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Predictive AI-Based Battery cooling and Thermal control system for EV Vehicles: A Literature Review

H R Patil[1], M M Ganganallimath[2], Manu G. Hunagund[3], Naveen Itagi[4], Prajwal P. Kajagar[5], Prashant Y. Ghorpade[6]

[1,2]Associate Professor, Mechanical Engineering Department, Basaveshwar Engineering College, Bagalkot-587102. Karnataka
[3,4,5,6]Final Year Students, Mechanical Engineering Department, Basaveshwar Engineering College, Bagalkot-587102. Karnataka

Abstract-The necessity for effective Battery Thermal Management Systems (BTMS) to keep lithium-ion batteries within their ideal temperature range has grown due to the explosive growth of electric vehicles (EVs). Battery longevity, safety, charging efficiency, and overall vehicle performance are all strongly impacted by battery temperature. Although they offer efficient thermal management, conventional cooling techniques including air cooling, liquid cooling, phase change materials, and heat pipes are constrained in dynamic driving and fast-charging scenarios.Predictive battery temperature management employing machine learning, deep learning, reinforcement learning, and Model Predictive Control (MPC) has been made possible by recent developments in artificial intelligence (AI). These methods increase battery safety, minimize energy usage, optimize cooling procedures, and precisely anticipate battery temperature. Conventional cooling technologies, AI-based thermal prediction techniques, predictive control tactics, and current advancements in intelligent BTMS are all summarized in this paper. Additionally, it draws attention to present issues and potential paths, such as Edge AI, Physics-Informed AI, and Digital Twins. All things considered, predictive AI-based thermal management presents a viable way to improve battery safety, energy economy, and next-generation electric vehicle performance.

Keywords—Electric Vehicle, Thermal Management System, Artificial Intelligence, Predictive Control, Battery Cooling

I. INTRODUCTION

Electric vehicles (EVs) are becoming more and more popular in the transportation industry as a way to lessen pollution, greenhouse gas emissions, and reliance on fossil fuels. The performance, longevity, and safety of lithium-ion batteries, which are the main energy source in EVs, have a significant impact on the overall efficiency of the vehicle. Lithium-ion batteries produce a lot of heat when charging and discharging because of internal resistance and electrochemical processes. Thermal imbalance, increased degradation, decreased charging efficiency, and thermal runaway can all result from high-power driving and rapid charging. In order to guaranty battery dependability and increase service life, battery temperature must be kept within the ideal range of 20 to 40°C. Battery Thermal Management Systems (BTMS) use air cooling, liquid cooling, refrigerant cooling, heat pipes, and phase change materials to control battery temperature. Even though these traditional techniques efficiently remove heat, they mostly use reactive control schemes, which causes a delayed thermal response and increased energy consumption in dynamic operating circumstances.

By predicting future battery temperatures using operational data like current, voltage, state of charge, ambient temperature, and driving circumstances, recent developments in artificial intelligence (AI) have made predictive battery thermal management possible. Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and deep reinforcement learning are examples of machine learning and deep learning techniques that have shown excellent prediction accuracy. These methods improve battery safety, lower cooling energy usage, and prolong battery life when combined with Model Predictive Control (MPC) to optimize cooling decisions before critical temperatures are reached.

Recent advancements in predictive AI-based battery cooling and thermal control systems for electric cars are discussed in this article. Conventional BTMS technologies, AI-based temperature prediction techniques, predictive control schemes, recent research contributions, current issues, and future research goals are all covered.

II. LITERATURE REVIEW

Lithium-ion batteries used in electric vehicles (EVs) depend on Battery Thermal Management Systems (BTMS) to maintain their longevity, performance, and safety. Using air cooling, liquid cooling, phase change materials, and thermoelectric cooling, conventional thermal management strategies mainly concentrate on keeping battery temperature within the ideal operating range. However, the effectiveness and flexibility of battery thermal management systems have been greatly improved by recent developments in artificial intelligence (AI), machine learning (ML), and predictive control. The significance of efficient battery thermal management was emphasized in early foundational work by Pesaran (2001), who also noted important issues such temperature rise, thermal imbalance, and safety threats in EV battery packs [1].

