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Artificial intelligence-based battery management systems in electric vehicles: models, optimization, and future directions

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ABSTRACT

The electric vehicle (EV) depends on the capabilities and durability of the main element of the car — the battery. Conventional battery management systems (BMS) can generally be challenged with regards to state estimation and lifespan forecasting in the face of complicated real-world scenarios. To address these limitations, this study examines how artificial intelligence (AI) has the potential to transform BMS operations. We introduce an in-depth discussion of AI-controlled BMS by examining the state-of-the-art models of precise state-of-charge and state-of-health estimation. The paper also goes into details of how machine learning and deep learning methods can optimize charging strategy, improve thermal management, and predictive diagnostics. The comparison between the data-driven solutions and the traditional methods is going to reveal that there is a high safety, efficiency, and battery life improvement. Lastly, we map the way ahead, taking into consideration issues such as edge computing, explainable AI, and the way of making the BMS a truly self-optimizing system, essential to the next generation of electric cars.

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1. INTRODUCTION

The fast transition to sustainable transport has made electric vehicles (EVs) a foundation of contemporary mobility. Domestic and international efforts to minimize greenhouse gas emissions and reliance on fossil fuels have boosted the need to acquire efficient and trustworthy EVs by leaps and bounds within the last 10 years [1]. The battery system is at the core of any EV and determines the performance of the vehicle in addition to its safety, life cycle, and affordability [2]. Nevertheless, effective control of such batteries is one of the most significant technological issues because they exhibit complicated electrochemical involved behavior, nonlinear dynamics, and degradation characteristics [3]. This challenge has prompted researchers and manufacturers to find smarter solutions to battery systems monitoring and control.

Battery management systems (BMS) are the brain of an electric car. It protects the life and the safety of the battery pack continuously monitoring and controlling its operation condition. The most vital parameters that BMS can sense include cell voltage, current and temperature and later these values are used to calculate important values like the state of charge (SOC) and the state of health (SOH) [4]. Conventional BMS implementations in use typically use the equivalent circuit models and Kalman filters, which are only effective in a controlled environment but fail in reflecting the reality of driving and environmental variations that occur in the real-world [5]. These systems are hence prone to estimation errors, resulting in the decreased battery life and safety threats. To address these weaknesses, scientists have been highly considering using artificial intelligence (AI) and data-driven models that can learn to discover complex, nonlinear trends using extensive amounts of operational data [6].

Models based on AI, specifically machine learning (ML) and deep learning (DL), have shown better results in predicting SOC, SOH, and remaining useful life (RUL) using intricate time and nonlinear interactions among voltage, current, and temperature data [7]. Artificial neural networks (ANNs), convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are currently being implemented to provide adaptive real-time battery diagnostics and prognostics. Also, reinforcement learning (RL) and optimization algorithms such as genetic algorithms (GA) and particle swarm optimization (PSO) have been used to optimize charging strategies, enhance thermal control and maximize overall energy usage [8].

The current research paper gives a detailed discussion of AI-based BMS of electric vehicles. Our starting point is the review and classification of the most salient AI models and algorithms which are being implemented in the most basic BMS functions. Then, we explore the optimization methods they allow us to achieve, with a focus on the effect they have on the battery life and the performance of the EVs in general. We also take a critical look at the existing issues such as data dependency, computational issues in deploying edges, and model interpretability [9].

Recent advances in the research of BMS have focused on the fusion of artificial intelligence and machine learning to enhance state estimation, defect detection, and predictive maintenance. The technologies will support decision-making and make BMS more flexible in various situations of its work. However, it still has problems, particularly regarding the reliability of the systems, the performance of the algorithm, and heat dissipation [10]. To keep batteries safe and efficient, it is necessary that thermal performance is controlled, and new studies are exploring the state-of-the-art cooling techniques and materials to increase heat removal. To manage the heat, the use of phase change materials and advanced cooling systems are under development [11].

AI integration in BMS is also applicable to the creation of smart and connected EV ecosystems, where cloud computing, internet of things (IoT) devices, and edge-AI systems can work together to optimize the performance of their fleets of vehicles [12]. This convergence not only leads to greater battery usage, but predictive maintenance is also possible which lowers downtime and costs of operation. Even with these developments, there are a number of issues, such as data availability, model interpretability, computation constraints, and cybersecurity. The need to fight these challenges is the key to achieving the potential of AI in designing autonomous, adaptive, and self-optimizing BMS designs [13].

