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IoB

Internet-of-batteries for electric Vehicles–Architectures, opportunities, and challenges

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Review article

IoB: Internet-of-batteries for electric Vehicles–Architectures, opportunities, and challenges

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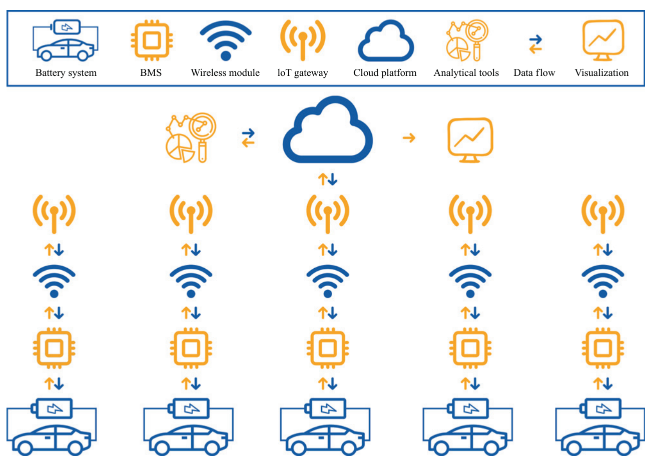
HIGHLIGHTS

- A thorough review on Internet-of-Batteries technologies is presented, analyzing the advancements, gaps, and meaning.
- Cloud-based BMS, wireless systems, IoT applications, and artificial intelligence are analyzed comprehensively.
- IoB implementation challenges and potential advantages for more efficient and safe EVs are discussed.
- Future research are prospected for advanced battery diagnostics and prognosis within the IoB framework.

GRAPHICAL ABSTRACT



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ABSTRACT

The concept of the Internet-of-Batteries (IoB) has recently emerged and offers great potential for the control and optimization of battery utilization in electric vehicles (EV). This concept, which combines aspects of the Internet-of-Things (IoT) with the latest advancements in battery technology and cloud computing, can provide a wealth of new information about battery health and performance. This information can be used to improve battery management in a number of ways, including continuous battery prognosis and improved battery and vehicle management. In this paper, we reviewed in detail the basic structure of IoB, based on many existing studies. We also explored the potential benefits of this new approach, such as continuous battery prognosis and improved battery and vehicle management. Implementing the IoB in EVs is not without challenges, as the IoB faces a number of challenges, including the security of battery data, cross-platform functionality, and the technical complexities of applying IoB on a large scale. However, the potential benefits of the IoB are significant and with continued research and development, it has the ability to revolutionize the EV industry. The purpose of this review paper is

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to provide a comprehensive overview of the IoB, discussing its potential benefits and challenges. The paper also provides a roadmap for the future development of IoB, highlighting the key areas that need to be addressed to fully realize the potential of this technology.

1. Introduction

Electric vehicles (EVs) have surged in popularity in recent years, attracting attention as an environmentally friendly mode of transportation. These innovative vehicles promise to significantly reduce emissions and lower the environmental impact compared to their traditional counterparts powered by internal combustion engines. However, the large-scale adoption of EVs has encountered many problems, primarily due to the limitations of current battery technology [1].

The present battery technology employed in EVs faces several critical challenges. Firstly, the limited operation range of EVs remains a major concern for potential users, as it affects their ability to travel long distances without the need for frequent recharging [2]. Additionally, long charging times are inconvenient for users and can hinder the widespread adoption of EVs. Alongside these limitations, the possibility of battery faults such as thermal runaway, can lead to safety risks including fires or explosions [3]. These factors, including technical concerns about battery health and safety, the need for frequent recharging, and long charging times, could discourage potential users from adopting EVs [4]. Furthermore, EV batteries experience degradation over time, resulting in decreased performance and battery lifespan reduction [5]. It leads to an increase in maintenance and accident risk for EV owners.

The Internet-of-Batteries (IoB), which emerges as a promising solution to these issues, is a networked system that utilizes the principles of the Internet-of-Things (IoT) to gather data from EV batteries. This data is subsequently transmitted to a cloud server, where it is utilized for battery state estimation, predictive analytics, and fault diagnosis [6]. In contrast to traditional battery management systems (BMS), IoB leverages advanced technologies like IoT, cloud computing, and machine learning to provide intelligent battery management. This pioneering approach consisted of three main components: batteries, IoT technologies, and cloud servers. The batteries, being the primary power source for EVs, are integral to the IoB framework [7]. The integration of IoT technologies enables continuous monitoring and management of battery performance within this system. The cloud server provides a strong computing capacity to support more intelligent applications.

The integration of the IoB in EVs offers many benefits and potential for the EV industry. Continuous battery health monitoring is among its key advantages. This allows for the early detection of degradation patterns and potential battery failures [8,9]. This proactive approach enhances safety, extends the battery lifespan, and improves overall vehicle reliability. Furthermore, the IoB optimizes energy management by ensuring efficient power allocation and utilization, thereby extending vehicle operation range and improving charging efficiency [10]. The IoB also supports advanced state estimation and fault diagnosis, which are essential for designing optimized control strategies and enhancing EV performance. Especially, battery information can be shared across multiple levels - national, regional, and even local ones, such as those maintained by the manufacturers, providing the overall lifespan profile of batteries [11]. This large-scale information sharing highlights the potential of IoB to regularize data access and improve the efficiency and reliability of EVs.

Despite the potential benefits offered by the IoB, the implementation of this concept into EVs presents a unique set of challenges. One of the primary concerns is the issue of data security, considering that the IoB involves the exchange of sensitive battery information [12]. To protect against unauthorized access or manipulation of this data, the implementation of robust encryption methods and secure communication protocols become important [13]. Furthermore, ensuring compatibility across the different systems and communication protocols employed by various battery and vehicle manufacturers emerges as another challenge [14]. To facilitate seamless integration and interoperability among IoB-enabled EVs, coordinated efforts towards standardization are crucial.

The topic of BMS has attracted the attention of researchers in recent years, with many surveys and reviews conducted to investigate different aspects of BMS, particularly in the context of cloud-based and IoT-based technologies. Samanta et al. [15] provided a thorough review of wireless battery management systems (WBMS), highlighting their potential benefits over traditional wired systems in scalability and reduced wiring complexity. Despite the promise, it was noted that the technology is in its early stages with significant research needed for industrial readiness. The authors identify several challenges, such as high implementation cost, management of wireless communication among nodes, and potential interference from other wireless networks, underscoring the need for future research to overcome these obstacles. In another study, Pourrahmani et al. [16] highlighted the transformative role of IoT in facilitating remote monitoring and diagnostics in connected vehicles. However, these advances come with inherent challenges such as high implementation costs, and wireless communication management difficulties. Tran et al. [17] put forth the benefits and potential drawbacks of cloud-based BMS, and proposed a novel approach that addresses the limitations of traditional BMS by improving the reliability and accuracy of battery algorithms through enhanced computational capabilities and data storage. Shi et al. [18] discussed the increasing role of artificial intelligence (AI) and machine learning (ML) in managing and deriving valuable information from a large amount of battery data. They proposed that incorporating cloud-based digital solutions into BMS could lead to improved battery diagnosis and prognosis accuracy. Meanwhile, Mohammadi et al. [19] stressed on the role of Battery Energy Storage Systems (BESSs) in EVs, particularly in the context of smart cities and 5G technology. They presented an overview of the technical challenges of real-time monitoring and control of energy storage systems for EVs in smart cities, and discussed the potential of IoT technology in enhancing the efficiency of BMS.

Overall, these studies have made significant contributions to the understanding of BMS, highlighting the benefits, challenges, and potential future directions of different technologies such as wireless systems, IoT, cloud-based solutions, AI, ML, and BESSs in the context of BMS. Despite these advancements, there exists a notable gap in the existing literature regarding a comprehensive review that combines the various advancements in BMS, particularly focusing on the integration of cloud, wireless, and IoT technologies. Furthermore, the existing works lack sufficient discussion on key issues such as security and privacy concerns, latency, scalability, and cost-effectiveness associated with these systems. Additionally, the potential and challenges associated with the application of AI and ML in the context of BMS have not been thoroughly investigated.

The purpose of this review paper is to bridge these gaps by providing an integrative analysis of the application of cloud, wireless, and IoT technologies in BMS. It also provides a thorough analysis of the IoB concept, its architecture, benefits, challenges, and potential future directions. By critically analyzing existing research and exploring the current state of the IoB in the context of EVs, this paper aims to shed light on the advantages and limitations of this technology. Our main contribution is to provide a comprehensive overview of the IoB concept and its potential applications in EVs. We also identify areas of future research and development required to fully utilize the potential of IoB in optimizing battery use in EVs.

The remainder of this paper is organized as follows. In Section 2, the architecture of IoB is presented. The machine learning approaches in IoB applications are reviewed in Section 3. In Section 4, the potential opportunities presented by IoB are discussed. The challenges associated with IoB are discussed in Section 5. In Section 6, the future research perspectives of IoB are discussed. The paper is concluded in Section 7.

2. The architecture of the internet-of-batteries (IoB)

The Internet-of-Batteries (IoB) can be defined as an integrated system that uses the IoT and cloud computing technology to monitor and manage batteries. IoB systems can collect data from batteries in real-time, such as voltage, current, temperature, and other parameters [20]. This data can be used to analyze battery health and performance, identify potential faults, and optimize battery usage [21]. IoB systems can also be used to remotely control batteries. This can help to improve battery efficiency and extend battery life.

The architecture of IoB is illustrated in Fig. 1. It comprises three main components, battery systems, IoT gateway, and cloud platform, and two additional components, i.e. BMS and wireless module, which are integrated inside the battery systems. Each component is described as follows.

2.1. Battery systems

Battery systems form the foundational layer of the IoB architecture, particularly within the context of EVs. Their role is to store and distribute energy, serving as the core of the entire IoB framework. Several key parameters and vital metrics are monitored at this level. These include the voltage, which signifies the electric potential difference, and the current, which represents the rate at which the battery is charged or discharged [22]. The temperature, another crucial parameter, directly influences the performance and life expectancy of the battery [23,24]. Moreover, the state of charge (SoC) indicates the existing energy capacity as compared to the maximum energy capacity [25]. Lastly, the state of health (SoH) offers insights into the overall battery health by reflecting its degradation over time [26,27]. The global EV battery market is projected to grow from $37.91 billion in 2021 to $98.97 billion in 2029, at a CAGR of 10.5% [28]. The growth of the EV battery market is being driven by the increasing demand for EVs, as governments around the world implement policies to reduce greenhouse gas emissions. In EVs, three types of batteries dominate the market i.e., Lithium-ion (Li-ion), Lead-Acid, and Nickel Metal Hydride (NiMH). Li-ion batteries dominate the market, holding more than 90% of the market share, primarily because of their high energy density, which allows them to store a large amount of energy in a small space [29,30]. This makes them ideal for EVs, which need to be lightweight and have a long range. Li-ion batteries are also relatively efficient, meaning that they lose less energy when they are used [31]. Lead-acid batteries are the oldest type of rechargeable batteries. They have a relatively low energy density and short lifespan, but their low cost and high availability make them suitable for some applications, such as auxiliary power units in EVs [32]. However, their poor energy-to-weight ratio and shorter lifespan make them less ideal as the main power source for EVs. Nickel Metal Hydride (NiMH) batteries have a higher energy density than lead-acid batteries, and they are more environmentally friendly, but they are more expensive. They were commonly used in hybrid electric vehicles (HEVs) before Li-ion batteries became dominant [33]. Their main drawback is the “memory effect”, where repeated partial discharge/charge cycles can decrease their capacity. A summary comparing these types of batteries used in EVs is presented in Table 1 [34].