In a similar vein, Wang et al. (2021) examined a number of cooling systems and highlighted the necessity of clever thermal management techniques to boost dependability and energy efficiency [2]. In their investigation of thermal runaway mechanisms in lithium-ion batteries, Feng et al. (2018) emphasized the significance of precise temperature prediction for safety assurance [3]. Furthermore, Liu et al. (2019) recognized heat control as a critical function for battery longevity and discussed important Battery Management System (BMS) technologies [4]. Additionally, Huo et al. (2015) showed that liquid cooling with mini-channel cold plates greatly enhances heat dissipation performance in comparison to traditional cooling techniques, making it appropriate for high-power EV applications [5]. In order to increase battery cooling efficiency, recent research has increasingly concentrated on combining artificial intelligence with predictive control algorithms.

Kurt et al. (2025) suggested a machine learning-based predictive thermal management system that uses neural networks to anticipate battery temperature and maximize compressor performance, resulting in notable energy savings [6]. An Artificial Neural Network (ANN)-based Model Predictive Control (MPC) architecture that minimizes cooling energy while preserving thermal safety was created by Nam and Ahn (2025) [7]. In a similar vein, Ma et al. (2025) presented an approximation scenario-based MPC technique that manages temperature prediction uncertainty and lowers computational cost for real-time applications [8]. When compared to conventional reactive cooling systems, these experiments show that proactive thermal regulation made possible by AI-based predictive control improves battery performance and energy efficiency.

Battery heat management now faces more difficulties due to the quick development of fast-charging infrastructure. In order to minimize energy usage and control battery temperature during fast charging, Acker et al. (2026) suggested a nonlinear Model Predictive Control (NMPC) framework in conjunction with dynamic programming [9]. Improved thermal stability under dynamic operating circumstances was demonstrated by Luo et al.'s (2024) investigation of thermoelectric cooling integrated with MPC [10]. By employing energy-efficient predictive control to further optimize EV thermal management, Xu et al. (2026) showed notable decreases in the total system energy consumption [11]. Furthermore, Amini et al. (2018) highlighted the advantages of coordinated energy-thermal control techniques by developing a two-layer predictive optimization framework that jointly regulates battery thermal behavior and vehicle energy usage in connected and automated EVs [12].

Battery heat management now faces more difficulties due to the quick growth of fast-charging infrastructure. In order to control battery temperature during fast charging while reducing energy usage, Acker et al. (2026) introduced a nonlinear Model Predictive Control (NMPC) framework in conjunction with dynamic programming [9].

Thermoelectric cooling combined with MPC was studied by Luo et al. (2024), who demonstrated enhanced thermal stability under dynamic working conditions [10]. By employing energy-efficient predictive control to further enhance EV thermal management, Xu et al. (2026) showed notable reductions in the total system energy consumption [11]. Furthermore, Amini et al. (2018) highlighted the advantages of coordinated energy-thermal management strategies by creating a two-layer predictive optimization framework that simultaneously controls vehicle energy consumption and battery thermal behavior in connected and automated EVs [12]. This researchshows a definite trend toward AI-powered intelligent, adaptive, and real-time thermal control systems.

Overall, it is evident from the literature that traditional cooling techniques are giving way to AI-enabled predictive thermal management systems. Battery safety, cooling energy usage, and temperature forecast accuracy have all been greatly increased by machine learning, neural networks, deep reinforcement learning, and model predictive control. However, there are still issues with battery aging effects, real-time implementation, computing efficiency, and validation in real-world driving scenarios. Future research into creating reliable AI-based predictive battery cooling and temperature control systems for electric vehicles has a lot of potential because of these gaps.

Battery Thermal Management Systems (BTMS)

Lithium-ion batteries must be kept within their ideal operating temperature range while maintaining temperature consistency throughout all battery cells, which is the responsibility of battery thermal management systems. Four main tasks are carried out by an effective BTMS:

- The elimination of heat when charging and discharging
- Heating batteries in the winter
- Preventing thermal runaway
- Battery cell temperature balancing

An efficient BTMS increases passenger safety, prolongs cycle life, lowers deterioration, and increases battery economy.