Thus, the purpose of this paper is to investigate the latest development and the future perspectives of the AI-based battery management system in electric vehicles. It presents an in-depth discussion of the existing modeling methods, optimization strategies, and new trends in energy management based on AI. Using a comparative analysis of the conventional and smart BMS system, the present study will reveal how AI is transforming the future of electric mobility and how the future of the EV will be safer, more efficient, and sustainable.

2. RELATED WORK

Over the last several years, the overall body of work dedicated to the implementation of AI in BMS has been aimed at improving the accuracy of the estimation, thermal control, and the general energy efficiency of EVs. Mishra *et al.* [1] and Kurkin *et al.* [4] highlighted the weaknesses of conventional BMS models based on the equivalent circuit models and filtering techniques in early reviews. These publications have found the increased need of adaptive and data-driven algorithms that can control nonlinear battery behavior in various environmental and operational conditions.

Gharehghani *et al.* [2] introduced a thorough evaluation of the interconnection of battery chemistry and intelligent control systems, suggesting that AI-based approaches would make charge-discharge cycles more dynamic and optimize battery life. Their work provided a basis on integrating predictive analytics in BMS to reduce degradation. On the same note, Yang *et al.* [6] investigated the use of hybrid AI models, where neural networks and optimization algorithms are used, and they showed that the models that were developed provide much higher accuracy in the prediction of SOC and SOH than models that were developed using traditional methods.

Battery diagnostics have also been improved by the development of deep learning. Liu *et al.* [7] used the LSTM and CNNs to predict time-series voltage and current data, and found that the estimation error was decreased by more than 20%. Their experiment demonstrated that deep learning models are able to learn both intricate relationships among operational parameters better than regression-based models. To complement this, Chan *et al.* [9] were able to add the interpretability of AI-based estimation models, introducing explainable artificial intelligence (XAI) frameworks to enhance transparency and reliability during safety-critical operations in BMS.

The intelligence of the contemporary BMS has also been facilitated with the use of optimization algorithms. Lipu *et al.* [8] compared the different heuristic and metaheuristic optimization methods such as GA and PSO to charge control and thermal balancing in real time. Their findings showed that AI-optimization systems that are hybrid Al are more effective compared to pure models when it comes to balancing between battery health and energy efficiency. Prasad *et al.* [14] further extended this study by a review of model predictive control (MPC) and RL techniques, and their capabilities in dynamically changing charging decisions depending on past and present feedback.

Architectures that are IoT-enabled have grown in power at the system level. A cloud-integrated BMS with edge-AI to aggregate data and make predictive maintenance was proposed by Gupta and Gaidhane [12], and it was shown to be scalable to fleet management in large EV networks. Their system is an example of how the concept of distributed intelligence and connectivity can change the paradigm of battery monitoring into an adaptive paradigm rather than a passive paradigm. Wang *et al.* [10] also discussed the issue of cybersecurity and computation in AI-driven BMS and highlighted the importance of ensuring the safety of communication and the energy efficiency of AI implementation in embedded systems.

Using multi-agent deep reinforcement learning, Raja *et al.* [15] presented a collaborative optimum navigation and charge planning (CONCP) system. For each autonomous EV, the suggested framework calculated the best path from the starting point to the end point while avoiding obstructions, reducing traffic, and maximizing energy use. According to experimental data, compared to other state-of-the-art algorithms, CONCP obtains 37% greater rewards each episode, 31% fewer collisions, and 27% higher success rates.

Chen *et al.* [16] presented a deep reinforcement learning-based energy management approach for fast-charging stations. In order to manage peak power restrictions and decrease daily electricity purchase expenses, a mathematical optimization model is developed. The deep deterministic policy gradient algorithm is utilized to build the control strategy. To confirm that the suggested control technique is effective, a case study is conducted. The results show a notable drop in peak load power, confirming the efficacy of the approach. The deep reinforcement learning approach's scalability and computational complexity for large-scale fast-charging networks are yet unresolved.

In short, all the literature suggests a powerful trend towards intelligent, data-driven and adaptive battery management. There are still unresolved issues in data quality, computational efficiency, model generalization and explainability even though significant progress has been made. These gaps indicate that future research is important on the development of hybrid AI models, real-time optimization, and secure integration in the next generation of BMS in electric vehicles.