The Li-ion batteries are further divided into different types based on cathode chemistries. These chemistries affect the performance, lifespan, and cost of the batteries. The most common cathode chemistries used in EVs are.

- *LFP (Lithium Iron Phosphate)*: LFP batteries are the most affordable and safest type of lithium-ion battery. They have a lower energy density than other chemistries, but they offer longer cycle life and better thermal stability. LFP batteries are often used in EVs and energy storage applications [35];
- *NCA (Lithium Nickel Cobalt Aluminum)*: NCA batteries have a higher energy density than LFP batteries, but they are also more expensive

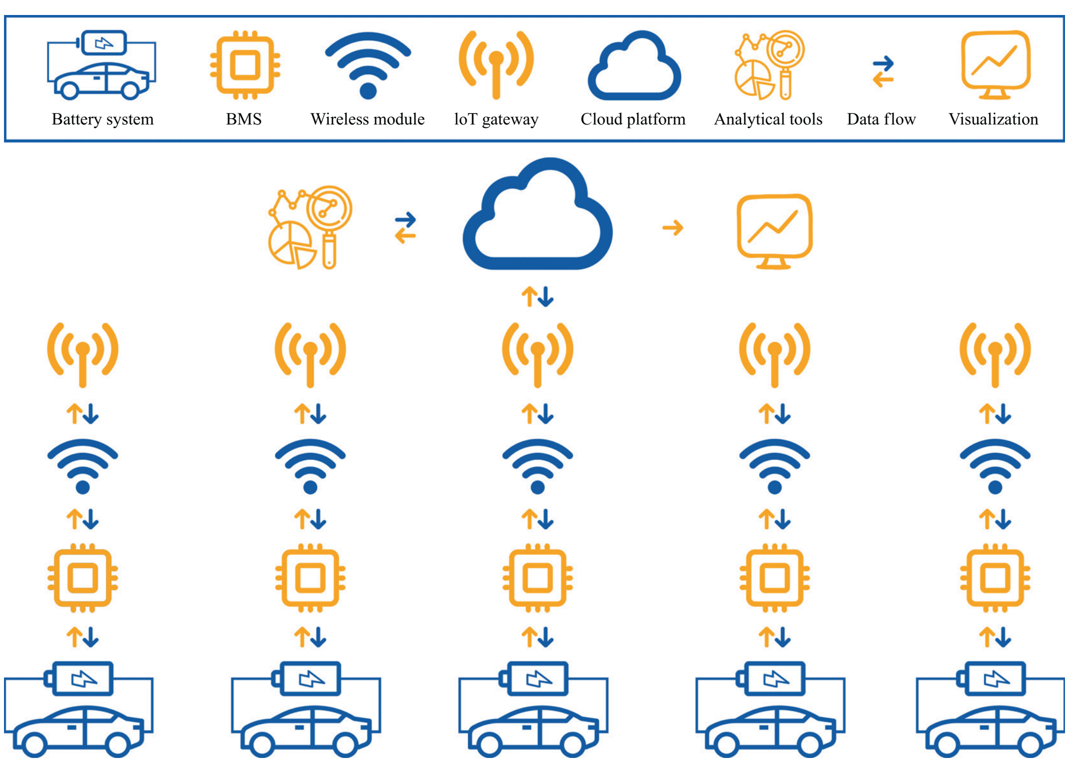

Fig. 1. The architecture of IoB.

Table 1
A comparison between Lead-Acid, Nickel Metal Hydride, and lithium-ion batteries used for EVs.

Specifications	Lead Acid	Nickel Metal Hydride	Lithium-ion		
			Cobalt	Manganese	Phosphate
Main components	Metallic lead, lead dioxide, lead sulfate, and sulfuric acid	Hydrogen, nickel hydroxide, and potassium hydroxide	Lithium, iron, aluminium, copper, cobalt	Lithium, manganese, graphite	Lithium, iron, phosphate, aluminium, copper, organic electrolyte, graphite
Specific energy (Wh·kg^{-1})	30–50	60–120	150–190	100–135	90–120
Internal resistance (mΩ)	<100 (12 V pack)	200–300 (6 V pack)	150–300 (7.2 V pack)	25–75 (per cell)	25–50 (per cell)
Life cycle (80% discharge)	200–300	300–500	500–1,000	500–1,000	1,000–2,000
Fast-charging time (h)	8–16	2–4	3–4	≤1	≤1
Overcharge tolerance	High	Low	Low, cannot tolerate trickle charge		
Self-discharge/month (25 °C) (%)	5	30	<10		
Cell voltage (nominal) (V)	2	1.2	3.6	3.8	3.3
Charge cut-off voltage (V·cell^{-1})	2.40	Full charge detection by voltage signature	4.20	3.60	
Charge cut-off voltage (V·cell^{-1}, 1 C)	1.75	1.00	2.50–3.00	2.80	
Peak load current (C)	5	5	>3	>30	>30
Charge temperature (°C)	−20 to 50	0–45	0–45		
Discharge temperature (°C)	−20 to 50	−20 to 65	−20 to 60		
Maintenance requirements	3–6 months	60–90 days	Not required		
Safety requirements	Thermally stable	Thermally stable, fuse protection common	Protection circuit mandatory		

and less safe [36]. NCA batteries are often used in high-performance EVs, such as Tesla Model S and Model X;

- *NMC 111 (Lithium Nickel Manganese Cobalt Oxide, 1:1:1 ratio of nickel, manganese, and cobalt)*: NMC 111 batteries were the first generation of NMC batteries. They have a good balance of energy density, cost, and safety [37]. NMC 111 batteries are still used in some EVs, but they have been largely replaced by newer NMC chemistries;
- *Lithium Nickel Manganese Cobalt Oxide, 5:3:2 ratio of nickel, manganese, and cobalt*: NMC 532 batteries are a newer generation of NMC batteries that have a higher nickel content than NMC 111 batteries. This gives NMC 532 batteries a higher energy density, but also makes them more expensive [38]. NMC 532 batteries are a good option for applications that require a high energy density and fast charging speed. However, they are more expensive than NMC 111 batteries and have a higher risk of fire or explosion;
- *NMC 622 (Lithium Nickel Manganese Cobalt Oxide, 6:2:2 ratio of nickel, manganese, and cobalt)*: NMC 622 batteries have a higher energy density than NMC 532 batteries, but they also contain more cobalt [39]. Cobalt is a relatively expensive and scarce material, so NMC 622 batteries are more expensive than NMC 532 batteries. NMC 622 batteries are still used in some EVs, but they are being replaced by newer NMC chemistries with lower cobalt content;
- *NMC 811 (Lithium Nickel Manganese Cobalt Oxide, 8:1:1 ratio of nickel, manganese, and cobalt)*: NMC 811 batteries have the highest energy density of any Li-ion battery chemistry [40]. However, they also contain the most cobalt, which makes them the most expensive;
- *NMC 9.5.5 (Lithium Nickel Manganese Cobalt Oxide, 9:5:5 ratio of nickel, manganese, and cobalt)*: NMC 9.5.5 batteries are a newer type of NMC battery that has a lower cobalt content than NMC 811 batteries [41]. This makes them less expensive and more sustainable. NMC 9.5.5 batteries are still in the early stages of development, but they have the potential to become the standard for EV batteries in the future.

Fig. 2 [42] illustrates the current market share and trends of various cathode chemistries for EV batteries. As of 2022, the dominant cathode

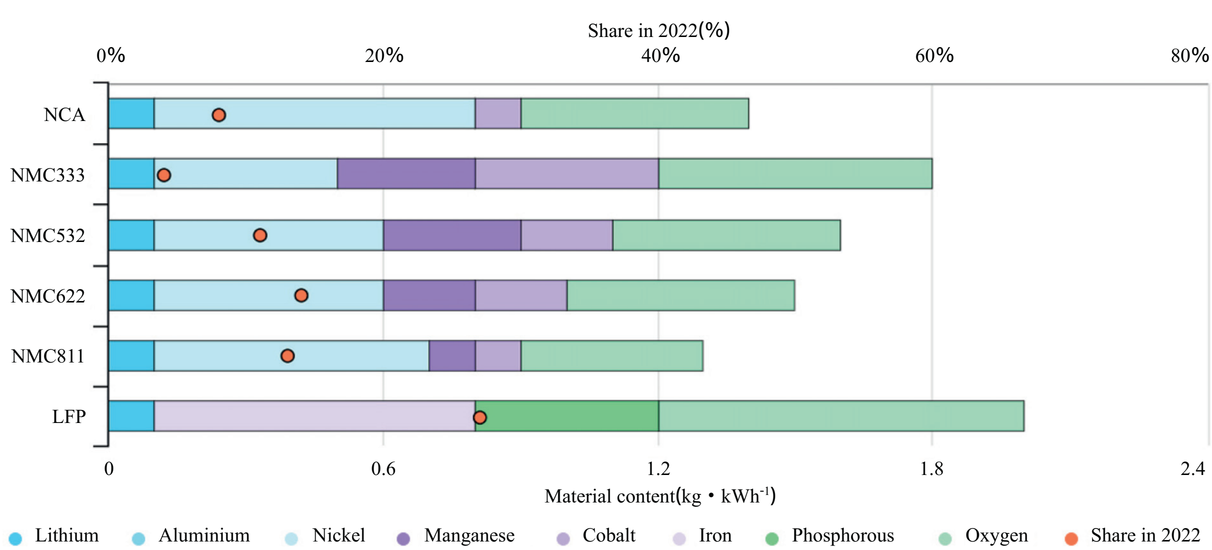

Fig. 2. Global market share of different types of EV cathode chemistries.

chemistries were LFP with approximately 30% market share, NCA with around 8% share, and NMC with a significant 60% market share. LFP batteries have experienced a surge in popularity, primarily driven by Chinese original equipment manufacturers (OEMs). Notably, 95% of LFP batteries used in EVs were installed in vehicles produced in China, with BYD accounting for half of the demand. Tesla, on the other hand, represented 15% of LFP battery demand, and its adoption of LFP batteries increased from 20% in 2021 to 30% in 2022, with a large proportion of those batteries used in cars manufactured in China. The adoption of LFP batteries by Tesla in the United States also increased, but the overall proportion of EVs with LFP batteries manufactured in the U.S. remained low at 3%.