Battery size, power density, vehicle type, operating environment, and cooling needs all influence the choice of thermal management system. In general, BTMS can be divided into two categories: passive systems and active systems. Without the need for external power, passive systems make use of naturally occurring materials or mechanisms like phase transition materials. To actively control battery temperature, active systems use compressors, fans, pumps, or refrigerant circuits. Several cooling technologies are combined in hybrid systems to optimize cooling efficiency and reduce energy usage. Research into intelligent BTMS that can forecast future thermal behavior instead of just responding to recorded temperatures has accelerated due to the growing demand for ultra-fast charging and high-power battery packs. AI-driven predictive thermal control systems have been made possible by this change.

III. CONVENTIONAL BATTERY COOLING TECHNIQUES

Operating temperature has a significant impact on lithium-ion battery longevity, performance, and safety. Overheating during high-power operation, charging, and discharging can hasten battery deterioration, lower efficiency, and raise the possibility of thermal runaway. Battery Thermal Management Systems (BTMS) use a variety of cooling techniques, such as air cooling, liquid cooling, phase change material (PCM) cooling, heat pipe cooling, refrigerant cooling, and hybrid cooling systems, to handle these problems. Depending on battery capacity and operating conditions, each method has particular benefits and drawbacks.

- Air Cooling System: The most straightforward and cost-effective cooling method is air cooling, which uses forced or natural airflow to dissipate battery heat. It is appropriate for low-power EVs and hybrid cars because it is lightweight, affordable, and requires little upkeep. However, under high-speed driving and fast-charging situations, air's limited thermal conductivity restricts its cooling capacity, leading to an uneven temperature distribution in big battery packs.

- Liquid Cooling System: Commercial EVs frequently use liquid cooling because of its excellent heat transmission capabilities. In order to transport battery heat to a heat exchanger, a coolant moves thru cooling channels or plates. It provides better thermal control, more consistent temperature, and quicker heat removal than air cooling. Coolant leakage is still a major issue, but it raises system complexity, cost, weight, and maintenance needs.
- Phase Change Material (PCM) Cooling: Without the need for external power, PCM cooling maintains a virtually constant temperature by absorbing battery heat thru latent heat throughout the melting process. It enhances temperature homogeneity and offers passive thermal regulation. However, once fully melted, its efficacy diminishes and its limited thermal conductivity restricts continued cooling. As a result, PCM is frequently used in conjunction with heat pipes or liquid cooling.
- Heat Pipe Cooling: Thru the evaporation and condensation of a working fluid inside a sealed tube, heat pipes effectively transport heat. They offer superior temperature homogeneity, small design, great thermal conductivity, and passive operation. However, solo heat pipe systems are frequently combined with additional cooling techniques because they are typically insufficient for high-power EV applications.
- Refrigerant Cooling: Refrigerant cooling uses an evaporator in the car's air conditioning system to remove battery heat. It is appropriate for high-performance EVs since it offers quick charging and good cooling performance in hot weather. Nevertheless, the system's performance is reliant on compressor operation and is costly, energy-intensive, and mechanically complicated.
- Hybrid Battery Cooling Systems: To increase cooling efficiency and temperature consistency, hybrid cooling systems integrate two or more cooling methods, such as liquid cooling with PCM or heat pipes. These solutions increase system complexity and manufacturing costs despite providing better thermal performance and flexibility.
- Limitations of Conventional Battery Cooling Techniques: Reactive control techniques, which only start cooling when battery temperature rises, are the mainstay of conventional BTMS. Higher energy consumption and a delayed temperature response result from this, particularly when fast charging and dynamic driving are involved. In order to get beyond these restrictions, AI-based predictive thermal management systems forecast battery temperature and proactively improve cooling measures using machine learning and model predictive control. These sophisticated technologies are a promising option for next-generation electric vehicles because they increase battery longevity, safety, and energy efficiency.