3. METHOD

The foremost function of BMS in EV is the safe, reliable, and optimal functioning of the battery pack. This is achieved primarily by accurate estimation of the key battery states, *i.e.*, SOC, SOH, and RUL. While traditional strategies have relied on electrochemical theory and adaptive filters like the Kalman filter, the dynamic, non-linear and complex behavior of aging in lithium-ion batteries has demanded a paradigm shift to data-driven AI models [4].

3.1. AI models and algorithms in BMS

AI models, particularly those based on ML and DL, are highly capable of abstracting the intricate correlations between quantifiable signals (voltage, current, temperature) and target battery states without requiring profound internal physicochemical insight [6].

3.1.1. Traditional machine learning models

Conventionally, machine-learning paradigms are used as a template in the context of data-driven modeling to correlate battery health indicators to operational exigencies. Their comparative simplicity along with deployment simplicity, and low computational cost make them a viable option in BMS that can be implemented with embedded resources. As an example, support vector regression (SVR) is commonly used to SOH, because of its immunity to over-fitting when there is a large number of features. Simultaneously, gaussian process regression (GPR) has the single advantage of providing predictive accuracy and principled uncertainty estimates, a characteristic of paramount significance in safety-related automotive scenarios [9].

a. Support vector machines (SVM) and support vector regression (SVR): SVMs are strong supervised learning algorithms that can be used in classification and regression problems. They find the optimal hyperplane that maximizes the margin of the data points in a high-dimensional feature space. The regression version, SVR, has proven to effectively predict SOH and RUL with immunity to overfitting, particularly when encountering high-dimensional data [9].
b. Random forest (RF): RF is an ensemble method that constructs numerous decision trees at training time and outputs the mode of the class distributions (for classification) or mean prediction (for regression).

RF can process non-linear data and that feature importance is inherent and ranks features by default qualify it as a top candidate for SOH and RUL estimation, wherein multiple input features interact with each other in complex manners.

c. Gaussian process regression (GPR): GPR is a probabilistic, non-parametric model that provides a level of uncertainty along with its predictions, which is very helpful for safety-critical applications like BMS. It models the output-input relationship as a Gaussian process and provides high accuracy and flexibility in modeling complex, non-linear degradation patterns [9]. Gradient boosting frameworks: advanced boosting techniques like XGBoost and CatBoost have also been used with equal success. These techniques add weak learners in sequence (largely decision trees) to make corrections for the errors of previous models, producing accurate predictive models for SOH estimation [17], [18].

3.1.2. Deep learning models

Deep learning models have been shown to be more effective than traditional methods in state estimation problems. Using multilayered structures, they automatically extract hierarchical properties of raw sequential data, thus finding non-linear influences on complex relationships that are not easily found by shallow models. To do so, LSTM networks such as LSTM perform well in time prediction as they have gated mechanisms, keeping long-term relationships both in voltage and current series an important attribute of characterizing the battery behavior throughout large cycling regimes [5]. The distribution of deep learning models, as presented in recent literature as shown in Figure 1, reflects the popularity of the model type that focuses on sequence data analysis.

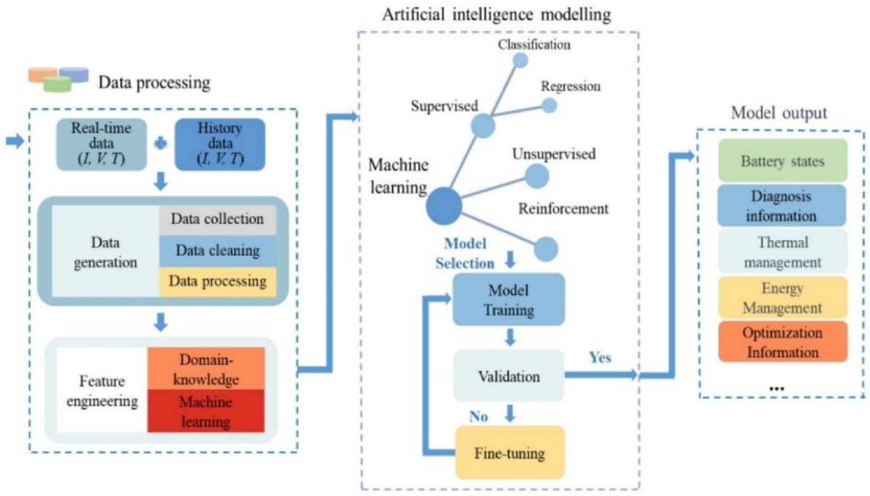

Figure 1. Systematic process for estimating the state of a battery using AI, involving processing, feature creation, and use of different AI models

