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TOPICAL REVIEW

# A Comprehensive Review of Cloud-Based Lithium-Ion Battery Management Systems for Electric Vehicle Applications

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**ABSTRACT** Electric Vehicles (EVs) are crucial in reducing greenhouse gas emissions and combating climate change. However, their adoption is hindered by range anxiety, high costs, and inadequate charging infrastructure. Battery Management Systems (BMS) are essential for EV efficiency, but current systems face limitations such as restricted computational resources and non-updatable software. Cloud computing offers a promising solution by providing enhanced computational power and storage. This paper reviews recent research on cloud-based BMS frameworks and applications, in addition to available industry solutions. The review is coupled with a review of the recent cloud developments, combining both reviews to reach a list of research gaps and suggested future work. The findings emphasize the need for improved online learning applications, connectivity, and security. Future work should focus on integrating recent cloud developments to enhance BMS functionality and reliability.

**INDEX TERMS** Electric vehicles (EVs), battery management systems (BMS), cloud-based architectures, Internet of Things (IoT), remote monitoring, lithium-ion batteries (LIB).

## I. INTRODUCTION

Global warming, primarily driven by the accumulation of greenhouse gases (GHGs) in the atmosphere, poses a significant threat to the environment and human well-being. GHGs like carbon dioxide (CO2) and methane (CH4) trap heat in the Earth's atmosphere, leading to a rise in global temperatures and resulting in various climate changes [1], [2]. The emissions of these gases, largely from human activities such as burning fossil fuels and deforestation, have intensified the greenhouse effect, exacerbating global warming [3]. Electric vehicles (EVs) play a crucial role in mitigating global warming by reducing the emissions of GHGs associated with transportation. Traditional internal combustion engine vehicles are major contributors to CO2 emissions, which are a primary driver of global warming [4]. In contrast, EVs produce significantly fewer emissions or even zero emissions during operation, especially when charged using renewable energy sources [5]. By transitioning to EVs, countries can reduce their carbon footprint and lessen the impact of transportation on global warming [6].

The adoption of EVs is influenced by various factors that impact consumer behavior and market trends. Statistics on the adoption of EVs reveal insights into the drivers and barriers affecting the transition to electric mobility. Studies have shown that incentives, policy support, performance features of EVs, and the presence of public charging infrastructure play significant roles in promoting EV adoption [7], [8], [9]. In countries like Norway and China, where EV adoption rates are relatively high, the availability of incentives and supportive policies has been instrumental in driving consumer interest in electric vehicles [7], [8]. Moreover, social factors, government initiatives, and infrastructure development have been identified as key determinants of EV adoption in different regions. In India, for example, while financial and infrastructure factors positively impact EV adoption rates, concerns related to vehicle performance can hinder the acceptance of electric vehicles [10]. Similarly, in Indonesia,

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factors such as government subsidies, vehicle performance, and charging infrastructure influence consumers' willingness to adopt electric motorcycles [11], [12].

In contrast to the previously discussed factors promoting them, EVs face several challenges that impact their widespread adoption and integration into the transportation sector. One significant issue is range anxiety, which refers to the fear of running out of battery charge before reaching a destination [13]. Range anxiety is a major concern for consumers considering EVs due to the limited driving range of electric vehicles and the insufficient number of charging stations in the transport network [13]. In this regard, there are 3 types of EVs: plug-in EVs which are charged by plugging into an electric power source, swappable batteries EVs which have batteries that can be swapped for a fully charged one at a station, and hydrogen fuel-cell EVs which use hydrogen fuel cells to generate electricity for propulsion [14], [15]. Addressing range anxiety through the expansion of charging infrastructure and advancements in battery technology is crucial to alleviating this barrier to EV adoption. Another challenge facing electric vehicles is the high initial cost compared to traditional internal combustion engine vehicles. The high prices of electric vehicles can deter potential buyers, especially in regions where financial incentives and subsidies for EVs are limited [16]. Additionally, the limited availability of EV models that cater to diverse consumer needs and preferences poses a challenge to the broader adoption of EVs [16]. Ensuring that electric vehicles are affordable and offer a variety of options to suit different consumer requirements is essential for increasing their market penetration. Moreover, concerns related to the environmental impact of electric vehicle production and disposal, particularly regarding the extraction and recycling of lithium-ion batteries, present sustainability challenges [13]. The storage and disposal of batteries, as well as the environmental implications of battery manufacturing processes, need to be addressed to ensure that electric vehicles contribute positively to reducing greenhouse gas emissions and environmental pollution [13]. Furthermore, the lack of a comprehensive charging infrastructure, especially in cold weather climates, poses a significant barrier to electric vehicle adoption [17]. Insufficient public charging stations and the need for fast and convenient charging solutions are critical factors that need to be addressed to encourage more consumers to switch to electric vehicles [17]. Enhancing the availability and accessibility of charging infrastructure is essential for promoting the widespread adoption of EVs and overcoming range anxiety concerns.

Battery Management Systems (BMS) are essential for EVs as they ensure the efficient and safe operation of the vehicle's battery system. A BMS is an electronic system that manages rechargeable batteries by monitoring and controlling their charging and discharging cycles, state of charge (SoC), state of health (SoH), temperature, and voltage levels [18]. They mitigate range anxiety by precise state of charge estimations and real-time range data while optimizing energy use for

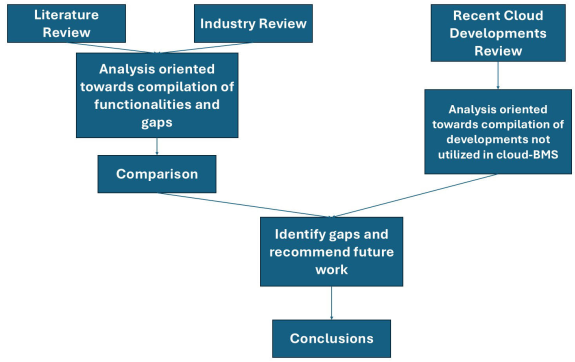


**FIGURE 1.** Flowchart visualizing the research methodology of this study.

extended driving range [19], [20]. BMS safeguards batteries from extreme charging conditions and thermal effects, thus prolonging their life [18], [19]. It also harmonizes energy distribution among cells to boost storage capacity and efficiency [19]. Furthermore, BMS enhances vehicle performance through accurate battery health monitoring, tailored charging methods, and support for rapid charging [18], [19]. Lastly, BMS's thermal management capabilities regulate battery temperature, which is crucial for maintaining battery efficiency and overall vehicle reliability [21].

BMS face challenges like limited computational power, inadequate data storage, reliability concerns, scalability issues, and the need for real-time monitoring. Cloud computing emerges as a solution, offering high computational power, vast data storage, enhanced reliability, scalability, and the ability to perform real-time data analysis [22]. Integrating cloud technologies with BMS can significantly improve their efficiency and reliability, ensuring they meet the growing demands of battery monitoring and management.