LFP batteries have distinct characteristics compared to other cathode chemistries such as NCA and NMC. LFP utilizes iron and phosphorus instead of nickel, manganese, and cobalt found in NCA and NMC batteries. While LFP batteries have lower energy density than NMC batteries, they face the challenge of containing phosphorus, a critical element used in food production. As the EV industry continues to evolve, it is likely that the market share of different cathode chemistries may fluctuate. NMC chemistry is expected to remain a crucial player, given its high energy density and established presence. However, LFP batteries may continue to gain momentum, especially in specific markets or for certain types of EV applications, owing to their safety features and cost-effectiveness.

2.2. Wireless module

The wireless module is a critical component of the IoB system for EVs. It serves as an interface between the battery system and the IoT gateway, and is responsible for collecting and transmitting data from the batteries in real-time. The wireless module is typically integrated with the BMS which is equipped with a variety of sensors that can monitor the performance and status of the batteries [43]. The BMS communicates directly with the wireless module, exchanging vital battery data and control commands. These sensors can measure voltage, current, temperature, and other parameters. The data collected by these sensors is then transmitted to the IoT gateway via a wireless communication protocol, such as Wi-Fi, Bluetooth, or cellular [44]. The data that is transmitted by the wireless module is essential for ensuring the availability of real-time, accurate data for further analysis and action. The type of wireless communication protocol used by the wireless module depends on the specific application. For example, Wi-Fi is a good choice for applications that require a high data rate, while Bluetooth is a good choice for applications that require low power consumption [45]. The range of the wireless module also depends on the specific application. For example, a wireless module that is used to monitor a fleet of vehicles needs to have a longer range than a wireless module that is used to monitor a single vehicle [46]. The security of the wireless module is also an important consideration. This is because the module is responsible for transmitting sensitive data from the batteries to the IoT gateway. If this data is compromised, it could lead to a variety of security incidents, such as unauthorized access to the batteries, data theft, or even physical damage to the batteries. The wireless module should be encrypted to protect the data that is transmitted from the batteries [47].

The wireless module is not just a communication medium between the battery system and the cloud platform. It serves many other purposes, including.

- *Integration with other components of the IoB system*: The wireless module can be integrated with other components of the IoB system, such as the battery management system or the cloud-based analytics platform [48]. This would allow for more comprehensive and sophisticated data analysis;
- *Collection of data from a variety of other sources*: The wireless module can be used to collect data from a variety of other sources, such as environmental sensors or vehicle telematics systems [49]. This would provide a more holistic view of the performance and status of battery;
- *Implementation of battery management strategies*: The wireless module can be used to implement a variety of battery management strategies, such as load balancing, thermal management, and battery health monitoring [50]. This would help to ensure that the batteries are used in a safe and efficient manner;
- *Remote battery management*: The wireless module can be used to remotely manage the battery, such as adjusting the battery settings or performing firmware updates. This would allow for greater flexibility and control over the battery operation [51].

Fig. 3 presents a comprehensive overview of a wireless module used within an IoB system for EVs. At its core, the wireless module operates as the connecting bridge between the battery systems and the IoT gateway, ensuring seamless real-time data transmission.

Starting from the battery systems, arrays of sensors and actuators are installed in BMS to continuously monitor crucial battery and vehicle parameters. The BMS communicates directly with the wireless module, exchanging vital battery data and control commands. The wireless module acts as a bridge between the BMS and the IoT gateway. It contains a microcontroller unit (MCU) that processes the data from the BMS sensors and prepares it for transmission to the IoT gateway. The wireless module also communicates with the IoT gateway to receive and execute control commands for the battery system.

Once the data is ready, it is passed to the wireless transceiver, which can support multiple wireless communication protocols like Wi-Fi, Bluetooth, or cellular. This adaptive functionality allows the module to

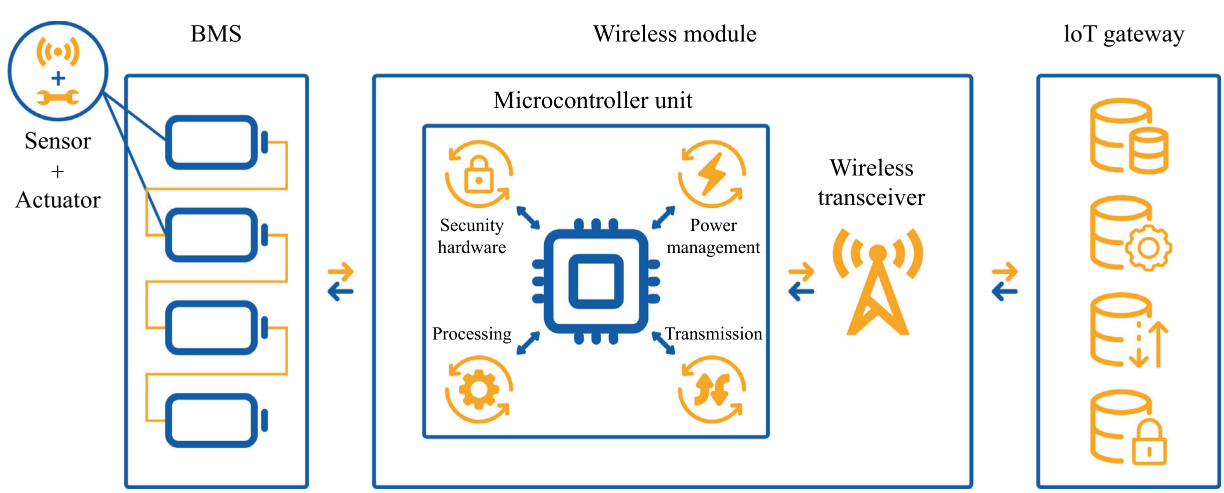

Fig. 3. Block diagram of a wireless module in an IoB system.

communicate effectively with the IoT gateway in diverse operational scenarios.

Essential to the integrity of the data being transmitted is the security hardware. The security hardware provides necessary encryption and other protective measures, ensuring that sensitive battery data remains secure during transmission.

A Power Management Unit is incorporated within the wireless module to ensure efficient power consumption during all these operations. The module needs to be power efficient so it does not drain the batteries it is designed to monitor.

Finally, the IoT gateway receives the transmitted data, where it can be analyzed, stored, and leveraged for various applications, completing the communication loop within the IoB system. Through this complex yet efficient coordination of components, the wireless module significantly contributes to the operational efficiency of the IoB system in EVs.

2.3. IoT gateway

The IoT gateway serves as a bridge between the wireless module and the cloud platform, ensuring safe and efficient transmission of data. The IoT gateway typically performs the following functions.

2.3.1. Data collection

The primary function of an IoT gateway is to collect voltage, current, and temperature, among other battery parameters from the wireless module [52].

In addition to the wireless module, the IoT gateway collects data from other sources to gain a better understanding of the state of the battery system [53]. For example, additional sensors installed in the vehicle or attached to the battery system provide a more detailed, real-time view of various system parameters. Actuators, on the other hand, respond to the commands of the gateway based on the interpreted sensor data, providing a feedback loop that helps to manage the battery efficiently [54]. Environmental monitors provide crucial data about external conditions, such as temperature and humidity, which can affect battery performance and lifespan. Collectively, the data gathered is invaluable for monitoring the health of the battery system, predictive maintenance, and optimal utilization of the battery resources.

However, data collection is not a straightforward task. IoT gateway receives data from IoT devices in a variety of formats, including text, binary, and JSON. The gateway must parse this data and convert it into a format that can be processed by the cloud platform [55]. This is a critical role of the gateway, as it ensures that the data is properly formatted and can be used by the cloud platform to generate insights and take action. For example, the IoT gateway in an EV BMS might gather data from various vehicle sensors, including those monitoring battery health, vehicle performance, and external environmental conditions [56]. Additional data from smart devices integrated into the vehicle, such as the infotainment system, navigation system, or advanced driver-assistance systems (ADAS), can also feed into the data pool [57]. By collecting and analyzing data from a variety of sources, the IoT gateway can build a comprehensive understanding of the vehicle. This understanding allows the system to make intelligent decisions about how to optimize battery performance and extend its lifespan [58]. For example, the system can use data about the speed, location, and temperature of the vehicle to determine when to enter a low-power mode or when to charge the battery.

2.3.2. Data processing

The IoT gateway performs preliminary data processing before the data is transmitted to the cloud platform, which helps to improve the efficiency and accuracy of data analysis [59].

The IoT gateway aggregates the data from various sources, which reduces the load on the cloud platform and improves the overall performance of data analysis [60]. The gateway collects and organizes all relevant data about the battery system, providing a holistic view of its current state and performance. This information can be used to identify potential problems early on, prevent failures, and optimize battery life.

The IoT gateway also filters the gathered data to remove noise and outliers. Noise can often lead to inaccurate analysis and predictions, so by filtering out this noise, the gateway enhances the precision of data analysis [61].

The IoT gateway then normalizes the collected data, which standardizes the data by adjusting the values measured on different scales to a common scale. This process is crucial in cases where data is collected from diverse sources, each possibly operating on different units or scales [62]. Normalization makes the data easier to analyze and compare, thereby facilitating a more straightforward and meaningful analysis.

In addition to these preliminary data processing steps, the IoT gateway may perform some initial analytics on the data, such as identifying trends and patterns [63]. This capability can provide valuable insights into the battery system, helping to identify potential issues or opportunities that may not be evident from the raw data. For example, trends in battery temperature or discharge rates could indicate emerging problems that need attention, which could help with preemptive actions to maintain the health and efficiency of the EV battery system [64].

2.3.3. Data transmission

The IoT gateway is responsible for transmitting data to the cloud platform in the IoB system. The data can be transmitted using a variety of protocols, including.

- *Long range (LoRa)*: LoRa is a low-power, long-range protocol that is well-suited for applications that require communication over long distances [65];
- *Bluetooth*: Bluetooth is a short-range, low-power protocol that is well-suited for applications that require communication between devices that are in close proximity [66];
- *Low-Rate Wireless Personal Area Networks (LR-WPAN)*: LR-WPAN is a low-power, low-bandwidth protocol that is well-suited for applications that require communication between devices that are in close proximity [67];
- *Mobile communication*: Mobile communication protocols, such as 4G LTE and 5G, can be used to transmit data over long distances [68];
- *Worldwide Interoperability for Microwave Access (WiMAX)*: WiMAX is a high-speed, long-range protocol that is well-suited for applications that require high-bandwidth communication over long distances [69];
- *Wi-Fi*: Wi-Fi is a high-speed, short-range protocol that is well-suited for applications that require high-bandwidth communication between devices that are in close proximity [70].