IV. ARTIFICIAL INTELLIGENCE IN BATTERY THERMAL MANAGEMENT

By substituting intelligent predictive systems for traditional rule-based controllers, artificial intelligence (AI) has emerged as a major technology in Battery Thermal Management Systems (BTMS) for electric vehicles. In contrast to reactive thermal management, AI learns intricate thermal behavior, forecasts future battery temperatures, and optimizes cooling techniques in real time. AI enhances battery safety, energy economy, and overall system reliability by combining machine learning, deep learning, reinforcement learning, and predictive control algorithms.

1. Machine Learning for Battery Temperature Prediction

Current, voltage, state of charge (SOC), state of health (SOH), ambient temperature, charging rate, and other real-time and historical data are used by machine learning (ML) models to estimate battery temperature. Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, Decision Trees, and Gaussian Process Regression are examples of common machine learning approaches. ML techniques offer greater prediction accuracy with less processing complexity when compared to conventional mathematical models.

ML combined with Model Predictive Control (MPC) lowers cooling energy while keeping battery temperature within safe bounds, according to studies by Kurt et al. and Nam and Ahn.

2. Deep Learning Techniques

By learning highly nonlinear thermal parameters from massive datasets gathered by Battery Management Systems (BMS), Deep Learning (DL) improves battery temperature prediction. Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and hybrid CNN-LSTM networks are examples of popular models. While CNN automatically extracts thermal properties from sensor data, LSTM is especially useful for predicting time-dependent battery temperature fluctuations. Compared to traditional neural networks, these models forecast temperature more accurately.

3. Reinforcement Learning for Thermal Control

Thru constant communication with the battery system, intelligent controllers can discover the best cooling techniques thanks to Reinforcement Learning (RL). Deep Reinforcement Learning (DRL) optimizes cooling choices under dynamic driving situations by combining reinforcement learning (RL) with deep neural networks. DRL-based thermal control lowers cooling energy usage while preserving safe battery temperatures, as Jia et al. showed. Without the need for manual controller tuning, RL continually modifies its control policy in response to battery age, charging behavior, and environmental factors.

4. AI-Integrated Model Predictive Control

In order to meet safety and energy requirements, Model Predictive Control (MPC) forecasts future battery temperatures and chooses the best cooling strategies. While AI-based MPC substitutes machine learning predictors for precise mathematical models in order to increase accuracy and minimize processing cost, traditional MPC depends on these models. Nonlinear MPC (NMPC) and hybrid AI-MPC systems enhance battery thermal stability, lower compressor energy usage, and offer proactive cooling.

5. Physics-Informed AI and Digital Twins

Neural networks and electrochemical battery models are used in Physics-Informed Artificial Intelligence to increase forecast accuracy and resilience in a variety of operating environments. These hybrid models maintain battery thermal properties while using less training data. By building a virtual battery model that continuously collects real-time sensor data for temperature forecast, battery health estimation, fault detection, and predictive maintenance, digital twin technology significantly improves BTMS. Intelligent fleet-level battery monitoring is made possible by integration with IoT and cloud computing.

6. Advantages of AI-Based Battery Thermal Management

AI-driven BTMS is superior to traditional rule-based systems in a number of ways. • Precise battery temperature forecast prior to overheating. • Adaptive cooling under a range of driving and environmental circumstances. • Less energy is used for cooling thanks to clever optimization. • A longer battery life and more consistent temperature. • Improved thermal safety and fast-charging capabilities. • Constant learning that adjusts to operational conditions and battery aging. • Increased driving range and energy economy.

All things considered, AI has changed battery thermal management from reactive cooling to intelligent predictive control. Accurate temperature prediction and energy-efficient cooling are made possible by machine learning, deep learning, reinforcement learning, physics-informed AI, and digital twin technologies. By enhancing battery safety, prolonging service life, and facilitating high-performance thermal management, these technologies are anticipated to be crucial to the development of future electric vehicles.

V. PREDICTIVE AI-BASED BATTERY COOLING SYSTEMS

Intelligent Battery Thermal Management Systems (BTMS) are now required due to the growing energy density of lithium-ion batteries and the use of fast-charging technologies.

Reactive control solutions used in conventional cooling systems cause a delayed response and increased energy usage because they only start cooling when battery temperatures rise above acceptable limits. By predicting battery temperatures and putting proactive cooling techniques into place, predictive artificial intelligence (AI)-based BTMS get beyond these restrictions. Predictive AI enhances battery safety, energy efficiency, and lifespan by combining machine learning, deep learning, real-time sensor data, and optimization approaches.