This paper aims to review the existing frameworks, proofs-of-concept, and applications in both academic literature and solutions available in the industry, acting as a comprehensive reference for researchers and people in the industry in the domain of cloud-based battery management systems. It also aims to review recent developments in cloud computing. These developments, along with the research gaps identified from reviewing current work, are then used to suggest future streams of research and development in this domain. Fig. 1 shows a flowchart describing the research methodology used in this study. While other review papers exist in the literature, they focus on work in the literature. None of them currently review solutions available in the industry, or analyze the gaps in current work and suggest areas of research based on this analysis in combination with developments in the cloud domain. Table 1 shows a comparison between currently available reviews in the literature and this review. In addition, the paper offers a guideline for those interested in using a cloud-BMS solution that is already available whether in the literature or the industry, showcasing the common functionalities to look for in the solutions they're considering. It can also be used by researchers as a starting point for

**TABLE 1.** A comparison between this review and other reviews in the literature on cloud-based BMS.

| Paper | Year Published | Reviews recent cloud developments | Reviews work in literature | Reviews industry solutions | Suggests research based on literature gaps | Suggests research based on recent cloud developments |
|---|---|---|---|---|---|---|
| This paper | 2024 | ✓ | ✓ | ✓ | ✓ | ✓ |
| [23] | 2024 | | ✓ | | ✓ | |
| [24] | 2023 | | ✓ | | ✓ | |
| [25] | 2023 | | ✓ | | ✓ | |
| [22] | 2022 | | ✓ | | ✓ | |

**TABLE 2.** List of nomenclature mentioned throughout the text.

| Nomenclature | Full Form |
|---|---|
| AEHF | Adaptive Extended H-infinity Filter |
| BESS | Battery Energy Storage System |
| BMS | Battery Management Systems |
| CBMP | Cloud Battery Management Platform |
| CEC | Cloud-End Collaboration |
| CH4 | Methane |
| CNN | Convolutional Neural Network |
| CO2 | Carbon Dioxide |
| CRM | Customer Relationship Management |
| CV | Constant Voltage |
| DCF | Data Confidence Fabric |
| EKF | Extended Kalman Filter |
| EV | Electric Vehicle |
| FaaS | Function as a Service |
| GHG | Greenhouse Gas |
| GRU | Gated Recurrent Unit |
| H-BMS | Hybrid Battery Management Systems |
| HI | Health Indicator |
| HIF-PF | High Integrity Filter-Particle Filter |
| IaaS | Infrastructure as a Service |
| IoT | Internet of Things |
| KBMP | Kubernetes-Orchestrated IoT Online Battery Monitoring Platform |
| LFP | Lithium Iron Phosphate |
| LIB | Lithium-ion Batteries |
| LSTM | Long Short-Term Memory |
| MAE | Mean Absolute Error |
| MLOps | Machine Learning Operations |
| NIST | National Institute of Standards and Technology |
| PHEV | Plug-in Hybrid Electric Vehicle |
| PSO | Particle Swarm Optimization |
| PaaS | Platform as a Service |
| RFR | Random Forest Regressor |
| RMSE | Root Mean Square Error |
| RUL | Remaining Useful Life |
| SaaS | Software as a Service |
| SoC | State of Charge |
| SoH | State of Health |
| SoP | State of Power |
| SoX | State of Everything |
| TR | Thermal runaway |
| TRFS | Three-round Feature Selection |
| UKF | Unscented Kalman Filter |
| VIL | Vehicle-in-the-loop |
| WBMS | Wireless Battery Management System |

prioritizing functionalities and deciding on unique features to experiment with that are not found in other bodies of work.

The rest of this paper is structured as follows: Section II goes into details about BMSs including their functionalities, challenges, and drawbacks. Section III covers background information on cloud computing, its different service models, benefits, challenges, and recent developments. Section IV reviews the work done in the literature regarding cloud-based battery management systems on the cloud. Section V lists the identified gaps in research and recommends areas of research for future work.

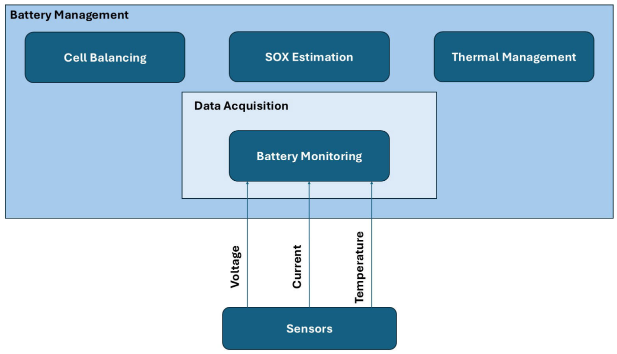


**FIGURE 2.** Functionalities of a BMS.

Table 2 contains a list of nomenclature used throughout the text.

## II. BATTERY MANAGEMENT SYSTEMS

A BMS in EVs is a critical component responsible for monitoring, controlling, and ensuring the optimal performance and safety of the battery pack. The BMS plays a vital role in enhancing battery life, efficiency, and overall vehicle performance.

BMS have evolved significantly over the years to meet the increasing demands of EVs and to ensure the safe and efficient operation of batteries. Several key technologies and advancements have shaped the evolution of BMS in electric vehicles. Fig. 2 visualizes the key functionalities of a BMS. Initially, BMS focused on basic functions such as monitoring battery cells and ensuring safety during charging and discharging [26]. This involves acquiring readings from different sensors, including current and voltage, and ensuring that the battery stays in a safe state during operation.

However, with the growing usage of EVs, there has been a shift towards more advanced technologies in BMS to enhance battery performance and longevity [27]. One notable advancement in BMS evolution is the incorporation of deep learning and machine learning algorithms for battery's SoC and SoH [28], [29], [30]. SoC refers to the current charge level of a battery, typically expressed as a percentage of the total capacity of the battery. On the other hand, SoH represents the overall health and performance capability of the battery, indicating how well the battery can deliver its rated capacity over time. They are joined by the State of Power (SoP) to form the battery states, where estimating all of them is referred to