In the design of the IoB system for EVs, the selection of suitable communication protocols is critical for ensuring seamless internal and external communication. The following factors should be considered when making an informed decision.

1. *Internal communication (within the vehicle)*
   - *Energy efficiency*: Internal communication within the BMS of EV requires low-power communication to conserve energy and extend the range of the vehicle [71]. For this reason, Bluetooth Low Energy (BLE) stands out as a strong candidate. The low power consumption of BLE makes it ideal for connecting sensors and actuators within the BMS, enabling efficient data exchange without draining the battery;
   - *Short range requirement*: Internal communication typically involves short-range connections within the vehicle [72]. The short-range capabilities of BLE make it ideal for internal communication within the BMS of EV. BLE can be used to connect temperature sensors, voltage monitors, and current sensors, allowing for seamless communication between these components;
   - *Interoperability*: Bluetooth technology is widely supported by modern devices, making BLE-enabled sensors and actuators readily

available for integration within the BMS [73]. This interoperability simplifies the development and deployment of the IoB system within the EV;
- *Safety and reliability*: The utilization of BLE within IoB adheres to strict security protocols. The data exchanged between battery components is secured through encryption mechanisms, safeguarding it from unauthorized access and potential breaches. Authentication protocols add an extra layer of protection by verifying the identities of communicating devices, preventing unauthorized entry into the system. The BLE in the IoB is used solely for internal communication, specifically for the secure and reliable exchange of battery-related information. This isolation from external networks greatly reduces the risk of cyber threats and unauthorized interference. By assuring the safety and reliability of battery data, this approach aligns with the essential goal of safeguarding the integrity and safety of the overall IoB framework.

Based on these factors, BLE emerges as the most suitable communication protocol for internal communication within the vehicle. It enables low-power, short-range connections, and is widely compatible with various sensors and actuators commonly used in EVs.

2. *External communication (vehicle-to-cloud)*

External communication in the IoB system involves transmitting data from the vehicle to a cloud-based analytics platform. This communication must support real-time data transmission, handle significant amounts of charging and diagnostic data, and provide broad coverage for fleet management scenarios. Moreover, robust security measures are necessary to protect sensitive battery information during transmission.

- *Data rate and real-time communication*: LoRaWAN, with its improved data rate capabilities compared to traditional LoRa, enables efficient real-time data transmission from the EV to the cloud platform [74]. It efficiently handles the data demands of real-time monitoring, ensuring timely updates and responses;
- *Charging and diagnostic data*: During charging sessions and remote diagnostics, the improved data rate of LoRaWAN allows for the efficient transmission of large amounts of charging and diagnostic data [75]. This ensures that crucial information about the state and performance of the battery is seamlessly relayed to the cloud platform;
- *Connectivity and coverage*: Long-range communication capabilities of LoRaWAN make it ideal for fleet management scenarios where vehicles may be spread across large geographic areas [76]. Its broad coverage ensures continuous connectivity to the cloud platform, even in remote locations;
- *Security*: LoRaWAN is equipped with strong security features, including encryption and authentication, to protect data during transmission [77]. This ensures the integrity and confidentiality of sensitive battery-related information, safeguarding against unauthorized access and data breaches.

Based on these factors, LoRaWAN presents itself as a highly suitable communication protocol for external communication in the IoB system for electric vehicles. By leveraging LoRaWAN for external communication, EV manufacturers and fleet operators can establish a robust and efficient IoB system that enhances EV performance, optimizes battery management, and facilitates seamless integration with cloud-based analytics platforms for centralized monitoring and control.

Table 2 [78] summarizes the comparison of transmission protocols in IoT gateway based on notable attributes, such as standard, energy consumption, frequency band, data rate, transmission range, cost, and suitability.

The data transmission function is more than just relaying data to the cloud platform. It also plays an integral role in ensuring that the data is transmitted reliably and efficiently. To do this, the IoT gateway uses a variety of techniques, such as.

- Optimizing the data packet size to minimize the bandwidth requirements;
- Scheduling the data transmission to avoid peak traffic times;
- Using error-correcting codes to ensure that the data is received without errors.

By using these techniques, the IoT gateway can ensure that the data is transmitted to the cloud platform reliably and efficiently, even in challenging conditions.

2.3.4. Data security

The IoT gateway plays a critical role in securing data during its transmission between the wireless module and the cloud platform [79]. As cyber threats become more common and sophisticated, IoT gateways are increasingly attractive targets for cybercriminals. Therefore, robust security measures are essential to protect data from unauthorized access, modification, or destruction. The IoT gateway employs a multi-dimensional approach to data security. First, it uses encryption to encrypt data into an unreadable format during transmission, making it useless to potential hackers [80]. Second, authentication mechanisms verify the identities of the sender and recipient, ensuring that data only reaches its intended destination.

In addition to encryption and authentication, the IoT gateway also incorporates firewalls and intrusion detection systems. Firewalls control incoming and outgoing network traffic based on predetermined security rules, acting as a barrier between a trusted and an untrusted network [81]. Intrusion detection systems monitor network traffic for suspicious activity and alert the system or administrator when potential security threats are detected.

The sensitive nature of data collected and processed by the IoT gateway in the context of EV makes data security even more critical. The

Table 2
A comparison of transmission protocols in IoT gateway.

Parameters	LoRa	Bluetooth	LR-WPAN	Mobile communication	WiMAX	WiFi
Standard	LoRaWAN R1.0	IEEE 802.15.1	IEEE 802.15.4 (ZigBee)	2G-GSM, CDMA 3G-UMTS, CDMA2000 4G-LTE-A	IEEE 802.16 IEEE 802.11 a/c/b/d/g/n	
Energy consumption	Very low	Bluetooth: Medium; BLE: Very low	Low	Medium	Medium	High
Frequency band	868/900 MHz	2.4 GHz	868/915 MHz, 2.4 GHz	865 MHz–2. GHz	2–66 GHz	5–60 GHz
Data rate	0.3–50 kb/s	1–24 Mb/s	40–250 kb/s	200 kb/s – 1 Gb/s	1 Mb/s – 1 Gb/s (fixed) 50–100 Mb/s (mobile)	1 Mb/s – 6.75 Gb/s
Transmission range	<30 km	8–10 m	10–20 m	Entire cellular area	<50 km	20–100 m
Cost	High	Low	Low	Medium	High	High
Suitability	High	Very low	Very low	High	High	Medium

data collected from EV batteries can include sensitive information such as battery health, charge cycles, temperature readings, and usage patterns. If this data were to be accessed by unauthorized individuals, it could be used to disrupt operations, control the vehicle remotely, or even cause physical damage [82]. Therefore, it is essential to implement strong data security measures to protect the confidentiality, integrity, and availability of this information.

2.4. Cloud platform

The cloud platform is a critical component of the IoB architecture for EVs. It provides a centralized hub for storing, processing, and analyzing battery data collected from various EVs [83]. This data is essential for managing and optimizing EVs. The conceptual overview of the cloud platform is illustrated in Fig. 4. It typically performs the following key functions.

- *Scalability and robustness for IoB*: The dynamic and expanding nature of IoB systems demands a scalable and robust storage solution. As the number of connected devices and data points increases, the cloud platform ensures seamless accommodation of the growing data volumes [84]. Moreover, its robustness guarantees data availability even during hardware outages or network disruptions [85]. For IoB in EVs, where numerous vehicles continuously generate battery-related data, the cloud platform's ability to scale and handle data efficiently is essential for smooth operations;
- *Data security and privacy*: IoB systems deal with sensitive battery-related information, such as battery health data, charging schedules, and driving patterns. This information is valuable to hackers, who could use it to steal personal information, track vehicles, or even disable batteries. The cloud platform implements robust security measures, including encryption techniques to protect data from unauthorized access [86]. Additionally, data redundancy methods safeguard against data loss, while access control policies control data access and usage [87]. By addressing these security concerns, the cloud platform ensures the confidentiality and integrity of battery data, enabling user trust in IoB systems;
- *Real-time data processing and analytics*: The cloud platform's data processing capabilities play a crucial role in extracting valuable insights from battery data [88]. Real-time processing helps identify patterns and anomalies, enabling timely detection of potential battery issues. Predictive analytics, based on historical and real-time data, aids in forecasting battery behavior and predicting maintenance needs [89]. These analyses are instrumental in optimizing battery management, enhancing performance, and extending battery lifespan [90];
- *Parallel computing for efficiency*: With the massive amounts of data generated by IoB systems, the cloud platform employs parallel computing to handle complex computations efficiently [91]. Parallel computing divides tasks into smaller sub-problems, which are then processed simultaneously by multiple computing resources [92]. In the context of IoB in EVs, where the volume of battery data can be substantial, parallel computing ensures quick and accurate analyses, enabling effective decision-making and maintaining system responsiveness [93];
- *Intuitive visualization interface*: The cloud platform offers a user-friendly visualization interface that presents battery data in easily understandable formats, such as graphs, charts, and tables [94]. This visualization simplifies complex data, making it easier for users to identify trends and anomalies. For IoB in EVs, the visualization interface empowers fleet managers and operators to gain quick insights into battery performance. This information can be used to detect potential issues, such as battery degradation, and optimize fleet operations. For example, fleet managers can use the visualization interface to identify EVs that are not performing as well as others and take corrective action The visualization interface is a valuable tool for fleet managers and operators. It helps them to make informed decisions about the management and operation of their EV fleets [95].

In conclusion, the cloud platform is a critical component of the IoB architecture for EVs. It is not a generic solution, but a tailored and indispensable component. The cloud platform's scalability, robustness, security measures, real-time data processing, parallel computing capabilities, and intuitive visualization interface all converge to create an IoB system that optimizes battery management, enhances EV performance, and facilitates informed decision-making for EV fleet operators.

3. Machine learning in IoB

Machine learning is a powerful tool that can be used to improve the efficiency and effectiveness of Internet-of-Batteries (IoB) systems. By analyzing data and learning from patterns, machine learning can help IoB systems make more informed decisions about battery management, charging, usage, and vehicle management. This can lead to improved battery performance, increased range, and reduced costs for EV owners. Machine learning approaches can be broadly classified into three main categories: supervised learning, unsupervised learning, and reinforcement learning. Fig. 5 demonstrates the functioning of machine learning within the IoB system.