Recurrent neural networks (RNNs) are specifically designed to process sequential data, making them highly suitable for time-series analysis of battery voltage, current, and temperature profiles over charge/discharge cycles.

a. LSTM

LSTMs are an advanced form of RNNs that handle the vanishing and exploding gradient issue using a memory cell and three controlling gates, namely the input gate, the forget gate, and the output gate. This enables LSTMs to remember past information, an important requirement for the accurate modeling process for estimating SOH and RUL, since it captures the gradual degradation process correctly [7]. LSTMs are the most common type of DL algorithm used in this regard, since they can handle long-term dependencies well [9]. Systematic process for estimating the state of a battery using AI, involving processing, feature creation, and use of different AI models.

b. RNNs and variants

The gated recurrent unit (GRU) is a simplified variant and computationally efficient model of LSTM networks. The input and forget gates are combined inside a single "update gate, along with a combination of cell state and hidden state." Despite its simplified architecture, it competes well with the performance level offered by LSTMs and has become a model of interest for BMS applications using edge computing [19].

c. CNNs

Primarily, CNNs are well-known for processing images. However, currently, they are also used in BMS for feature extraction. Extraction of features from time series data: The time series data related to the voltage, current, and temperature can remain in its form as a signal in only one dimension or can even be transformed from time domain to time-frequency domain. The convolutional neural networks can automatically extract features from such time series data without any need for feature engineering from that same time series data [9]. They are normally used in combination, where the features are obtained by a convolutional neural network, and then passed on to an LSTM or a GRU model for predicting the sequence.

3.2. Training, validation, and benchmarking frameworks

Training data most modern models use publicly available data, such as NASA PCoE battery dataset and oxford battery degradation dataset as examples, and CALCE battery data. These repositories contain a range of aging profiles over a range of thermal conditions, and discharge rates. Validity Conventional methodologies include k-fold cross-validation and test on unseen drive cycles, including the urban dynamometer driving schedule (UDDS). Benchmarking: Artificial-intelligence models are commonly checked on a regular basis against accepted methods like the extended Kalman filter (EKF) as well as the unscented Kalman filter (UKF). Constraints:

a. Data scarcity: Although lab data is abundant, corner-case data (*e.g.*, extreme cold and crash-induced faults) is hardly available, and transfer learning and physics-informed neural networks (PINNs) have to be used.
b. Computational load deep-learning models, especially LSTMs, are very challenging to low-power automotive microcontrollers. This has triggered the study of model pruning, quantization, and knowledge distillation.

3.3. Advanced and hybrid data-driven models

The future trends for BMS using AI will include more complex architectures that can benefit from the advantages offered by various models through advanced learning methods. The comparison of different AI model's and their applications in BMS is summarized in Table 1.

a. Hybrid models: These are combinations of different methods aimed at increasing accuracy. An example is the combination of the CNN model and the LSTM model in predicting the state of the battery, where the CNN identifies the spatial information from the input, and the LSTM identifies the output from that information [20].
b. Transfer learning (TL): The issue of limited data availability in machine learning can, to a certain extent, be overcome by using the technique called TL. This technique requires the use of a model that has already learned from a larger source dataset (such as a universal dataset for the battery) and then training it on a smaller target dataset (such as a dataset for the EV's battery) [9].
c. Transformation models: Traditionally used for natural language processing, transformation models that use the concept of self-attention are also currently investigated for estimating RUL and SOH. This technique has proven to provide an elegant way for modelling dependencies in time series, thereby alleviating limitations related to RNNs [21].