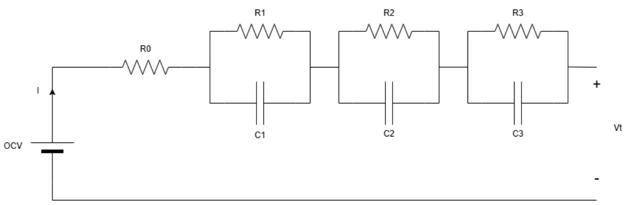


**FIGURE 3. Third-order RC equivalent circuit model for a lithium-ion battery.**

as State of Everything (SoX) estimation. There are different techniques employed for a battery's state estimation. First, there are experimental methods: they involve conducting physical tests and measurements on batteries to gather data for SoC and SoH estimation [31]. These methods may include impedance measurements, voltage and current monitoring, and capacity tests to assess the battery's health and charge level [31]. Incremental Capacity analysis is an example of an experimental method used for SoH estimation which analyzes the capacity changes of batteries under different operating conditions [32]. These methods do not perform well in real conditions [33]. There are also model-based methods: that utilize mathematical models of battery behavior to estimate SoC and SoH [34], [35], [36]. These models may incorporate electrochemical principles, equivalent circuit models, and system dynamics to predict battery performance and health [37], [38], [39]. Equivalent circuit models use simple electrical components, namely resistances, capacitcances, and inductances, to model the battery behavior. One example is the RC equivalent circuit model, where a resistance component is used to represent the battery's internal resistance, while RC (resistance and capacitance connected in parallel) branches are used to model the battery dynamics. A higher-order equivalent circuit model refers to the number of RC branches. Fig. 3 depicts a third-order RC equivalent circuit model. The voltage drop across each RC branch can be calculated using (1), with the terminal voltage of the battery calculated using (2). $V_{OC}$ refers to open-ciruit voltage. $I$ refers to current, $V_{RCn}$ refers to the voltage drop across an RC branch, and $V_t$ refers to the battery's terminal voltage. Finally, there are data-driven methods, which rely on machine learning algorithms and neural networks to analyze historical data and predict SoC and SoH. These methods can identify patterns, trends, and correlations in the data without knowledge of how batteries internally function [40], [41]. Data-driven methods are usually computationally expensive, which hinders their wide adoption in BMS, as they put extra strain on the vehicle's battery [33].

$$\dot{V}_{RCn} = -\frac{1}{R_n C_n} V_{RCn} + \frac{I}{C_n} \tag{1}$$

$$V_t = V_{OC} - I \cdot R_0 - V_{RC1} - V_{RC2} - V_{RC3} \tag{2}$$

Efforts have also been made to develop effective BMS for EVs, considering factors like battery chemistry, power requirements, and thermal management [42]. The integration of passive BMS and thermal management systems has become crucial for extending battery life and ensuring optimal performance in electric vehicles. This feature of BMS has now become more relevant with the increasing need for ultra-fast charging [43]. The performance of the electric vehicle battery is closely related to its operating temperature. The charge of the battery is depleted quickly under low temperatures, while elevated temperatures enhance the electrochemical reactions in the battery, leading to the battery emitting even more temperature, which may result in a thermal runaway and an explosion [44], [45].

Moreover, the introduction of wireless smart BMS has revolutionized battery management in EVs, allowing for efficient monitoring and control of battery cells [46]. This wireless technology enhances the flexibility and accessibility of BMS, contributing to improved overall performance of electric vehicles. Furthermore, the development of hybrid battery management systems (H-BMS) has provided a comprehensive approach to managing different types of batteries in electric vehicles [47]. H-BMS combines various technologies to address the diverse requirements of hybrid energy storage systems in EVs. Battery charging technology is tailored to different battery types such as Li-Ion, Li-SO4, and Ni-MH, selected for their unique performance benefits. Remote Terminal Units play a vital role in remotely monitoring and controlling battery usage, ensuring both optimal performance and safety. The system also includes thermal management to address heat generated during charging and discharging, utilizing models to predict and manage temperature variations. Furthermore, simulation frameworks are employed to optimize battery pack design, enhancing the economic feasibility of EVs by extending battery life and boosting reliability [47]. These combined technologies significantly improve the efficiency, safety, and durability of EV batteries.

While many efforts have been made to advance BMS, they still suffer from drawbacks and challenges that prevent them from reaching their full potential. One such problem is the limited computation resources available. Any extra computation to be done takes a toll on the vehicle's battery. This, in turn, leads to the use of not-so-accurate state estimation techniques just for the sake of saving energy and computation power. This is one of the main reasons that data-driven methods are not widely adopted in BMS despite the higher accuracy they offer compared to other methods. Another problem facing BMS is that they cannot be updated remotely. Batteries' behavior changes with aging, and this requires an occasional tweak to the BMS software to stay accurate. This also prevents BMS manufacturers from offering new features to their clients remotely.

## III. CLOUD

Cloud computing, as defined by the National Institute of Standards and Technology (NIST), is a service model that provides easy, on-demand access to a variety of shared

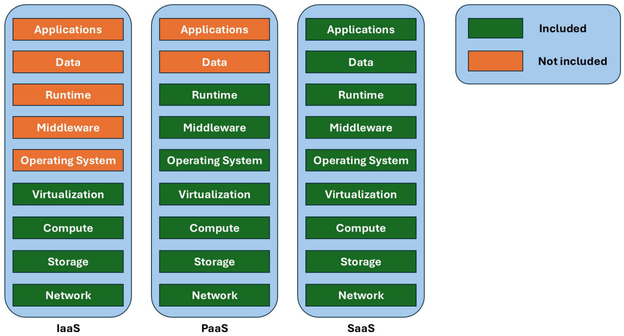


**FIGURE 4.** Services offered by IaaS, PaaS, and SaaS.

computing resources, like networks, servers, storage, and applications [48]. This model is characterized by its ability to offer self-service provisioning of resources as needed, accessibility over a wide range of devices via the network, a multi-tenant environment where resources are shared among multiple users, the flexibility to scale services up or down based on demand, and a pay-per-use system that ensures resource usage is measured and transparent for both the provider and the consumer [48]. These fundamental attributes make cloud computing a dynamic and efficient way to handle computing needs.

Cloud computing offers different service models that cater to various user needs and requirements. The primary cloud service models are Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS) [48], [49], [50], [51], [52]. These models provide distinct levels of abstraction and functionality, allowing users to access computing resources and services based on their specific needs. Fig. 4 visualizes a comparison between the different services offered by IaaS, PaaS, and SaaS. It can also be perceived as the separation between what the service model and the user manages.

1) IaaS: IaaS provides virtualized computing resources over the internet. Users can rent virtual machines, storage, and networking resources on a pay-as-you-go basis. This model offers flexibility and scalability, allowing users to manage and control their infrastructure, including operating systems, applications, and data, while the cloud provider manages the underlying hardware.
2) PaaS: PaaS offers a platform that allows developers to build, deploy, and manage applications without the complexity of infrastructure management. Users can access development tools, databases, middleware, and other resources needed to develop and run applications. PaaS providers manage the underlying infrastructure, allowing developers to focus on application development and deployment.
3) SaaS: SaaS delivers software applications over the internet on a subscription basis. Users can access and use software applications hosted in the cloud without the need for installation or maintenance. SaaS applications cover a wide range of services, including email, collaboration tools, customer relationship management (CRM), and productivity software.