3.1. Supervised learning

Supervised learning approaches use labeled historical data to predict specific battery parameters, such as state of charge (SoC), state of health (SoH), and remaining useful life (RUL). For example, a supervised learning model could be trained on data that includes the battery's

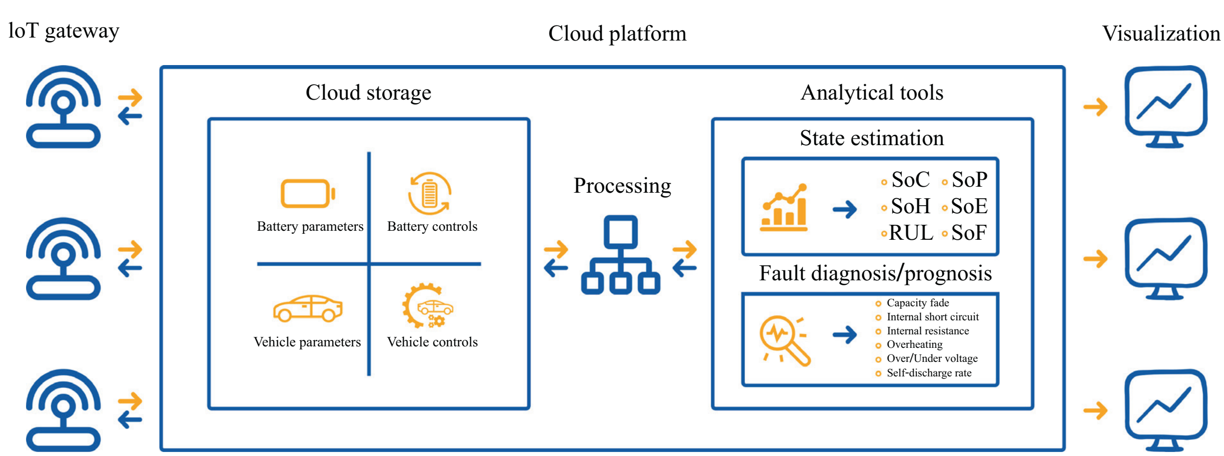

Fig. 4. Conceptual overview of the cloud platform.

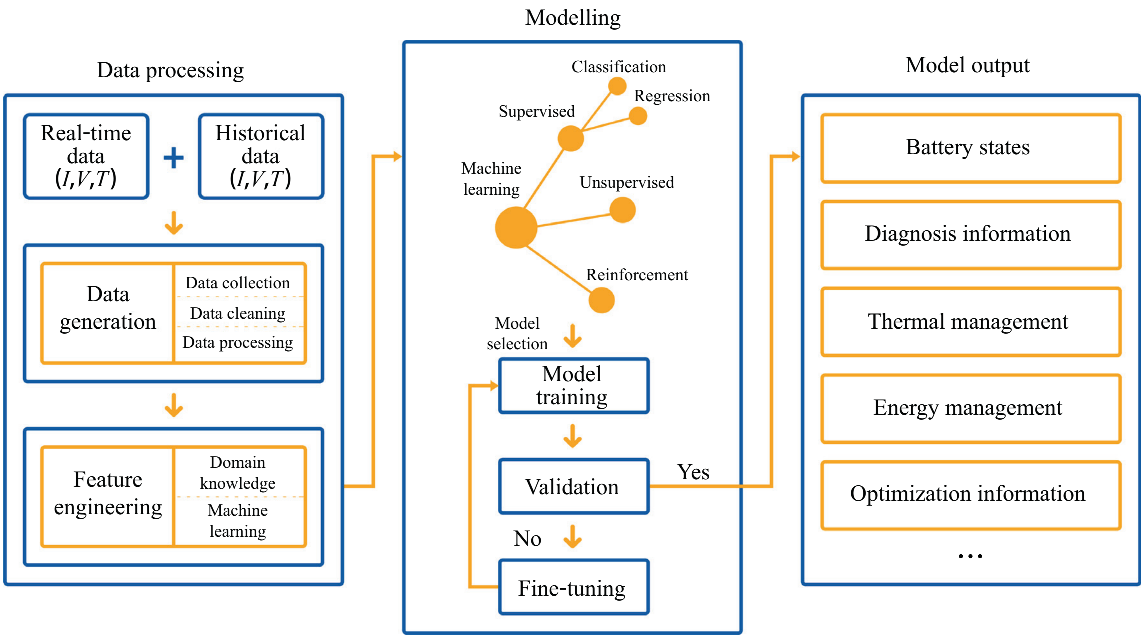

Fig. 5. Illustration of machine learning in an IoB system.

voltage, current, temperature, and other parameters to predict the battery's SoC. This information could then be used to optimize the battery's charging and discharging cycles, leading to improved battery performance and longevity.

Various supervised learning algorithms, such as support vector machines (SVMs) and neural networks, have been utilized to accurately predict the SoC of batteries. For instance, Song et al. [96] employed an SVM-based approach to estimate the SoC of lithium-ion (Li-ion) batteries in electric vehicles, achieving high prediction accuracy with low computational overhead. The estimation of battery SoH is crucial for predicting battery degradation and remaining useful life. Researchers have explored different supervised learning models, including decision trees and random forests, to accurately estimate battery SoH. Yang et al. [97] utilized a convolutional neural network (CNN) and random forest-based approach to predict the SoH of lithium-ion batteries, demonstrating excellent performance in accurately assessing battery health. Predicting the RUL of batteries is essential for proactive maintenance and ensuring optimal battery performance. Supervised learning algorithms like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been employed for RUL prediction. Zhang et al. [98] presented an LSTM-based model to forecast the RUL of Li-ion batteries, resulting in precise predictions and effective battery management.

Supervised learning approaches have also been applied for battery fault detection. Through labeled data, algorithms like logistic regression, SVMs, and neural networks can identify anomalous behavior in batteries, indicating potential faults or failures. Zou et al. [99] proposed a logistic regression-based model for the diagnosis of accelerating aging faults in Li-ion batteries, enabling timely maintenance actions. Yao et al. [100] proposed a novel method of fault detection of Li-ion batteries based on a wavelet-neural network for guaranteeing the safety and reliability of EVs. Hong et al. [101] proposed a deep learning method using LSTM to perform accurate multi-forward-step voltage prediction for battery systems and assess battery safety by predicting voltage to determine the occurrence of battery faults.

3.2. Unsupervised learning

Unsupervised learning techniques are used to identify patterns and anomalies in battery data without labeled training data. This can be used to group batteries together based on their behavior and characteristics. For example, an unsupervised learning algorithm could be used to identify batteries that are experiencing similar degradation patterns. This information could then be used to target these batteries for preventive maintenance, leading to increased battery life. Some of the most common unsupervised learning algorithms used for BMS applications include clustering, principal component analysis (PCA), and anomaly detection.

Clustering algorithms are extensively used in BMS applications to group batteries based on their behavior and characteristics. For instance, Li et al. [102] conducted a study focusing on enhancing the electrochemical performance of lithium-ion battery modules utilized in new energy vehicles. The research addressed the issue of manufacturing defects leading to performance variations among battery cells used in series or parallel configuration. To tackle this problem, the authors utilized experimental and numerical methods to cluster battery cells with similar performance characteristics, aiming to create battery modules with improved performance. They employed two clustering algorithms, namely k-means and support vector clustering (SVC) to group battery cells into modules, each composed of 12 cells. Subsequently, experimental verification was carried out to compare the performance of different battery modules. The findings of this study demonstrate the potential benefits of clustering battery cells with similar performance characteristics, which can lead to improved electrochemical performance in energy-storage systems for new energy vehicles.

PCA is another commonly employed unsupervised learning technique in battery analysis. It reduces the dimensionality of the battery dataset while retaining essential features. Schmid et al. [103] proposed a new method for fault diagnosis in BMS of EVs. Their method, called Cross-Cell Monitoring (CCM), compares the voltages of individual cells in the battery pack to identify any abnormalities. If a cell voltage is significantly different from the others, it is likely to be faulty. CCM uses Principal Component Analysis (PCA) to identify the most important features in the data, which helps to improve the accuracy of the fault detection process. The CCM method was applied to a large battery pack with 432 cells, and it was able to successfully detect and localize faults. Cross-validation showed that CCM was able to learn from the data and generalize to new data. Guo et al. [104] proposed a method for predicting the degradation and cycle to failure of Li-ion batteries using functional PCA. Their approach involves breaking down the observed degradation data into mean and variance-covariance functions. By analyzing these functions, they were able to accurately predict battery capacity and estimate the cycle to failure distribution. This method contributes to a better understanding of battery degradation and can help improve the reliability and performance of Li-ion batteries.

Anomaly detection algorithms have proven valuable in identifying abnormal battery behavior and potential faults. Jiang et al. [105] proposed a fault diagnosis method for Li-ion batteries using the isolated forest algorithm. Their approach involves signal processing and decomposition of voltage data into static and dynamic components. These components are used to extract characteristic parameters for anomaly detection, enabling the identification of anomalous cells. The method was tested with voltage data from four faulty vehicles, showing good advance detection ability for both progressive and sudden failures. This confirms its effectiveness in Li-ion battery fault diagnosis and its potential for real-time application in real vehicles.

Incorporating deep learning in unsupervised techniques has also garnered attention. Xu et al. [106] developed a novel physics-informed machine learning prognostic model called PIDDA for accurate SoH prediction in Li-ion batteries. The model comprises an autoencoder, physics-informed model training, and physics-based prediction adjustment. They benchmarked PIDDA against alternative data-driven SOH prediction models using the NASA battery prognostic dataset. The results demonstrated that PIDDA outperforms other models in terms of prediction accuracy, requires less prior data, and produces more informative and interpretable predictions. The ablation study revealed that the physics equations in the model training contributed significantly to accuracy improvement.

Furthermore, researchers have focused on integrating unsupervised learning with real-time data streams from IoT-enabled batteries. Sun et al. [107] introduced a novel iterative clustering method for classifying time series of EV charging rates based on their “tail features.” Their approach involves extracting charging tails from diverse time series with varying lengths, missing data, and distortions caused by scheduling algorithms and measurement noise. These charging tails are then clustered into a small number of types, and their representatives are used to improve tail extraction. The iterative process continues until convergence is achieved. The method was applied to ACN-Data, a fine-grained EV charging dataset, showcasing its effectiveness and potential applications in EV charging rate classification.

3.3. Reinforcement learning

Reinforcement learning approaches develop adaptive and dynamic battery management strategies. The models learn from feedback provided by the environment to optimize charging and discharging decisions over time. For example, a reinforcement learning model could be used to learn how to charge a battery in a way that maximizes its range while minimizing the risk of damage.

Reinforcement learning models are trained on a trial-and-error basis. They are given a reward signal for making decisions that lead to desired outcomes, and they are penalized for making decisions that lead to undesired outcomes. Over time, the models learn to make decisions that maximize the reward signal. Some of the most common unsupervised learning algorithms used for BMS applications include Q-Learning, Deep Q-Networks (DQN), Proximal Policy Optimization (PPO). Deep Deterministic Policy Gradient (DDPG), Soft Actor-Critic (SAC).