1. Principle of Predictive Battery Cooling

Current, voltage, state of charge (SOC), state of health (SOH), ambient temperature, charging rate, and battery temperature are all monitored by predictive battery cooling systems. AI models use this data to forecast battery temperatures in the future. Optimization algorithms choose the most energy-efficient cooling method while preserving safe operating temperatures based on these forecasts. Predictive systems, in contrast to traditional controllers, start cooling before overheating happens, lowering thermal stress and enhancing battery performance.

2. Architecture of Predictive AI-Based BTMS

There are four main layers in a predictive AI-based BTMS:

- Data Acquisition Layer: Gathers temperature, voltage, current, and vehicle operating conditions in real time from battery sensors and the Battery Management System (BMS).
- AI Prediction Layer: Estimates future battery temperatures using AI models including Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM).
- Optimization Layer: To maximize cooling operations while reducing energy consumption, this layer uses Model Predictive Control (MPC), Nonlinear MPC (NMPC), Dynamic Programming (DP), or Deep Reinforcement Learning (DRL).
- Thermal Actuation Layer: This layer regulates battery temperature in real time by controlling pumps, cooling fans, compressors, valves, and heat exchangers.

3. AI Algorithms for Predictive Battery Cooling

Predictive BTMS makes extensive use of a number of AI algorithms. For embedded systems, ANN offers quick and precise temperature estimation. Particularly during rapid charging, LSTM accurately forecasts time-dependent battery thermal behavior. For increased accuracy, CNN is frequently used in conjunction with LSTM to extract intricate thermal features from sensor data. While Physics-Informed Neural Networks (PINNs) integrate AI with physical battery models to increase forecast accuracy and robustness, DRL learns the best cooling strategies under shifting operating conditions.

4. Model Predictive Control

Model Predictive Control (MPC) calculates the best cooling strategies while meeting safety and energy requirements by forecasting future battery temperatures. AI-based MPC increases prediction accuracy and minimizes computational cost by substituting machine learning predictors with intricate mathematical battery models. According to recent research, AI-integrated MPC increases overall EV energy efficiency, improves temperature uniformity, and lowers compressor power usage.

5. Recent Research Trends

Intelligent predictive cooling employing machine learning, ANN-based MPC, nonlinear MPC, and deep reinforcement learning is the main focus of current research. Compared to traditional controllers, these methods offer more precise temperature forecast, adaptive cooling control, and reduced energy use. Battery monitoring, heat prediction, and predictive maintenance are further enhanced by new technologies like Digital Twins and Physics-Informed AI.

6. Advantages and Challenges

Early temperature prediction, adaptive cooling control, better battery safety, higher fast-charging capabilities, lower cooling energy consumption, longer battery life, and improved vehicle efficiency are all benefits of predictive AI-based cooling systems. Large training datasets, high processing demands, real-time embedded implementation, battery aging prediction, cybersecurity, and interaction with current battery management systems are some of the issues that still need to be resolved. EV thermal management has advanced significantly with predictive AI-based battery cooling systems. These systems improve battery safety, energy efficiency, and lifespan by enabling proactive thermal control thru the combination of real-time monitoring, AI-based temperature prediction, and optimization algorithms. Predictive thermal management is anticipated to become a key component of next-generation electric vehicles as AI and embedded computing continue to advance.

VI. COMPARATIVE ANALYSIS OF EXISTING RESEARCH

Battery Thermal Management Systems (BTMS) for electric vehicles have seen a substantial transformation thanks to the recent development of Artificial Intelligence (AI), which has made it possible for energy-efficient thermal management, adaptive cooling techniques, and predictive temperature prediction. To increase battery safety and cooling efficiency, a number of academics have suggested AI-based strategies that incorporate Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), and Model Predictive Control (MPC). The main contributions, approaches, benefits, and drawbacks of typical studies are listed in Table 6.1.