Despite its numerous benefits, cloud computing faces several challenges and drawbacks that impact its adoption and effectiveness. Some of the key challenges and drawbacks facing cloud computing include:

1) Latency: One of the significant challenges in cloud computing is latency, especially for real-time applications. The distance between remote cloud servers and end-users can result in delays in data processing and communication, affecting the performance of time-sensitive applications [53], [54], [55].
2) Security and Privacy Concerns: Security and privacy issues remain a major drawback of cloud computing. Data breaches, unauthorized access, and lack of control over sensitive data stored in the cloud pose significant risks to organizations and users [53], [54], [56].
3) Reliability and Availability: Cloud services are susceptible to outages and downtime, impacting the availability of applications and services. Reliability concerns arise due to the dependence on third-party cloud providers for critical IT infrastructure [53], [54], [55].
4) Cost: While cloud computing offers cost-saving benefits, the overall cost of cloud services can escalate, especially for resource-intensive applications. Organizations may face unexpected expenses related to data storage, data transfer, and additional services [53], [54], [57].
5) Data Transfer Bottlenecks: As applications become more data-intensive, data transfer bottlenecks can occur, complicating data placement and transport within cloud environments. This can lead to increased costs and inefficiencies in data management [58].
6) Dependency on Internet Connectivity: Cloud computing heavily relies on Internet connectivity for data access and communication. Any disruptions in internet connectivity can impact the availability and performance of cloud services [54], [55].
7) Lack of Location Awareness: Cloud computing may lack location awareness, leading to challenges in data placement, resource allocation, and ensuring compliance with data sovereignty regulations [58], [59].
8) Limited Mobility Support: Cloud computing may face limitations in supporting mobile and Internet of Things (IoT) devices that require seamless mobility and connectivity. Lack of mobility support can hinder the effectiveness of cloud-based applications [54], [59].
9) Ethical and Legal Concerns: Cloud computing raises ethical and legal challenges related to data ownership, data privacy, compliance with regulations, and the ethical use of data stored in the cloud [54].

With the wide appeal of cloud computing in different industries and use cases, intensive research has been driving further advancements to address the aforementioned issues and drawbacks. Some relevant advancements are as follows:

1) Edge Computing: Edge computing has emerged as a significant trend in cloud computing, enabling data processing closer to the source of data generation. This approach reduces latency, enhances real-time processing capabilities, and improves overall system efficiency [60].
2) Fog Computing: Fog computing has gained traction as a complementary approach to cloud computing, focusing on dispersing computing resources throughout the network's edge. This model addresses the limitations of traditional cloud computing by bringing computing resources closer to the data source, enabling faster data processing and analysis [60].
3) Hybrid Cloud Solutions: Organizations are increasingly adopting hybrid cloud solutions, which combine public and private cloud services. This approach offers greater flexibility, scalability, and data security, allowing organizations to leverage the benefits of both cloud deployment models [60].
4) Serverless Computing: Serverless computing, also known as Function as a Service (FaaS), has gained popularity for its ability to execute code in response to events without the need to manage servers. This model offers cost-efficiency, scalability, and simplified application development and deployment [61].
5) Green Computing: With a growing focus on environmental sustainability, green computing practices have become a key consideration in cloud computing. Efforts to reduce energy consumption, optimize resource utilization, and minimize carbon emissions are driving advancements in eco-friendly cloud solutions [62].
6) Blockchain Integration: The integration of blockchain technology with cloud computing has introduced new possibilities for enhancing data security, transparency, and trust in cloud-based systems. Blockchain-based solutions are being explored to address data integrity and security challenges in cloud environments [63].
7) Data Security Enhancements: Advancements in cloud computing have led to improved data security measures, including enhanced encryption techniques, secure data storage solutions, and robust access control mechanisms. These developments aim to address data privacy concerns and ensure the confidentiality of sensitive information [64], [65].
8) IoT Integration: Cloud computing has played a crucial role in supporting the IoT ecosystem by providing scalable infrastructure, real-time data processing capabilities, and seamless connectivity for IoT devices. Cloud platforms are evolving to meet the demands of IoT applications and enable efficient data management and analysis [66], [67].
9) Multicloud Computing: Multicloud Computing strategies involve utilizing multiple cloud services from various providers to fulfill specific business needs, offering benefits like redundancy, performance optimization, cost savings, and enhanced security. This approach ensures operational continuity, allows for performance tuning based on workload requirements, enables cost-effective resource utilization, and provides robust security measures. Additionally, multicloud offers scalability and flexibility, allowing businesses to adjust resources according to demand and adapt to evolving needs without being tied to a single provider's limitations [68], [69], [70], [71].

When the IoT is augmented with cloud computing, it leads to a synergy that significantly boosts the performance and functionality of IoT networks. The merger of these technologies brings forth critical improvements such as the ability to scale systems more effectively, superior processing power for handling vast amounts of data, greater storage capabilities, the provision of analytics in real-time, a reduction in operational costs, and the strengthening of security protocols [72], [73], [74], [75], [76], [77]. One significant benefit is the scalability that cloud computing provides to IoT systems. Cloud resources can easily scale up or down based on the demand of IoT applications, ensuring optimal performance and resource utilization [75]. Additionally, cloud computing offers high computational power that is essential for processing the vast amounts of data generated by IoT devices, enabling efficient data analysis and insights [73], [76]. Moreover, cloud computing enhances storage capacity for IoT systems, allowing for the seamless storage of large volumes of data generated by IoT devices [74]. Real-time analytics is another advantage, as cloud platforms can process data quickly and provide instant insights, enabling timely decision-making in IoT applications [77]. The cost-effectiveness of cloud computing benefits IoT deployments by reducing infrastructure costs and operational expenses [72].

In conclusion, while the service models of cloud computing offer unparalleled scalability and flexibility, they are not without drawbacks, such as concerns over security, privacy, and data management. However, recent developments in the field have begun to address these challenges, paving the way for a more robust and secure cloud infrastructure. As we continue to innovate and refine cloud technologies, we can see cloud computing being utilized in many industries, electric vehicles being no exception.

## IV. CLOUD-BASED BATTERY MANAGEMENT SYSTEMS

To address the previously listed limitations of BMSs, cloud computing can be leveraged to enhance performance and reliability. By utilizing the vast computational resources and storage capabilities of the cloud, data from multiple BMS can be aggregated and analyzed in real-time. More demanding estimation techniques can also be offloaded from onboard the car to a cloud server. This allows for advanced algorithms to predict battery life, optimize charging cycles, and prevent failures through predictive maintenance. Moreover, cloud-based platforms can facilitate remote firmware updates, ensuring that BMS are always equipped with the latest software enhancements. The scalability of cloud services also means that as the number of batteries increases, the system can easily expand to meet the growing demand without the need for significant hardware investments. Thus, cloud computing not only overcomes the inherent limitations of standalone BMS but also adds a layer of intelligence that can lead to more sustainable and efficient battery usage. Fig. 5 showcases a general architecture for cloud-BMS. Each vehicle has on-board sensors for current, voltage, and temperature. On the cloud side, each of the vehicles has a corresponding instance of the BMS with its functionalities operating over its data. The readings from each vehicle join readings collected from multiple other vehicles, over the lifetime of the system. The data from multiple vehicles can be analyzed and managed together to reach what is called fleet management. The previously discussed features of a BMS are now offloaded on the cloud side. This offloading allows access and control of this data through remote machines.