Q-Learning is a widely used reinforcement learning algorithm that involves estimating the value of an action in a given state. The algorithm updates its Q-value based on the rewards received for taking actions and uses this updated Q-value to make decisions about which action to take in the future [108]. Ahmadian et al. [109] conducted a study on energy management strategies for series-parallel hybrid vehicles. They proposed a novel approach using a Q-Learning algorithm, to optimize fuel consumption and battery life cycle. The method did not require prior knowledge of the cycle or detailed vehicle modeling. The simulations showed promising results, with a 1.25% reduction in fuel consumption and a 65% increase in battery life compared to the rule-based method. The approach also demonstrated good adaptability to different driving cycles, maintaining its performance and outperforming the rule-based controller in various scenarios.

DQN is an extension of Q-Learning. DQN uses a deep neural network to approximate the Q-values, which are the expected rewards for taking an action in a given state [110]. This allows DQN to learn more complex policies than Q-Learning, and is, therefore, suitable for battery management in real-world environments. Li et al. [111] presented an energy management strategy based on deep reinforcement learning for a hybrid battery system in EVs. Their strategy focused on minimizing energy loss and enhancing the electrical and thermal safety of the entire system by leveraging the electrical and thermal characteristics of the battery cells. The researchers introduced a novel reward term to optimize the high-power pack's operating range without imposing strict SoC constraints. To prevent overfitting, they trained the deep Q-learning model using various randomly combined load profiles. The results of training and validation demonstrated the effectiveness and reliability of their proposed strategy in reducing losses and enhancing safety. Comparing their energy management strategy to other reinforcement learning-based methods, the proposed method demonstrated superiority in terms of computation time and energy loss reduction, thus showcasing its potential for future energy management systems.

PPO is a policy gradient method that updates the policy parameters to maximize the expected cumulative reward. It is known for its stability and efficient use of samples, making it suitable for battery management tasks with continuous action spaces [112]. Zhang et al. [113] introduced a PPO-based multi-objective energy management strategy (EMS) for plug-in hybrid electric buses considering battery thermal characteristics. The goal was to enhance vehicle energy-saving performance while maintaining rational battery SoC and temperature levels. By intelligently adjusting weights during training, the proposed strategy achieved an optimal tradeoff between the conflicting objectives. Simulation results highlighted the effectiveness of the proposed strategies in battery thermal management, achieving minimum energy consumption, faster computing speed, and lower battery temperature compared to other reinforcement learning-based EMSs. In comparison to dynamic programming (DP) as the benchmark, the PPO-based EMSs demonstrated similar fuel economy and exceptional computation efficiency. The adaptability and robustness of the proposed methods were confirmed in various driving cycles including real driving conditions.

DDPG is an actor-critic algorithm that combines policy gradient and Q-learning methods. It uses deep neural networks to approximate both the policy and Q-values, making it suitable for battery management tasks with continuous action spaces [114]. Li et al. [115] proposed a cloud-based multi-objective energy management strategy for a hybrid battery system in battery electric vehicles, comprising a high-energy and a high-power battery pack. The strategy utilized DDPG to enhance electrical and thermal safety while minimizing energy loss and aging costs. Electro-thermal dynamics and aging behavior of batteries were simulated using models developed based on characterization and aging tests for both high-energy and high-power cells. Real-world vehicle data collected from diverse road conditions were employed for cloud-based training. Results demonstrated improved electrical and thermal safety, along with reduced energy loss and aging cost for the entire system with the proposed strategy based on real-world driving data. Processor-in-the-loop tests further validated the higher convergence rate of the proposed strategy and superior performance in minimizing both energy loss and aging cost compared to state-of-the-art learning-based strategies.

SAC is an off-policy reinforcement learning algorithm that combines maximum entropy reinforcement learning with soft value functions. SAC maximizes the expected cumulative reward while encouraging exploration and maintaining a distributional representation of the policy [116]. In a recent study, Wu et al. [117] proposed a novel knowledge-based, multiphysics-constrained energy management strategy for hybrid electric buses. The strategy focuses on the thermal safety and degradation of onboard Li-ion battery systems. The strategy introduces a multiconstrained least costly formulation that incorporates overtemperature penalty and multistress-driven degradation cost of Li-ion batteries, enhancing existing indicators. To achieve an intelligent balance between conflicting objectives and optimize power allocation, a soft actor-critic deep reinforcement learning strategy is utilized, resulting in accelerated iterative convergence. The proposed strategy was tested under various road missions, demonstrating its superiority over existing methods in terms of convergence effort, LIB thermal safety, and overall driving cost reduction.

The studies reviewed in this section provide substantial evidence for the effectiveness and benefits of machine learning approaches in the domain of IoB. These approaches have proven instrumental in enhancing various aspects of battery performance, such as the accurate prediction of critical battery parameters like SoC, SoH, and RUL. Through supervised learning techniques, BMSs can make informed decisions based on historical data, leading to optimized charging and discharging cycles that promote improved battery longevity. Additionally, the implementation of unsupervised learning algorithms has facilitated the identification of meaningful patterns and anomalies within battery datasets, enabling the grouping of batteries based on their behavior and characteristics. This clustering of batteries with similar degradation patterns has opened up possibilities for targeted preventive maintenance, effectively extending the battery life and reducing operating costs. Moreover, reinforcement learning models have demonstrated their ability to dynamically adapt battery management strategies based on real-time feedback from the environment, ultimately maximizing energy efficiency and performance. These machine learning-driven advancements have significantly contributed to improving battery performance, extending battery life, and overall enhancing the efficiency and effectiveness of IoB systems in various transportation applications, including EVs and hybrid electric buses.

4. Opportunities presented by IoB

The Internet-of-Batteries (IoB) present numerous promising opportunities, particularly for the electric vehicles (EV) industry. This digital technology promise benefits such as ongoing battery health checks, improved energy management, state estimation, prediction, and fault diagnosis, significantly transforming the landscape of EV technology [118,119].

The potential benefits of IoB begin with the possibility of continuous health checks of the battery. Traditionally, battery health checks have been conducted at specific intervals, often leading to gaps in understanding the real-time health of the battery [120]. However, the advent of IoB and cloud-based BMS allows real-time health monitoring [121]. This development can extend the life of EV batteries, improve their performance, and prevent unexpected failures [122]. In addition to direct benefits to battery health, it can also contribute to improved energy management in EVs. The analysis and prediction capabilities of these digital systems allow for better power allocation, charging strategies, and energy recovery [123,124].

Additionally, IoB provides opportunities for advanced state estimation and prediction. As seen in the work by Li et al. [125], these technologies improve the ability to monitor the current battery state and prediction of future states. This information can be used to optimize charging and discharging cycles, which can extend battery life [126]. The capability to promptly diagnose faults is another key advantage of IoB. Real-time monitoring and advanced analytics enable fault detection in a timely manner, leading to quick corrective measures that reduce downtime and repair costs [127,128].

The transformative potential of IoB is substantial and is not just limited to the battery of EVs, but to the vehicle itself. It can significantly enhance the management of EVs, leading to improved vehicle range, control, and management [129]. For example, IoB can be used to estimate the state of the EV, such as its range, and driving conditions. This information can be used to optimize and improve the performance of EVs. Additionally, IoB can be used to detect faults in the EV, such as a failing brake or low tire pressure [130]. This information can be used to alert the driver to potential problems and prevent accidents. IoB can also be used to control and manage the EV [131]. This includes tasks such as setting the cruise control, adjusting the climate control, and scheduling maintenance. By collecting and analyzing data from the EV, IoB can be used to improve the performance and reliability of EV.

To fully understand the potential opportunities presented by IoB, it is helpful to consider them at two distinct yet interrelated levels: battery-level and vehicle-level opportunities.

4.1. Battery level opportunities

EV battery management has witnessed a significant transformation over recent years. This transformation has been driven by the integration of various technologies, such as wireless communication, IoT, and cloud computing [132]. The integration of these cutting-edge technologies into EV BMS has opened up a wide range of opportunities in several key areas. Firstly, battery state estimation is now more precise than ever, allowing us to accurately measure the state of charge (SoC) and state of health (SoH) of batteries [133,134]. This is essential for ensuring optimal battery operation, as it allows us to track the performance of the battery and take steps to prevent battery degradation. Secondly, these advancements have also led to new prospects in the area of battery health prognosis and prediction. By using sophisticated algorithms and real-time data analysis, the remaining useful life (RUL) or the end of life (EOL) of a battery can be accurately predicted [135]. This information can be used to improve planning and maintenance strategies, ensuring that batteries are replaced or repaired at the optimal time. Thirdly, fault diagnosis and prognosis have also benefited from these advancements. By detecting potential faults early and accurately, catastrophic battery failures can be prevented, increasing the reliability and safety of EVs [136]. Finally, these technologies have also led to innovations in advanced battery management. Reconfigurable smart BMS can adapt to varying operating conditions, improving both battery performance and lifespan [137]. In summary, the convergence of wireless, IoT, and cloud technologies in BMS has enabled new opportunities for ensuring the efficient and effective operation of EV batteries.

An extensive body of literature supports these promising opportunities. Wang et al. [138] provided a comprehensive overview of battery modeling and state estimation methods for BMS. They discussed a variety of battery models, including physics-based electrochemical models, integral and fractional-order equivalent circuit models, and data-driven models. They also described several state estimation approaches that consider multiple factors such as remaining capacity, energy estimation, and power capability prediction. The review highlighted the emerging trend of cloud-based, data-driven BMS that use big data for advanced battery state estimation. This approach has the potential to significantly improve the accuracy of SoC and SoH estimation. Zhao et al. [139] explored the complexities and limitations of estimating the SoC, SoH, and RUL of Li-ion batteries. They highlighted challenges such as computational intensity, poor generalizability, and difficulties with parameter setting that can lead to model overfitting. Additionally, current methods are largely designed for single batteries, not battery packs, further limiting their practical applicability. In this context, the advent of cloud-based BMS presents significant opportunities. The computational power of cloud technology could help address the complexities of state estimation and RUL prediction, particularly for large-scale battery systems. Cloud-based systems could facilitate the development of more sophisticated models that perform at pack-level, cluster-level, and system-level, improving computational efficiency and enhancing prediction accuracy. In conclusion, their work underlines the potential for cloud-based BMS to revolutionize Li-ion battery state estimation and RUL prediction, particularly in renewable energy storage and EV sectors.

