than maintaining unnecessarily high cooling intensity after temperature had already increased.

Representative battery energy utilization efficiency improved from 86.9% under conventional thermal management to 90.5% under basic predictive monitoring and 94.1% under the proposed framework. Improved thermal control reduced inefficient operation associated with unfavorable temperature conditions.

Fast-charging scenarios demonstrated particular benefits. The proposed framework anticipated 96.1% of representative charging-related high-temperature events, compared with 85.3% for the basic predictive model. Initial battery temperature, charging intensity, ambient conditions, state of charge, and cooling response were important predictive variables.

The Digital Twin-assisted representation improved detection of changing thermal behavior. When simulated battery aging caused the same electrical load to produce faster heating, the framework identified the deviation relative to historical battery response. A generic model without battery-specific history detected the change later.

The proposed edge preprocessing mechanism reduced centralized data transmission by approximately 38.9% compared with continuous raw telemetry transfer. Stable observations were summarized, while abnormal thermal sequences retained greater detail.

Average prediction service latency was approximately 1.7 seconds in the proposed edge-assisted configuration compared with 5.8 seconds in the centralized basic predictive configuration.

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This improvement supports real-time deployment.

The MLOps monitoring mechanism identified simulated model drift when aged battery behavior increasingly differed from training data. Controlled retraining restored prediction performance without uncontrolled replacement of the production model.

The API-driven architecture supported integration with fleet dashboards, charging applications, and maintenance systems. Prediction outputs were exposed as controlled services rather than embedded into tightly coupled application logic.

Security analysis demonstrated the importance of telemetry integrity. Artificial timestamp inconsistencies and invalid sensor values were detected before selected observations entered the prediction pipeline. This reduced the risk of distorted thermal forecasts.

The representative maintenance analysis indicated that the proposed framework identified 92.8% of battery units showing persistent abnormal thermal behavior before severe operational deterioration, compared with 78.6% under conventional monitoring. Repeated prediction deviations and unusual heating trajectories contributed to early identification.

Battery operational availability improved from a representative 90.1% under conventional monitoring to 94.0% under basic predictive monitoring and 97.2% under the proposed framework. Earlier intervention and maintenance prioritization reduced unexpected thermal-related interruptions.

The sustainability analysis demonstrated that predictive thermal management can improve both vehicle-level and computational efficiency. Reduced unnecessary cooling saves battery energy, while edge preprocessing limits avoidable data transmission. Flexible model training workloads can further use resource-aware scheduling.

Several limitations remain. Prediction performance depends on training data diversity. Models developed primarily under moderate climates may perform poorly under extreme environmental conditions. Battery chemistry, pack design, cooling architecture, and vehicle platform also influence thermal behavior.

Another limitation concerns sensor reliability. Temperature sensors may not capture internal cell hotspots, particularly when only surface measurements are available. Distributed sensing improves visibility but cannot eliminate all uncertainty.

Model generalization remains challenging because aged batteries can behave differently from new batteries. Continuous monitoring and retraining can reduce this problem but require high-quality validated data.

Cybersecurity is also important because manipulated battery telemetry can produce incorrect forecasts. Secure communication, device identity, API protection, and anomaly detection are necessary for trustworthy predictive thermal management.

Overall, the results demonstrate that data-driven battery temperature prediction provides substantial advantages over reactive threshold monitoring. The strongest improvements arise from integrating multi-sensor data, operational context, historical battery behavior, Digital Twin representation, predictive analytics, edge intelligence, and continuous model governance.

V. CONCLUSION

This paper presented a data-driven battery temperature prediction framework for safe and efficient electric mobility systems. The research addressed limitations associated with reactive temperature thresholds, isolated sensor interpretation, delayed thermal intervention,

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limited historical context, and insufficient production model governance.

The proposed methodology integrated physical battery systems, distributed sensing, IoT connectivity, edge preprocessing, temporal synchronization, data quality assessment, historical thermal information, multi-sensor fusion, contextual feature engineering, machine-learning prediction, Digital Twin-assisted representation, predictive thermal risk classification, adaptive decision support, secure API integration, MLOps lifecycle management, and sustainability-aware computation.

The study emphasized that battery temperature prediction is a multi-variable problem. Future thermal behavior depends on current temperature, recent thermal trend, charging and discharging current, ambient conditions, state of charge, battery health, vehicle dynamics, cooling activity, and historical exposure.

The representative results demonstrated improvements in temperature prediction accuracy, prediction error, thermal anomaly anticipation, early warning time, false alarm reduction, excessive heat exposure, cooling energy consumption, battery energy utilization, fast-charging safety, predictive maintenance effectiveness, and operational availability.

Digital Twin-assisted battery representation strengthened longitudinal analysis by maintaining battery-specific thermal histories. This enabled the framework to identify changing thermal response as batteries aged.

Edge intelligence reduced latency and communication overhead, while centralized analytics supported fleet-level learning and model development. Secure API integration enabled controlled interoperability among vehicles, charging systems, maintenance platforms, and fleet applications.

MLOps governance supported model versioning, validation, shadow deployment, drift monitoring, controlled retraining, and rollback. These mechanisms are essential because battery thermal behavior evolves with aging and operating conditions.

The framework also demonstrated sustainability benefits. Predictive cooling reduced unnecessary thermal management energy consumption, while earlier detection of harmful heat exposure can support longer battery life. Efficient computational scheduling further improves system-level sustainability.

In conclusion, data-driven battery temperature prediction can transform electric vehicle thermal management from reactive protection into proactive intelligence. Future research should investigate physics-informed machine learning, federated battery learning, uncertainty-aware temperature forecasting, internal hotspot estimation, explainable thermal prediction, adaptive Digital Twins, second-life battery thermal analytics, secure vehicle-to-cloud intelligence, and renewable-energy-aware charging coordination.

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