Regarding proposed frameworks in literature for cloud-based BMS, [78] presents the CHAIN framework, a cyber hierarchy and interactional network designed to optimize battery performance across its full lifespan. As shown in Fig. 6, it introduces a multi-scale, multi-condition control system that leverages cloud-based data management and artificial intelligence to enhance the security and stability of battery systems, particularly for electric vehicles. Through its multi-scale design, CHAIN enables the integration of data from different scales, from molecular to system level. The incorporation of this multi-scale modeling enhances battery characterization by modeling electrochemical kinetics. Multi-condition control refers to managing the battery under various conditions, not just while the vehicle is driving. These conditions include charging, driving, and parking. The CHAIN framework faces five key challenges: Multi-physical Modeling, which requires detailed models to understand electrochemical reactions; Perception and Data Space, which needs high-precision sensors and tools for nondestructive evaluation; Network and Communication, demanding efficient networks with low latency; Hash Rate and Computing, which calls for high computing power for big data and model processing; and Safety and Security, to protect against cyber threats in network-connected vehicles. Addressing these challenges is crucial for the practical application of CHAIN in managing battery systems and ensuring their safety and efficiency.

Capitalizing on the work done in [78] and [79] presents a cloud-based BMS utilizing the CHAIN framework. It introduces a layered "cloud to things" architecture comprising end sensing, edge computing, cloud computing, and a knowledge repository. This structure enables complex detection, prediction, and optimization functions for battery management across multiple scales, from individual cells to entire transportation systems. The CHAIN framework is leveraged to provide multi-scale data visualization and hierarchical functional display, enhancing the BMS's capabilities in state estimation, thermal management, cell balancing, and fault diagnosis. The paper contributes to the CHAIN framework by proposing a multi-scale integrated modeling strategy for batteries and remote upgrading capability of the controller, aiming to improve the precision and adaptability of battery management systems.

Staying within the same territory of work under the CHAIN framework, a method for estimating the SOH of LIBs is presented in [80]. This method utilizes an end-cloud collaboration approach, which merges a cloud-based deep learning model and an end-based empirical model, thereby achieving high accuracy and real-time performance in SOH estimation. The cloud-side model, which is based on the Transformer architecture, performs feature extraction and estimation, having Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) of approximately 0.8%. The collaboration between the cloud and the end is facilitated through the application of the Kalman Filter and Unscented Kalman Filter (UKF), which are used to integrate and iteratively update the models. Despite the significant contributions of this research, the work in this paper can be affected by connectivity issues when the cloud and end models cannot communicate.

A similar approach under CHAIN was introduced for SOC estimation in [81]. The proposed method involves end-cloud collaboration, combining a high-accuracy deep learning model on the cloud side based on Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks with a fast estimation model on the end side, and utilizing an Extended Kalman Filter (EKF) to fuse results from both ends. The method demonstrates high accuracy, real-time performance, and robustness under various dynamic driving conditions and temperatures, achieving a RMSE and MAE of approximately 1.5% and 1%, respectively. However, the paper identifies gaps in the generalizability of SOC estimation under different operating conditions, particularly for different aging states of batteries. Future work should focus on enhancing the model's adaptability to diverse conditions and further optimizing computational efficiency to ensure real-time performance in practical applications.

Implementations and proof-of-concepts for different cloud-based BMS have been introduced in literature, with some of them proposing solutions to different problems such as data complexity, network bandwidth consumption, visualization, monitoring, and operational cost efficiency.

Reference [82] introduces an algorithm for joint estimation of SoC using High Integrity Filter-Particle Filter (HIF-PF), validated under Beijing Bus Dynamic Stress Test (BBDST) conditions. The system demonstrates monitoring capabilities for battery voltage, temperature, and current, alongside real-time SoC estimation utilizing tools like Texas Instruments' BQ76PL455EVM board, ACS712-ELC-30A Hall current sensor, and software such as 3dsMax and Unity3D. The proposed system features communication in a single direction, physical system to the digital twin system. Communication in the opposite direction can offer updating of the model parameters on the physical side.