Ren et al. [140] explored the use of ML in estimating the SOC and SOH for lithium-ion batteries in electric vehicles. They reviewed four ML algorithms: shallow neural network, deep learning, support vector machine, and Gaussian process regression, examining their application in SOC and SOH estimation. With regards to cloud-based BMS, their findings indicate a potential for improved efficiency and accuracy. Cloud computing can manage the computational needs of these ML algorithms and address challenges related to data quality and model selection. Moreover, the authors suggested the potential for online retraining and full life cycle prediction in a cloud environment. In conclusion, they highlighted the emerging role of cloud-based BMS in enhancing SOC and SOH estimation through machine learning, promising better performance and safety of EV batteries. Yao et al. [141] investigated the SoH estimation and prediction for Li-ion batteries. They highlighted the safety risks resulting from inaccurate SOH estimation and advocated for better estimation methods. They classified these methods into three categories: model-based, data-driven, and fusion technology methods, each with its own strengths and weaknesses. In the context of cloud-based BMS, the paper presents promising prospects. By leveraging cloud computing capabilities, data-driven methods can overcome the challenges of heavy computation and local extreme values. Additionally, the use of multi-algorithm coupling can improve estimation accuracy and system robustness, which is consistent with the inherent scalability and versatility of cloud computing. Zhou et al. [142] conducted a study on Li-ion battery state estimation. They reviewed the state-of-the-art, challenges, and future prospects of battery state estimation, providing a thorough analysis of its technical difficulties. The paper discusses four key battery states (SoC, SoH, SoE, and SoP) and their joint estimation methods, proposing feasible frameworks for each. The authors also predicted a future in which intelligent sensing, cloud computing, big data, and intelligent algorithms will be combined to improve state estimation. This supports the idea that cloud-based BMS can significantly contribute to the development of a smarter and more efficient BMS.

Che et al. [143] provided a comprehensive analysis of Li-ion battery aging mechanisms and health prognostics. They discussed the complex relationships between aging mechanisms, modes, factors, and types. They also reviewed state-of-the-art health prognostic methods, including short-term SoH estimation, long-term end-of-life prediction, and degradation trajectory prediction. The paper highlighted the unique advantages and challenges of each method, and explored the specific characteristics of each prognostic task. The authors emphasized the use of advanced data-driven methods and coupled physics models in cloud-based BMS. Cloud platforms can provide the substantial computational power needed to run complex prognostic algorithms, which can lead to more reliable battery health predictions. The authors also acknowledged that the robustness and generalization of these methods are critical metrics and that cloud-based systems are well-positioned to improve these aspects by leveraging large datasets from multiple sources. The discussion of future trends and research prospects highlighted the potential for novel methodologies in battery health prognostics. Xiong et al. [144] discussed the complex aging mechanisms of Li-ion batteries in their paper. They take into account factors such as battery type, electrochemical reactions, and operating conditions. They reviewed three commonly used diagnostic methods for battery aging: disassembly-based post-mortem analysis, curve-based analysis, and model-based analysis. This paper has important implications for cloud-based BMS. It acknowledged the potential of online diagnostics enabled by cloud computing, machine learning, and digital twins. However, the authors also highlighted challenges, such as handling multi-source, fragmented, and asynchronous sparse data, and accommodating batteries with different application scenarios and sizes. The research pointed to a future where intelligent BMS, underpinned by advanced diagnostic methods and technologies, can offer real-time health prognosis and predictions for batteries. This could potentially extend battery lifespan and performance. Yang et al. [145] investigated fault diagnosis in battery storage systems, specifically Li-ion batteries. They reviewed various modeling approaches used for battery fault diagnosis, from microscopic to macroscopic scales. The authors acknowledged several challenges in model-based battery fault diagnosis, such as the estimation of internal parameters during battery aging, data management, and the development of hybrid models that integrate physics and data-driven methods. However, they proposed that these challenges could be addressed with the advent of cloud control and intelligent battery networking. This study emphasized the future role of cloud-based BMS in enhancing diagnostic performance. The authors suggested that merging physical models with machine learning approaches can provide fast and accurate simulations. The cloud BMS is presented as a key opportunity in the large-scale application of Li-ion batteries. It has the potential to improve safety and full life cycle management through data analysis, artificial intelligence, and synchronized data transfer.

A study by Zhang et al. [146] provided a comprehensive overview of Li-ion battery fault diagnosis methods. They categorized the methods into four categories: statistical, model-based, signal processing-based, and knowledge and data-driven methods. Each approach has its own strengths and weaknesses, and there are still many practical challenges to overcome, such as the high computational power required for parameter extraction and the lack of understanding of the different fault causes and their interrelationships. The paper highlighted the potential of cloud and integrated end-edge-cloud technology to address these challenges. These technologies can enable efficient real-time monitoring and condition assessment of batteries by leveraging the IoT for computation and cloud servers for data mining and complex modeling. Despite some challenges, the paper underscored the significant potential of cloud-based BMS for advancing battery fault diagnosis and prognosis. Hu et al. [147] studied the evolution of BMS in automotive applications, focusing on the challenges and opportunities presented by cloud-based BMS. They identified three main challenges in current BMS: limited knowledge of battery internal states and parameters, poor adaptability to extreme conditions, and lack of efficient predictive maintenance. The authors discussed potential solutions for these challenges, introducing the concept of multi-physics coupled battery modeling to improve BMS algorithms. They also highlighted how electrothermal modeling, advanced optimization routines, and predictive control with vehicular autonomy and connectivity can lead to innovative designs and improved thermal management. They suggested integrating battery models, machine learning, and cloud computing to improve battery life prediction and fault diagnosis. They concluded by emphasizing the crucial role of cloud-based systems in handling the computation and information requirements of the proposed solutions. They suggested that with the integration of such advanced BMS technologies, future EVs are expected to operate safer and with more accurate and reliable modeling, diagnosis, and control of battery systems. Panwar et al. [148] performed a detailed review of BMS with a specific focus on advancements from 2006 to 2020. The authors discussed critical BMS functions such as cell balancing, thermal management, and protection against overvoltage and overcurrent, as well as estimating battery SoC and SoH. They identified significant gaps in current methodologies that suggested areas for future research. A key aspect of the review is the potential of emerging intelligent technologies for enhancing BMS. Among these, the authors highlighted the importance of cloud-based, self-reconfigurable batteries. These batteries can alter their configuration in response to changing conditions, enhancing efficiency, longevity, and overall performance.

Wei et al. [149] discussed the advancement of smart battery systems, which are transforming traditional Li-ion batteries into more intelligent and flexible BMS. The authors explored the role of embedded sensing techniques and internal temperature measurements, which are essential for the smart operation of batteries. The paper identifies potential challenges with system-level integration, such as changes in pack configurations, sensor layouts, and data transmission needs. However, these challenges also present opportunities for leveraging cloud-based BMS solutions to manage the computational and data-intensive requirements of these advanced, reconfigurable battery systems. Komsiyska et al. [150] presented an extensive review on intelligent battery systems, emphasizing their transformative potential for the performance and longevity of electric vehicles. The key highlight of the review is the concept of reconfigurable battery systems, which can control the current of each cell individually, thereby optimizing battery operations. Despite current limitations, the paper stresses on the opportunities provided by cloud-based BMS in tackling the complexities of reconfigurable battery systems. Implementing such a concept requires advanced BMS and a sophisticated communication architecture, wherein cloud-based solutions could prove immensely beneficial. Therefore, the paper sets an optimistic stage for cloud-based BMS in managing the future demands of advanced battery management. Dai et al. [151] explored a multi-layered architecture for advanced BMS in Li-ion batteries. They highlighted the future role of data and artificial intelligence in battery management, particularly for EVs and renewable energy systems. The cloud-based and IoT-centric aspects of BMS can be inferred as key enablers for next-generation battery management technologies. Their insights into reconfigurable battery systems underscore the potential of IoT and cloud technologies in enhancing safety, longevity, and efficiency through data-driven decision-making and remote reconfiguration capabilities. He et al. [152] presented the three core components of a proposed technology system architecture for EVs, namely, the battery EV platform, charging/swapping station, and real-time operation monitoring platform. They highlighted the importance of cloud-based BMS for operational safety and the integration of intelligent and internet technologies. The authors emphasized the need for improved safety monitoring through a terminal-network-cloud architecture. They argued that cloud technologies could play a crucial role in collecting and managing real-time data to enhance safety. The study also highlighted the evolution of EVs towards software-defined vehicles and vehicle-cloud collaborative control. This suggests that cloud-based BMS will be essential for managing future battery systems and enhancing their operational performance.

As summarized in Table 3, the existing body of literature underscores the potential of utilizing IoT and cloud-based BMS for Li-ion batteries. It can elevate computational efficiency, enhance the accuracy of state estimation and health prognostics, and offer more robust solutions by utilizing big data analytics and machine learning algorithms.

4.2. *Vehicle level opportunities*

The integration of wireless communication, IoT, and cloud computing in EV management systems has also brought significant opportunities at the vehicle level [153]. These technologies can be used to improve state estimation, fault detection and diagnostics, vehicle control and management, and fleet management. By collecting real-time data from sensors throughout the vehicle, vehicles can more accurately estimate their

Table 3
Summary of literature on battery-level opportunities presented by cloud, IoT, and wireless technologies.

Paper	Year	Main discussion	Gaps
Wang et al. [138]	2020	Comprehensive overview of battery models and state estimation methods for BMS, discussing the emerging trend of cloud-based, data-driven BMS.	Limited discussion on the application of these methods to battery packs, not just single batteries.
Zhao et al. [139]	2023	Examination of complexities and limitations in estimating SoC, SoH, and RUL of Li-ion batteries, suggesting the potential for cloud-based BMS to address these complexities.	Overemphasis on computational intensity and generalizability problems, with less focus on the practical application of these models.
Ren et al. [140]	2023	Investigation of the use of machine learning in estimating SoC and SoH for Li-ion batteries in EVs with potential for improved efficiency and accuracy with cloud-based BMS.	Needs further exploration of the practical implications of cloud-based BMS in large-scale applications.
Yao et al. [141]	2021	Classification of SoH estimation methods and exploration of the potential advantages of cloud-based BMS in improving estimation accuracy and system robustness.	Emphasizes more on the advantages of individual estimation methods rather than their performance in conjunction with cloud-based systems.
Zhou et al. [142]	2023	Analysis of challenges and future prospects of battery state estimation. Proposes frameworks for estimation of four key battery states and envisions a future with intelligent sensing, cloud computing, and data-driven BMS.	Less emphasis on real-world constraints and considerations in the proposed frameworks.
Che et al. [143]	2023	Review of Li-ion battery aging mechanisms and health prognostic methods with an emphasis on data-driven methods and coupled physics models in cloud-based BMS.	Further investigation is needed to assess the practicality and effectiveness of proposed methods in large-scale, real-world applications.
Xiong et al. [144]	2020	Review of the complex aging mechanisms of Li-ion batteries, exploring the potential of online diagnostics enabled by cloud computing.	Highlights challenges, but lacks practical solutions to handle multi-source, fragmented, and asynchronous sparse data, and to accommodate different application scenarios and sizes.
Yang et al. [145]	2022	Overview of fault diagnosis in Li-ion batteries, noting the potential of cloud-based BMS to address challenges in model-based battery fault diagnosis.	Limited discussion on the practical implementation of hybrid models that integrate physics and data-driven methods in real-world applications.
Zhang et al. [146]	2023	Review of Li-ion battery fault diagnosis methods, identifying potential of cloud-based BMS in managing computational and data needs.	Does not sufficiently address the challenges related to parameter extraction and estimation in data-driven methods.
Hu et al. [147]	2022	Examination of the current state of research on battery thermal management systems, and the potential impact of cloud-based BMS on improving the efficiency and lifespan of batteries.	Further research needed on the impact of data processing and transmission speed on the practical implementation of cloud-based BMS.
Panwar et al. [148]	2022	Review of recent advancements in the methods for estimating the internal temperature of batteries, discussing the potential for cloud-based BMS in improving accuracy and efficiency.	Does not adequately address the challenges in measuring and modelling of thermal behaviour in large battery packs.
Wei et al. [149]	2023	Overview of the emerging trend of intelligent BMS, discussing the potential of cloud-based BMS in addressing the limitations of traditional BMS.	Lack of thorough discussion on the trade-off between complexity and performance in the implementation of intelligent BMS.
Komsiyska et al. [150]	2021	Comprehensive review of methods for estimating SoC, SoH and remaining useful life (RUL) of Li-ion batteries, identifying the potential for cloud-based BMS in addressing the limitations of traditional methods.	Insufficient discussion on the practical challenges in the implementation of hybrid estimation methods.
Dai et al. [151]	2023	Review of the application of data analytics in battery state estimation, exploring the potential of cloud-based BMS in overcoming limitations of traditional methods.	Does not thoroughly address the practical challenges in the implementation of data analytics-based estimation methods in real-world applications.
He et al. [152]	2022	Examination of the potential impact of artificial intelligence on battery management systems, specifically exploring the opportunities provided by cloud-based BMS.	Further research needed on the constraints and challenges in the application of AI to battery management, and how these can be addressed by cloud-based BMS.