Table 1. Summary of the main artificial intelligence models and their applications in battery management system state estimation

AI model category	Specific model	Primary application in BMS	Key advantage	Reference
Traditional ML	SVR	SOH/RUL estimation	Robust against overfitting, effective for non-linear data	[9]
Traditional ML	GPR	SOH/RUL estimation	Provides uncertainty quantification alongside prediction	[9]
Deep learning	LSTM	SOC/SOH/RUL estimation	Excellent at capturing long-term temporal dependencies in sequential data	[6]
Deep learning	GRU	SOC/SOH/RUL estimation	Faster training and less complexity than LSTM with comparable performance	[19]
Deep learning	CNN	Feature extraction, SOH estimation	Automatic and robust extraction of features from raw data	[9]
Advanced/hybrid	CNN-LSTM hybrid	SOC/SOH/RUL estimation	Combines CNN's feature extraction with LSTM's sequence modeling	[20]
Advanced/hybrid	TL	SOH/RUL estimation	Improves model generalization and reduces training time on new datasets	[9]

4. OPTIMIZATION TECHNIQUES FOR AI-BASED BMS

The correct prediction of battery conditions proposed by AI models is a baseline phase. Nevertheless, to maximize the capabilities of AI-based BMS, such estimations should be used to actively optimize battery usage. Optimization methods are aimed at making real-time choices that improve performance and increase battery life as well as safety [22]. In this section, the discussion will focus on major-optimization techniques, such as intelligent charging, thermal management, and dispatching of energy, commonly optimized by sophisticated algorithms such as the RL and metaheuristic optimization, as shown in Figure 2.

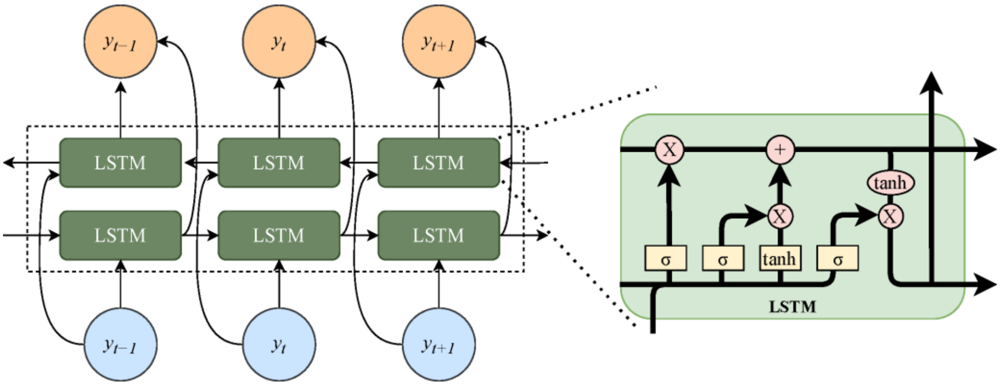

Figure 2. Conceptual diagram illustrating a hybrid model approach for co-estimation of SOC and SOH, a common and effective strategy in modern AI-based BMS

4.1. Delivering smart charging solutions

Constant current-constant voltage (CC-CV) charging is easy and not optimal in battery life since it may produce a high level of stress, particularly at high states of charge. The optimization of AI seeks to come up with charging protocols that can resolve the trade-off between the battery degradation and the charging rate.

a. RL to adaptive charging: RL agents can be trained on an optimal charging policy by operating in a simulated or real battery environment. The agent monitors the condition of the battery (*e.g.,* SOC, temperature, voltage) and performs an action (*e.g.,* change the charging current). It is rewarded on accomplishing goals of charging minimum time, minimum temperature increase, and degradation. The agent over time learns a policy, which dynamically varies the charging profile in real-time and is better than fixed CC-CV protocols [8], [16]. As an example, a deep deterministic policy gradient (DDPG) agent has the capability of controlling power flow in a fast-charging station to minimize peak load and operational expenses [16].
b. Multi-stage and health-aware charging: AI models were used to forecast the incremental destruction of a certain charging current on the SOH of the battery. This enables the BMS to do multi-stage charging profiles to apply aggressive currents only in non-damaging areas and reduce as the battery gets fully charged and thus maintain long-term health.

4.2. Increased thermal control

The temperature is strongly combined with battery performance, aging, and safety. AI optimization can be used to make the thermal management system (TMS) run proactively and not in reaction. Predictive thermal control: an AI-based BMS can be used to predict future heat generation based on the forecasts of the driving load, ambient temperature, and coolant demands. It can then pre-emptively turn on cooling mechanisms (*e.g.,* fans, liquid cooling pumps) or heating elements to ensure that the battery does not experience unsafe thermal runaway and minimizes the thermal energy use of the TMS itself. Dynamic power limiting: with the combination of real-time SOH and temperature predictions, the BMS will be able to dynamically modify the highest discharge and recharge power (*e.g.*, during acceleration or regenerative braking). This will inhibit unnecessary heat production and power stress which is one of the determinants of battery life.