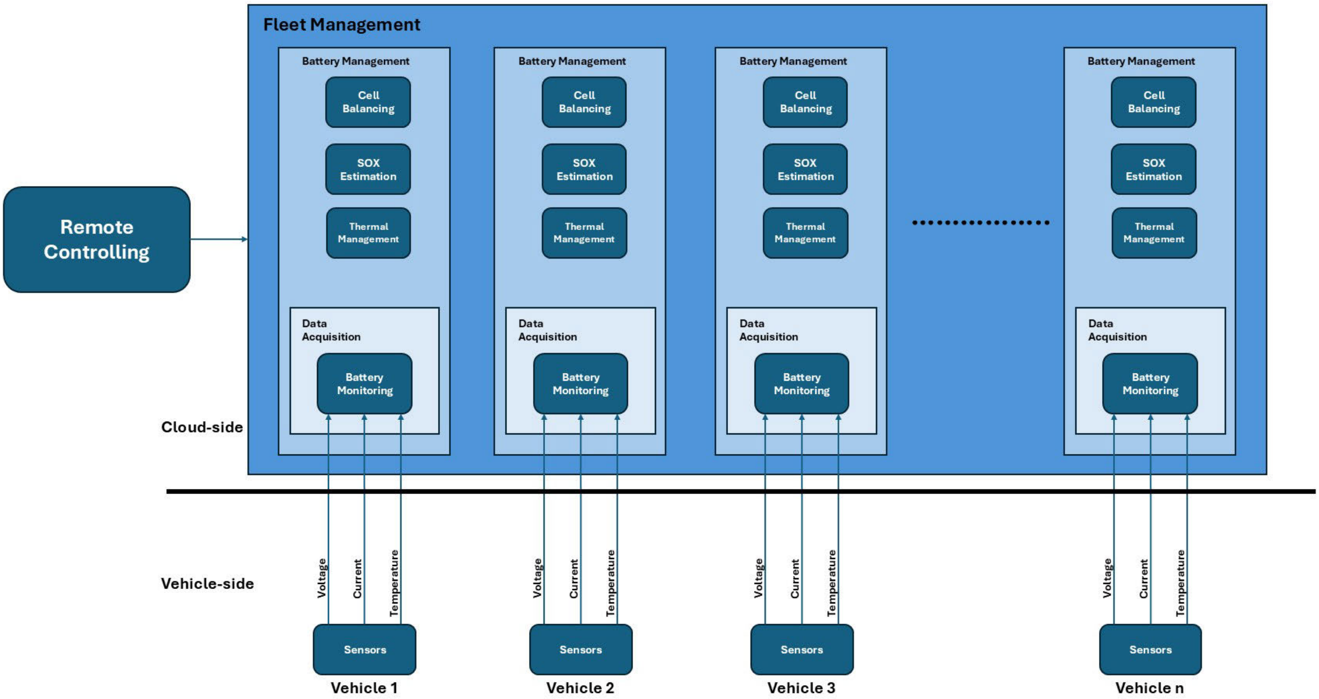


**FIGURE 5.** General Cloud-BMS architecture.

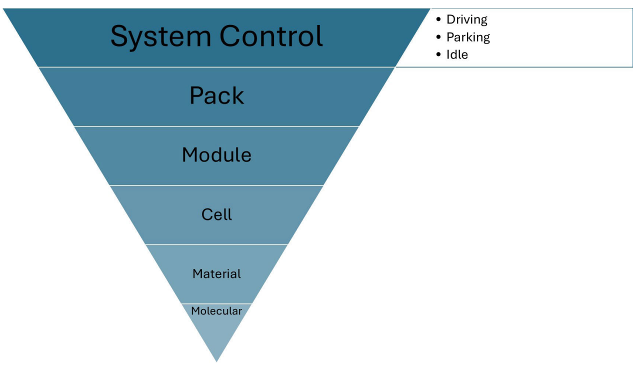


**FIGURE 6.** CHAIN framework involves data at multi-scales and multiple vehicle conditions.

Reference [83] introduces algorithms for SoC and SoH estimation using Adaptive Extended H-infinity Filter (AEHF) and Particle Swarm Optimization (PSO), respectively. The system was validated with prototypes and tested with lithium-ion and lead-acid batteries, demonstrating monitoring capabilities and diagnostics. Future work on machine learning algorithms is needed for predictive analytics and system optimization to further refine the digital twin's capabilities and extend battery life.

Reference [84] proposes a four-layer networked structure that integrates cloud computing and edge computing technologies to enhance BMS performance. The architecture includes an Edge Computing Layer for real-time data processing, a Data Access Layer for secure data transmission, a Data Storage and Analysis Layer for storing and analyzing battery operation data, and a Data-Based Application Layer for lifecycle management applications. This structure aims to improve decision-making and optimization in battery management by facilitating service integration across infrastructure, data, platform, and software domains. An equivalent circuit model is used for the battery's state estimation, which the paper states offers much faster calibration compared to more complicated models.

Reference [85] introduces a three-round feature selection (TRFS) approach to reduce data complexity and measurement noise impact, employing a Random Forest Regressor (RFR) for accurate SoH estimation. Experiments with different Lithium-ion batteries demonstrate the method's universality and robustness, achieving satisfactory SoH estimation with reduced data traffic and computation power. The paper has potential limitations in considering battery imbalance and temperature effects.

Reference [86] presents a proof of concept for the development of an IoT-based Wireless Battery Management System (WBMS) for monitoring the SoC of lead-acid batteries in electric vehicles, specifically three-wheeled vehicles known as 'TOTO' in rural Bengal. The system utilizes a real-time monitoring system to prevent battery depreciation by avoiding deep discharge cycles. Experiments showed that the WBMS could accurately predict the remaining travel distance and battery health, leading to improved battery utilization and longevity.

Reference [87] addresses the challenge of optimizing energy management in plug-in hybrid electric vehicles (PHEVs) by balancing fuel economy and battery health. It proposes a two-layered architecture: a cloud-based top layer for global optimization using machine learning and stochastic dynamic programming, and an onboard bottom layer with a fuzzy controller for real-time adjustments. The vehicle-in-the-loop (VIL) simulation integrates real hardware, like engines and batteries, with software simulations to test the energy management strategy in real-world conditions. The results show a 6.8% improvement in overall cost compared to a rule-based system. Future work includes integrating an online digital map for enhanced route prediction and energy management.

Reference [88] presents a digital twin architecture for real-time monitoring of EV batteries, focusing on SoC and SoH estimation. The authors propose a model that combines historical data and periodic retraining to reflect battery aging. The proposed architecture deploys the SoC estimation model onboard the vehicle since it needs to be real-time, while it offloads the SoH estimation to the cloud. It utilizes machine learning techniques like Random Forest, Light Gradient Boosting, and a Deep Neural Network. Possible future work is to optimize machine learning models and explore the digital twin infrastructure, including edge and cloud collaborative frameworks.

Reference [89] proposes a cloud-based method for estimating the SoH of lithium-ion batteries using sparse charging data. The authors propose a Health Indicator (HI) feature derived from sparse data and validate its correlation with battery health through experiments with NASA's 18650 lithium-ion batteries. Results show that the method achieves low test errors under 10s sparsity, but accuracy decreases with sparser data. There are limitations in this approach when data sparsity exceeds 30s and suggested future work is to optimize constant voltage (CV) interval selection and validate the method with real-world cloud data from more vehicles.

Reference [90] introduces a real-time monitoring system for multiple lead-acid batteries, integrating IoT technologies to enhance efficiency in industrial settings. The system's original contributions include a dedicated data acquisition system, the use of WLAN for the backbone network, and a novel two-electrode-based electrolyte level sensor. It also features a C# server program for data analysis, an Android application for mobile monitoring, and SQL database integration for data storage.

Reference [91] presents a cloud-based battery condition monitoring and fault diagnosis platform for large-scale lithium-ion battery energy storage systems (BESSs). The platform utilizes IoT-enabled wireless module management systems and a cloud battery management platform (CBMP) and aims to reduce overall system and maintenance costs while improving operational performance and safety for large-scale battery systems. Experiments using a cyber-physical testbed and computational cost analysis validated the platform's effectiveness. Results showed accurate estimation of individual battery cell conditions and effective fault detection. Future work includes designing wireless IoT network hardware, improving the CBMP with additional algorithms, and evaluating the impact of network latency on BMS.

Reference [92] proposes a Cloud-End Collaboration Battery Management System (CEC-BMS) designed for large-scale lithium-ion battery systems, crucial for energy storage and electric vehicles. The proposed CEC-BMS framework leverages cloud computing and machine learning, specifically a gated recurrent unit (GRU) neural network and transfer learning, to estimate SoC with high accuracy and flexibility. Experiments validated the method's precision, with a maximum estimation error of less than 1.5% for one battery type and 2% for another. Future work will focus on expanding functionalities like life prediction and fault diagnosis within the CEC-BMS framework.

Reference [93] presents a Decentralized Intelligent BMS designed for smart battery management using cloud computing, which improves the precision of key parameters like SOC and SOH, enhancing the safety and lifespan of battery-based energy storage systems. The contributions include a distributed BMS design for increased security and a Petri Nets-based modeling procedure for clear operational conditions. Future work involves refining measurements, particularly SOH, for accurate predictive diagnostics and battery remaining useful life (RUL) calculation.