Table 1: Comparative Analysis of Existing Research

Ref.	Author(s)	AI/Control Technique	Cooling Method	Major Contribution	Limitations
[1]	Pesaran (2001)	Conventional Control	Air/Liquid Cooling	Established the importance of BTMS and battery safety	No predictive intelligence
[2]	Wang et al. (2021)	Review Study	Multiple Cooling Methods	Comprehensive review of BTMS technologies	No experimental AI implementation
[3]	Feng et al. (2018)	Thermal Modeling	Battery Safety	Explained thermal runaway mechanisms	No cooling optimization
[4]	Liu et al. (2019)	Battery Management System	General BTMS	Reviewed key BMS technologies	Limited predictive analysis
[5]	Huo et al. (2015)	Experimental Analysis	Liquid Cooling	Improved heat dissipation using mini-channel cold plates	Higher manufacturing cost
[6]	Kurt et al. (2025)	Machine Learning + Neural Network	Compressor Cooling	Reduced cooling energy through predictive temperature estimation	Requires extensive training data
[7]	Nam &Ahn (2025)	ANN-Based MPC	Liquid Cooling	Optimized cooling energy while maintaining battery safety	High computational complexity
[8]	Ma et al. (2025)	Scenario-Based MPC	Active Cooling	Real-time predictive thermal control under uncertainty	Depends on model accuracy
[9]	Acker et al. (2026)	Nonlinear MPC	Fast-Charging Cooling	Optimized battery cooling during fast charging	Computationally intensive
[10]	Luo et al. (2024)	MPC + Thermoelectric Cooling	Thermoelectric Cooling	Improved temperature regulation using predictive control	Limited large-scale validation
[11]	Xu et al. (2026)	Energy-Efficient MPC	Integrated Thermal Management	Reduced overall vehicle thermal energy consumption	Requires integrated vehicle models
[12]	Amini et al. (2018)	Two-Layer Predictive	Integrated BTMS	Joint optimization of battery temperature and	Complex implementation

		Optimization		vehicle energy	
[13]	Jia et al. (2025)	Deep Reinforcement Learning	Intelligent Cooling	Adaptive cooling decisions under dynamic driving conditions	Long training time
[14]	Ripa et al. (2026)	Hierarchical NMPC + Neural Networks	Integrated Cooling	Improved prediction accuracy with reduced computational burden	Limited real-world testing
[15]	Wang (2026)	Physics-Informed AI	Predictive Thermal Management	Combined physics-based models with AI for higher accuracy	Early-stage development
[16]	Lokur&Murgovski (2026)	Predictive Optimization	Heat Pump BTMS	Balanced battery safety, cabin comfort, and energy efficiency	Requires accurate vehicle thermal model

Comparative Discussion

According to the literature, AI-based predictive thermal management has clearly replaced traditional battery cooling techniques. Early research concentrated on mini-channel cold plates, liquid cooling, and air cooling, which enhanced heat dissipation but relied on reactive control, delaying cooling and using more energy. Intelligent temperature prediction using battery data including current, voltage, state of charge, and ambient temperature was made possible by the development of machine learning. AI models decreased modeling complexity while increasing prediction accuracy. AI-integrated Model Predictive Control (MPC) has gained popularity as a proactive cooling method that lowers energy consumption and keeps battery temperature within safe bounds. AI-MPC offers higher thermal uniformity, quicker response times, and increased energy efficiency when compared to traditional PID controllers.

Prediction accuracy and adaptive cooling under dynamic operating conditions have been significantly improved using deep learning approaches such as ANN, LSTM, and Deep Reinforcement Learning (DRL). In order to increase vehicle efficiency and driving range, recent research also focuses on integrating battery thermal management with overall vehicle energy management. By integrating physical battery models with data-driven learning and facilitating real-time monitoring, fault diagnosis, and predictive maintenance, emerging technologies like Physics-Informed AI and Digital Twins have increased predictive thermal management.

These advancements demonstrate how intelligent, predictive BTMS is becoming more and more important in next-generation electric cars.