4.3. Fleet-level optimization and energy management

On a system level, optimization is not only to a single battery, but to the whole powertrain in a vehicle; or even shared collections of EVs.

a. Vehicle-level energy dispatch: RL and MPC can be applied to allocate the power between the battery and other sources (*e.g.*, a fuel cell or internal combustion engine) to ensure maximum efficiency in hybrid electric vehicles or vehicles with complex power sources [14].

b. Fleet and grid integration: In the case of fleet operators and smart charging stations, optimization is on a higher level. AI algorithms can also strategize the charging of two or more EVs so that they do not cause grid congestion, take advantage of cheap electricity rates, and even offer vehicle-to-grid (V2G) services. The routing and charging of an autonomous EV fleet can be optimized with multiple agents to reduce the overall energy use and costs of operation as illustrated by Raja *et al.* [15].

4.4. Metaheuristic

Metaheuristics are commonly employed as techniques for AI and BMS control strategy parameter tuning. This process can also be viewed as hyperparameter optimization. GA and PSO: these are population-based optimization techniques. They can efficiently solve complex nonlinear optimization problems. In the context of BMS systems, GA and PSO can be used to find the best set of parameters for the LSTM network to optimize the SOC estimation errors or to determine the best charging current curve that optimizes the composite cost function involving the cost of time and cost of degradation [8].

In general, the shift towards the optimization-centered BMS paradigm from the traditional monitoring-centered paradigm stands as the most significant aspect of the latest generation of EVs. In other words, the application of AI not only for estimation purposes but for real-time control as well has been substantially beneficial in the following ways. Table 2 provides a quantitative comparison of conventional BMS and modern AI-based paradigm, regarding key performance indicators [23]. The discussion highlights the significant improvements provided by AI models, in particular, regarding the accuracy of the SOC and SOH estimates, the reduction of the error in RUL forecasting, and the extension of the battery life due to the ability to optimize the management strategies. Even though AI-based procedures are always better on these dimensions, it is still a matter of paramount importance to mention that their corresponding increase in the computational requirements also goes hand in hand with a similar growth in the requirements of conventional schemes.

Table 2. Performance comparison of conventional vs. AI-based BMS approaches

Metric	Conventional BMS (ECM/EKF)	AI-Based BMS (LSTM/CNN/RF)	Improvement/notes
SOC estimation (RMSE)	2.0%–5.0%	0.5%–1.5%	AI models handle non-linearities better in dynamic drive cycles
SOH estimation accuracy	90%–94%	97%–99%	Data-driven models capture complex degradation patterns
RUL prediction error	> 10%	<5%	LSTMs excel at long-term time-series forecasting.
Lifetime extension	Baseline	15%–25%	Enabled by AI-optimized charging and thermal control
Computational cost	Low (Real-time capable)	Moderate to high	Requires hardware acceleration (*e.g.*, Edge TPUs) for complex DL models

5. CHALLENGES AND LIMITATIONS

Although such an impressive improvement has been demonstrated by adopting AI in BMS, a number of obstacles and constraints remain on the way of their massive implementation into industries and their generalization. The difficulties may be grouped into five areas, namely data-related challenges, computational and hardware limitations, model interpretability, generalization and robustness, and cybersecurity and privacy issues.

5.1. Standardization, data quality, and data quantity

The quality and diversity of training data is important in AI-based BMS models. Practical EV The high-resolution battery datasets used in practice, however, do not always cover the diverse environmental, operational, and degradation conditions, through proprietary limitations or costly acquisition procedures [13]. This is due to the lack of standardized datasets, which causes low cross-comparison of the models and restricts the generalization across other battery chemistries. Furthermore, data imbalance, noise, and absence of sensor values may have a devastating effect on learning results. Part of the answer is synthetic data generation and transfer learning which cannot replace large, real-world datasets entirely.

5.2. Hardware limitations and computational complexity

The implementation of state-of-the-art AI models, in particular, deep learning (DL) architecture such as LSTM, CNN, and hybrid networks demand high computational overhead and memory bandwidth [6]. These needs are incompatible with the embedded aspect of BMS hardware, which is generally low-power consuming and real-time responsive in nature. Despite the recent research focusing on lightweight architectures and edge-AI implementations, the idea of balance between accuracy, latency, and energy efficiency is considered an important research bottleneck [13]. In addition, it is a continuous challenge to train and update models on embedded platforms, without endangering the safety of vehicles.