Reference [94] presents the Kubernetes-Orchestrated IoT Online Battery Monitoring Platform (KBMP), which integrates Kubernetes and cloud-edge technology to enhance battery management. The platform ensures low-latency data transmission and analysis, utilizing a K-Means clustering algorithm for accurate thermal runaway (TR) warnings. Experimental results demonstrate that KBMP can provide TR warnings 30 minutes in advance, reduce data transmission latency by up to 20%, and decrease replica scaling latency by 50% compared to non-Kubernetes-integrated platforms. The main contributions include the development of a comprehensive battery monitoring system with high scalability, precise anomaly diagnosis, and efficient data visualization. Future work should focus on integrating predictive models for real-time battery state monitoring and enhancing thermal runaway warning accuracy. Additionally, the data scheduling mechanism of KBMP will be optimized for prioritizing batteries at risk, ensuring robust safety.

By analyzing the work done in the papers mentioned above, the main features of a cloud-based BMS have been identified as follows:

1) Monitoring & Diagnostics: the BMS stores collected data on the cloud, allowing access and further analytics to be performed on it.
2) Online Learning: the BMS models can learn from collected data.
3) Visualization: the BMS platform allows data visualization.

**TABLE 3.** Summary of work done by cloud BMS papers mentioned.

| Paper | Battery states estimated | | | Estimation algorithms used | Features | | | |
|---|---|---|---|---|---|---|---|---|
| | SoC | SoH | SoP | | Monitoring & Diagnostics | Online Learning | Visualization | Other |
| [80] | | ✓ | | Transformer + UKF | | | | Feature extraction |
| [81] | ✓ | | | CNN-LSTM + EKF | | | | |
| [82] | ✓ | | | HIF-PF | ✓ | ✓ | ✓ | Bi-directional communication |
| [83] | ✓ | ✓ | | AEHF, PSO | ✓ | | | |
| [84] | ✓ | ✓ | ✓ | PF | ✓ | ✓ | ✓ | |
| [85] | | ✓ | | RFR | | | | Noise reduction with TRFS |
| [86] | ✓ | | | 4th order polynomial fitting | ✓ | | ✓ | |
| [87] | | ✓ | | - | | | | Global optimization |
| [88] | ✓ | ✓ | | Random Forest, Light Gradient Boosting, Deep Neural Network | | | | |
| [89] | | ✓ | | Linear Regression, Support Vector Machine, Gaussian Process Regression | | | | Health indicator extraction, Sparse data (bandwidth efficiency) |
| [90] | ✓ | | | - | ✓ | | | |
| [91] | ✓ | ✓ | | HF | ✓ | | ✓ | Scalable |
| [92] | ✓ | | | GRU + Transfer Learning | ✓ | | | |
| [93] | ✓ | | | Petri Nets (for defining operational conditions) | ✓ | | | Decentralized synchronized management |
| [94] | | | | K-Means | ✓ | | ✓ | TR detection, Scalable |

Some BMS offer unique features. A summary of each cloud-based BMS mentioned with the features it provides is featured in Table 3. Rows without any asterisk in the "Features" column are cloud-end collaborative algorithms for estimating, rather than a cloud-based BMS platform.

In addition to the work introduced in the literature, multiple cloud-BMS solutions are offered in the industry market. Table 4 lists the features of different cloud BMS solutions available. Bosch's cloud BMS's aging prediction utilizes usage data from connected vehicles to forecast battery conditions up to eight years ahead, combining physical models with AI for high accuracy. Lifetime optimization is achieved through standard, health, and fast charging modes, calculated to extend battery life or expedite charging times. The usage certificate provides a secure, transparent record of battery information, enabling accurate valuation based on certified KPIs, thus facilitating market transactions. Additionally, the 'Usage certificate to go' service assesses the health of batteries in existing vehicles through cloud-uploaded data, ensuring a comprehensive evaluation of battery health [95]. The Elysia Cloud Platform provides detailed health and life insights, enabling users to make informed decisions to improve battery longevity. Its life forecasting feature captures non-linear degradation and predicts various states of health with precision. Elysia also monitors fleet-wide degradation trends, pinpointing batteries that may not meet life targets and offering tailored recommendations for each vehicle. The defect detection capability ensures early identification of potential issues at the cell and pack level, prioritizing safety and reliability. For OEMs, the platform identifies trends in battery production quality, fostering proactive collaboration with cell suppliers. Additionally, its simulation toolkit allows for the assessment of usage impact on battery life and performance, which is crucial for product development and cost management. The platform's embedded BMS algorithms provide health-adaptive BMS parameters by supporting updates over-the-air, optimizing performance while addressing warranty concerns. The platform can also integrate with Simulink models [96].

The TWAICE Battery Analytics Platform integrates deep battery knowledge, artificial intelligence, and real-life battery data to provide a single source of truth for effective battery development and operation. The platform features hybrid modeling, combining physical modeling with big data analytics for lifecycle accuracy and resilience. It ensures data security and compliance with industry standards like TISAX and offers real-time data integration services compatible with various systems such as BMS, EMS, and SCADA. Additionally, the platform provides instant battery development tools, SoH monitoring, and high-performance data processing engines for accurate battery insights. This solution is designed to enhance the transparency, efficiency, and reliability of battery systems, ultimately contributing to the sustainability of future energy and mobility markets [97]. Zitara offers a cloud and embedded battery management software called Zitara Live. It works with pack hardware across battery chemistries, including Lithium Iron Phosphate (LFP), and delivers customized, validated SoC, SoH, and safety outputs. Zitara Live continuously monitors the state of every battery in your fleet, updating critical performance parameters as they change over time. It also uses precise onboard simulations to predict energy, power, and heat generation into the future [98].

Eatron Technologies has developed a BMS known as BMSTAR. This system is built on a platform that is independent of hardware and is based on physical models.

It functions efficiently at the edge and is paired with a cloud counterpart for continuous, adaptive enhancements through over-the-air updates. The BMS solution from Eatron uses AI algorithms and cloud technology for precise estimation of the RUL of the battery, thereby reducing battery degradation. Additionally, it includes safety features powered by AI for detecting cell anomalies and early signs of thermal runaway events [99]. Newten has designed a BMS that creates digital replicas of physical systems, integrated into real-time firmware. The BMS from Newten uses Battery Models for estimating crucial battery states, which assist in preserving the life of the battery. They utilize cloud-based solutions for accurate estimations of the battery's RUL, thereby reducing battery degradation. Newten also underscores the importance of cloud BMS in enhancing battery lifetime, charging, and safety [100].