Research Trends

The comparison analysis reveals the following research trends: • Make the switch to predictive AI-based thermal management from traditional reactive cooling systems. • Machine learning and deep learning are being used more frequently to anticipate battery temperature. • Model Predictive Control (MPC) and Nonlinear MPC are widely used for thermal optimization. • Deep Reinforcement Learning is increasingly being used for adaptive cooling techniques. • Battery cooling is integrated with the vehicle's entire energy management system. • The creation of AI models informed by physics to improve forecast accuracy. • The development of digital twin technology for predictive maintenance and intelligent battery monitoring. • Concentrate on prolonging battery life while lowering cooling energy usage. • A greater focus on battery safety and fast-charging heat management.

In terms of temperature prediction accuracy, energy economy, thermal uniformity, and battery safety, the comparison research shows that predictive AI-based battery cooling systems routinely beat traditional thermal management techniques. There are still issues with real-time implementation, computing needs, battery aging prediction, cybersecurity, and large-scale industrial deployment, despite the encouraging outcomes of machine learning and predictive control techniques.

In order to enable intelligent battery temperature management in next-generation electric vehicles, future research should concentrate on creating lightweight AI models, explainable AI, federated learning, and edge computing solutions.

VII. SUMMARY AND DISCUSSION

According to the literature, sophisticated AI-based predictive thermal management has replaced traditional cooling techniques in battery thermal management systems (BTMS). Conventional methods, such as air cooling, liquid cooling, PCM, heat pipes, and refrigerant cooling, efficiently remove battery heat but depend on reactive control, which frequently leads to a delayed cooling response, increased energy consumption, and decreased performance during high-power and fast charging.

Predictive battery temperature estimates and improved cooling control have been made possible by recent developments in AI. Battery temperature is accurately predicted using real-time operating data by Machine Learning (ML), Deep Learning (DL), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Reinforcement Learning (RL), and Physics-Informed Neural Networks (PINNs). These methods offer proactive cooling, enhancing battery safety, temperature uniformity, energy economy, and battery lifespan when combined with Model Predictive Control (MPC) and Nonlinear MPC (NMPC).

AI-based thermal management often performs better than traditional cooling systems, according to comparative research. For real-time monitoring and predictive maintenance, current research also concentrates on integrated vehicle thermal management and cutting-edge technologies like digital twins, edge artificial intelligence, cloud computing, and the Internet of Things. Large training datasets, high processing demands, battery aging prediction, real-time embedded implementation, and cybersecurity are still issues despite recent developments. To create more effective, dependable, and intelligent Battery Thermal Management Systems for next-generation electric vehicles, future research should focus on lightweight and comprehensible AI models, enhanced embedded control, and Digital Twin integration.

VIII. CONCLUSION

In order to guaranty the longevity, performance, and safety of lithium-ion batteries in electric cars, battery thermal management systems, or BTMS, are essential. This analysis emphasizes the shift from traditional cooling techniques, such liquid and air cooling, to sophisticated AI-based predictive thermal management systems. Due to the reactive nature of conventional cooling methods, temperature response is delayed and energy consumption is increased. On the other hand, precise battery temperature prediction and proactive cooling are made possible by AI-based techniques including Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), and Model Predictive Control (MPC). These techniques support quick charging, increase battery safety, lower cooling energy usage, improve thermal management, and prolong battery life.

By enabling predictive monitoring and improved thermal regulation, emerging technologies like Digital Twins and Physics-Informed AI further strengthen intelligent BTMS. However, there are still issues that need to be resolved, such as data availability, real-time implementation, battery aging, and computational complexity. All things considered, predictive AI-based battery cooling solutions offer a practical way to enhance battery safety, energy economy, and overall EV performance. The creation of more dependable and environmentally friendly electric vehicles will be aided by ongoing research on lightweight AI models and sophisticated thermal management.

Future Scope

Digital twins, edge artificial intelligence (AI), cloud computing, the Internet of Things (IoT), and vehicle-to-everything (V2X) connectivity are anticipated to be integrated into future predictive battery cooling systems. Next-generation Battery temperature Management Systems are likely to include autonomous temperature management, explainable AI, federated learning, and physics-informed neural networks. With the help of these technologies, self-learning thermal controllers will be able to respond in real time to changes in weather, traffic patterns, driver behavior, battery age, and charging infrastructure.

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