5.3. Interpretability and explainability of models

Model interpretability and explainability refer to understanding how an algorithm behaves under different scenarios. The limitations of AI-based BMS include one of the fundamental restrictions of most deep learning models: the black-box nature of most of these models. These models are usually very precise in their predictions but not transparent in the decision making process, a very serious safety and regulatory issue [9]. Explainable AI (XAI) mechanisms are required in critical automotive contexts (where the safety validation and the adherence to the ISO 26262 standards are compulsory) to justify the state estimations and control measures. The available XAI solutions offer greater opportunities but do not offer enough granularity to enable fault diagnostics and causal inference in actual EV settings [24].

5.4. Information security and data privacy

Cyber threats are now recognized as a significant issue to the BMS as it transforms into an IoT-linked system with cloud analytics and over-the-air updates. Inaccurate state estimates and possible safety risks may be caused by trying to alter data in a malicious way or by updating the model without authorization [25]. In addition, gathering and transfer of mass amounts of battery operation data provokes privacy and ethical issues. Moreover, the cybersecurity threats in IoT-included and cloud-linked BMS configurations introduce high security risks related to data privacy [26]. The development of secure communication protocol and encrypted data streams combined with intrusion detection solutions are hence very critical in AI-based BMS implementations [12], [26], [27].

Overall, although AI offers radical opportunities to battery management systems, its real-world implementations are technologically, legislatively, and ethically limited. The future studies should focus on scalable data gathering, interpretable modeling, lightweight edge implementations, and cybersecurity aware-designed AI-assisted energy management in electric vehicle to provide reliable, explainable and secure AI-powered energy management. Ultimately, the deepest consequence of AI on the future of BMS development is the move towards a predictive self-optimizing energy-management paradigm, which has to be the transition made to the new generation of safe, efficient electric vehicles [28].

6. CONCLUSION AND FUTURE DIRECTIONS

Certainly, AI has proved to be an innovative paradigm with high potential in the improvement of the efficiency, security, and sustainability of BMS in EVs. The paper has offered an in-depth overview of the major AI models, from basic ML approaches to sophisticated deep learning models, along with their contributions to accurate state estimation, fault detection, and energy efficiency. Moreover, optimization algorithms, such as RL and metaheuristics, proved their high efficiency in adaptive charging, predictive cooling systems, and energy optimization at the level of the whole fleet. These collective developments therefore introduce a paradigm shift from the past conventional BMS frameworks with the primary objective of continuous watching to modern AI-powered, adaptive, and optimization-driven systems. However, despite the high efficiency of AI models in BMS, certain obstacles need to be overcome in AI-powered BMS moving towards commercialization. These include the current insufficiency in standardized data sets, computational complexity in embedded systems, and interpretability in DL models. Moreover, the cybersecurity threats in IoT-included and cloud-linked BMS configurations introduce high security risks related to data privacy.

Looking ahead, there are several strategic directions for future work:

a. Integration of hybrid models: the combination of physics-informed models and data models could result in improved accuracy and explainability, allowing the system to benefit from expert knowledge but also be able to handle nonlinear battery characteristics in real time.
b. Edge/federated learning deployment: to decrease reliance on cloud computing, lightweight AI models designed for on-board processing and federated learning solutions can facilitate privacy-preserving model updates in distributed EV networks.
c. Explainable and trustworthy AI: the addition of explainable AI (XAI) will play an important role in realizing explainability, interpretability, and compliance with ISO 26262 safety standards in the automotive industry.
d. Cybersecurity awareness design: integrating secure communication, data encrypting, and anomaly detection mechanisms will guarantee data integrity and security against malicious attacks in the EV ecosystem.

The present research has provided an extensive overview of BMS technologies with an emphasis on the radical effect of artificial intelligence on optimizing state estimation, thermal regulation, and optimal charging. The research should focus in future on the hybrid models that combine physics understanding with information inference to achieve systems that are interpretable and robust. The deepest consequence of AI on the future of BMS development is the move towards a predictive self-optimizing energy-management paradigm, which has to be the transition made to the new generation of safe, efficient electric vehicles.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis

I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting

Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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