Bacancy's Cloud BMS Solution is designed for real-time visualization and monitoring of large-scale battery systems in EVs. The solution, named IONDASH, integrates IoT and cloud computing technologies to offer a comprehensive BMS. It features remote data logging, real-time parameter tracking, and GPS navigation for precise location tracking. IONDASH provides an interactive user interface for monitoring multiple BMS devices, allowing users to view critical battery parameters such as SoC, SoH, cell temperature, and voltage levels. Additionally, the platform includes in-built fuse circuit protection to safeguard against voltage and current spikes, ensuring the safety and reliability of the lithium-ion battery pack. Bacancy's product range caters to various EV market requirements, offering BMS solutions for 16-cell, 22-cell, and high voltage systems, emphasizing customization as per specific cell requirements [101].

The EVE-Ai Fleet Analytics platform, developed by Electra, offers a BMS solution designed for EV fleets. It integrates seamlessly, providing real-time battery data analysis and insights for any fleet size. The system generates accurate SoH trends and predictive models, identifies potential battery faults and failures, and enhances overall fleet efficiency and performance. Additionally, it offers insights into charging patterns and driver behavior, enabling cost reduction and improved return on assets. The EVE-Ai 360 Adaptive Controls further optimize fleet management by resolving issues identified by the analytics, facilitated by cloud connectivity and over-the-air updates. This solution is pivotal for businesses aiming to monitor and predict electric fleet battery health effectively [102].

## V. ANALYSIS AND FUTURE WORK RECOMMENDATIONS

While Section IV listed significant efforts being made to leverage the power of cloud computing to address the drawbacks of BMS listed in Section II, there are still some areas that need further research and investigation:

1) Online learning: Online machine learning refers to a family of machine learning methods where a learner attempts to tackle predictive or decision-making tasks by learning from a sequence of data instances one by one at each time [103]. This approach has received attention for a wide range of applications, such as vehicle-to-grid services, fault diagnosis of EVs, and sentiment analysis in social media [104], [105], [106]. EVs generate a huge amount of data every day. Harnessing the power of connectivity and cloud computing allows for the collection of this data and using it to continuously train and improve existing models for functionalities like battery state estimation. While a few papers of those mentioned in Section IV address this feature, there is still a need for proof-of-concept using real vehicle data. This investigation could also encompass a comparison between using cloud provider tools and open-source alternatives such as River (online machine learning library for Python) [107] and Beaver (machine learning operations (MLOps) framework for online machine learning) [108] by The Fellowship of Online Machine Learning.
2) Internet connectivity: Offloading certain BMS functionalities to the cloud will add the requirement that the vehicle is continuously connected to the internet. This is unfortunately not the case since many remote areas do not have internet access. A possible solution to this problem that needs to be investigated would be to have simpler and less accurate models onboard the vehicle that can run and provide the required functionalities until the vehicle can connect again to the cloud and get more accurate results using the more complicated models.
3) Large-scale fleet management: Fleet management involves using big data collected from many vehicles for objectives such as monitoring the fleet's performance and making maintenance decisions. In Section IV, [91] used this kind of approach for managing maintenance costs. Fleet management could be taken further in use cases such as planning vehicles' availability for ride-hailing applications based on real-time demand, energy and fuel efficiency, waste management, controlling and diverting traffic in cities to less crowded routes, and predicting drivers' behaviors for safety.
4) Security: EVs connected to the cloud are susceptible to security threats at different levels. It could range from as simple as snooping on the data transmitted between the vehicle and the cloud, to more dangerous threats such as sending commands to the vehicle that can manipulate its control or sending false data to the cloud that can affect the algorithms that are making decisions. Data transfer can be secured by leveraging blockchain technologies. Their properties such as traceability, decentralization, and encryption allow for safe transmission of data. A notable e concept for security on the edge is Data Confidence Fabrics (DCF). DCFs are virtual overlays that enhance data security and trustworthiness. They combine various trust technologies, such as hardware-based integrity

**TABLE 4.** Detailed comparison of industrial cloud BMS solutions.

| Solution | Health Monitoring | Life Forecasting | Real-Time Data | Safety Features | Unique Features |
|---|---|---|---|---|---|
| Bosch's Cloud BMS [95] | ✓ | ✓ | ✓ | | 'Usage certificate to go' service |
| Elysia Cloud Platform [96] | ✓ | ✓ | | | Simulation toolkit, integration with Simulink models |
| TWAICE Battery Analytics Platform [97] | ✓ | | ✓ | | Hybrid modeling, data security and compliance |
| Zitara Live [98] | ✓ | ✓ | | | Works with various battery chemistries |
| BMSTAR by Eatron Technologies [99] | ✓ | ✓ | | ✓ | Hardware-independent platform |
| Newten's BMS [100] | ✓ | ✓ | | | Digital replicas of physical systems |
| IONDASH by Bacancy [101] | ✓ | | ✓ | ✓ | GPS navigation |
| EVE-Ai Fleet Analytics by Electra [102] | ✓ | ✓ | ✓ | | EVE-Ai 360 Adaptive Controls |

checks and blockchain, to measure data confidence. DCFs generate scores, normalize across systems, and enable risk-based decision-making, bridging security, privacy, and trust in interconnected ecosystems [109].

5) Recent cloud computing advancements: Research can be directed to investigating how recent developments in the cloud computing field can be leveraged for EVs. Edge and Fog computing can be used for distributing computation and decreasing latency by moving computation closer to vehicles. Reference [110] proposes a framework for provisioning resources according to vehicles' locations to reduce latency and cost. Serverless Computing can be used in cases like issuing safety alerts to drivers and sending control commands to vehicles on certain triggers. Multicloud computing can be used for redundancy and a better geographic distribution of computation. Research could be done to study the practical feasibility of using these technologies.

## VI. CONCLUSION

EVs play a critical role in mitigating global warming by reducing greenhouse gas emissions. However, the adoption of EVs is hindered by challenges such as range anxiety, high initial costs, and charging infrastructure. BMSs are essential for the efficient operation of EVs, and having a more accurate and reliable BMS directly addresses issues facing the adoption of EVs. BMS are continuously advancing due to intense research efforts, but they still suffer from drawbacks such as limited computation available onboard the vehicle and the lack of updatability of software components. They can also make use of big data generated by the many vehicles moving daily. Advancements in cloud computing offer promising solutions to BMS challenges. Research and proofs-of-concept were reviewed in this paper, showing efforts in creating frameworks for battery management systems on the cloud and in designing and implementing systems with different capabilities. Common features and functionalities were analyzed and extracted from work in the literature, comprising monitoring, diagnostics, online learning, visualization, and features unique to each body of work. Cloud-BMS solutions available as industry solutions have also been compared based on the unique features they offer. Possible future work was recommended, including a focus on online learning since it was lacking in many of the works reviewed, addressing connectivity and security issues that are hindering further adoption of cloud-BMS, shifting some focus towards fleet management applications, and exploring the potential of emerging technologies like edge and fog computing.

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