range and remaining battery life [154]. This can help drivers avoid range anxiety and plan their trips more effectively. Sensors can detect problems with the powertrain, thermal management system, and other components of vehicles. This data can be sent to the cloud for analysis, which can help to identify and fix problems before they cause a breakdown [155]. Advanced driver-assistance systems (ADAS) systems can provide real-time guidance on how to drive more efficiently, which can help to improve performance and reduce maintenance costs [156]. Cloud-based management systems can also be used to update software and firmware over-the-air for vehicles. Cloud-based systems can track and manage EV fleets in real time [157]. This can help fleet operators to improve efficiency, reduce costs, and make better decisions about fleet deployment.

Zhang et al. [158] explored the potential of cloud computing in self-driving vehicles. They discussed the progress that had been made in achieving Level-4 automation, as well as the challenges that still needed to be addressed in order to reach Level-5 full automation. The authors highlighted the role of vehicle teleoperation in handling complex situations that went beyond the programmed abilities of self-driving cars. They proposed a future where automated driving intelligence could have been offloaded from vehicles to the cloud. This shift, which would have been facilitated by 5G and AI, could have led to cost reductions and simplified on-vehicle systems. Zhang et al. [159] conducted a study on the potential of the Internet of Vehicles (IoV) to support a range of new applications. They argued that the increasing sophistication of vehicles and the massive amount of data they generate would require new approaches to data processing and management. One potential solution is the edge information system (EIS), which deploys storage and computing resources at the wireless network edge. This can provide low-latency services and localized data acquisition, aggregation, and processing. The authors argued that EIS could play a key role in vehicle management by providing real-time insights and reducing response times. They discussed key design issues, methodologies, hardware platforms, and use cases for intelligent vehicles, including edge-assisted perception, mapping, and localization. Chu et al. [160] investigated the potential of the cloud control system (CCS) for intelligent and connected vehicles (ICV). They proposed the CCS as a promising solution to overcome the data acquisition limitations of autonomous vehicles and improve operational efficiency, safety, and traffic flow optimization. They argued that a multi-stage cloud system, consisting of center and edge clouds and individual vehicles, could form the foundation of this structure. They also suggested that the CCS could be instrumental in managing vehicular traffic effectively and highlighted the use of cyber-physical system design methodology in its development. However, they acknowledged that there are challenges to the widespread adoption of CCS, such as data ownership issues, the need for national-level planning, and standardization. They suggested that research should focus on top-layer design development, establishing base platforms for CCS, and enhancing cooperation between vehicle, road, and cloud systems for holistic vehicle management. Ji et al. [161] reviewed the IoV and its potential in the automotive industry. They discussed the evolution of Vehicular Ad-hoc Networks (VANETs) and their role in the 5G era, as well as their impact on intelligent transportation systems. The paper emphasized cloud-based vehicle management and vehicle fault detection through service applications. They highlighted cloud-based maintenance systems that used IoV to diagnose vehicle problems and propose solutions, which could enhance driver and passenger experiences. The study also introduced safety applications that utilized vehicle-to-vehicle and vehicle-to-infrastructure communications to increase traffic safety and prevent accidents. The research provided insights into the potential of integrating IoV with cloud-based vehicle management for improved vehicle fault detection.

Abbas et al. [162] explored the use of IoT and cloud-based applications to reduce traffic accidents caused by driver fatigue. They focused on the development of low-cost, computerized driver fatigue detection systems (DFDs) that used multi-sensors and mobile and cloud-based computing architectures. The authors compared three IoT-based architectures for DFDs: multi-sensor, smartphone-based, and cloud-based. They evaluated the challenges of using machine learning techniques, especially deep learning (DL) models, to predict driver hypervigilance across these architectures. The authors found that multi-access edge computing (MEC) and 5G networks could improve the response time of DFD systems, which is essential for real-time fatigue detection. They identified a research gap in implementing DFD systems on MEC and 5G technologies using multimodal features and DL architecture. This paper is significant for cloud-based vehicle management, vehicle fault detection, and driving assistance. It explored how these architectures can be used to provide advanced solutions for safer driving environments. The paper also demonstrated the potential of using cutting-edge technologies to aid in predictive, real-time fatigue detection, which can improve vehicle management and driver safety. In addition to the insights provided by Abbas et al., the IoB can play a significant role in improving DFDs. IoB can optimize power management within these systems by providing reliable and continuous power supply to the various components of the DFD system, ensuring uninterrupted operation. This ensures that the fatigue detection sensors and algorithms have sufficient power to function effectively. Furthermore, IoB can facilitate the integration of data from fatigue detection sensors into broader connected ecosystems. By leveraging IoB, the collected data can be transmitted, stored, and analyzed within a networked framework. This integration allows for comprehensive insights into driver fatigue patterns, contributing to the development of more effective fatigue detection algorithms and safety enhancements. IoB can also enhance the connectivity and communication capabilities of DFDs. By leveraging wireless or cellular networks, DFDs can transmit real-time data to centralized servers or cloud-based platforms. This enables remote monitoring and analysis, facilitating prompt interventions or alerts when driver fatigue is detected. Moreover, IoB enables communication between DFDs and other vehicle systems, such as ADAS, enabling coordinated responses to mitigate fatigue-related risks. Lastly, data security and privacy are essential considerations within DFDs, and IoB can address these concerns. With increased connectivity and data exchange, robust security measures are necessary to protect the collected data from unauthorized access or tampering. By integrating encryption protocols, access controls, and authentication mechanisms into the IoB framework, the security and privacy of the driver fatigue-related data can be ensured.

Mei et al. [163] studied the importance of accurate remaining driving range (RDR) prediction in EVs to mitigate range anxiety. They identified four key challenges to RDR prediction: battery state estimation, driving behavior classification, driving condition prediction, and RDR calculation method. To address these challenges, they proposed a novel RDR prediction method based on vehicle-cloud collaboration. They presented a novel driving range prediction method based on vehicle-cloud collaboration, leveraging cloud computing and machine learning to address the identified challenges and highlighting the critical role of Li-ion batteries in EVs. The study contributed valuable insights into cloud-based vehicle management, fault detection, driving assistance, and vehicle range prediction. It proposed vehicle-cloud collaboration as a promising area for future research. Devi et al. [164] studied the challenges and opportunities in the field of intelligent transportation systems (ITS). They found that the integration of IoT, connected vehicles, and cloud technologies can help to improve vehicle management, fault detection, and driving assistance. Cloud technology can process vast amounts of data in real time to provide drivers with optimized routes, traffic updates, and other advisories. This can lead to improved fuel efficiency, a more pleasant driving experience, and reduced traffic congestion. The paper also discussed the challenges of connected vehicles, such as network topology changes due to vehicle mobility and data synchronization issues. The authors suggested that dynamic spectrum access (DSA) can be used to address spectrum scarcity in urban areas. In their paper, Yang et al. [165] acknowledged the rising issues in urban areas related to traffic congestion, air pollution, fuel wastage, and car accidents. They investigated the potential of vehicular communications to alleviate these issues and drive the development of intelligent transportation systems. The authors recognized the promising opportunities that vehicular communications can offer to both manual-driven and automated vehicles in terms of enhanced traffic security and augmented entertainment services. The discussion extended to various vehicular cloud topologies, detailing their associated security, architectural, and reliability issues. Furthermore, the authors considered the taxonomy of vehicular networks in relation to the service link between vehicular networks and cloud computing. The paper concluded that there is an urgent need to develop secure, efficient, and reliable 5G vehicular communication networks. The authors also advocated for better resource management infrastructures in vehicular clouds, recommending the use of clustering. The authors also highlighted the need for comprehensive security systems to protect from various security risks.

Iqbal et al. [166] explored the potential of using IoT devices in vehicles to create a Smart Vehicle Monitoring System (SVMS) that can monitor the health conditions of drivers and prevent accidents. By leveraging IoT and cloud computing, SVMS offered a novel way to increase road safety. The authors acknowledged that the implementation of an IoT-based health detection system presents several challenges. These challenges include managing real-time data retrieved from IoT devices, maintaining connectivity in remote areas, and the significant costs of maintaining the servers necessary for information exchange. Other considerations include ensuring the reliability of IoT data from accurate sources, selecting communication devices and protocols that are safe for human use, and the challenge of maintaining connections between nodes and allocating resources for real-time data exchange in fast-moving vehicles. The authors concluded that the challenges of implementing an IoT-based health detection system are significant, but the potential benefits are also great. They suggested that further research is needed to address the challenges and to develop a more comprehensive SVMS. In a study conducted by Qureshi et al. [167], the evolution of vehicular networks with the advent of the IoT was investigated. The authors highlighted the emerging importance of IoV, which aims to provide safe and secure networks for vehicle users, benefiting from services that range from network maintenance to security systems. The paper proposed various models for IoV, including a cloud-based model that takes advantage of the opportunities offered by cloud-based vehicle management systems. These include enhanced vehicle management, fault detection, and driving assistance. The authors presented a comprehensive, layered architecture for IoV, detailing the elements required to operate it. They also explored a network model that integrates cloud services, a big data analytical model for data acquisition and analytics, and a security model aimed at detecting and preventing systems faults The paper concluded by discussing the challenges and future directions of designing new integrated models in the IoV landscape.

As summarized in Table 4, the existing body of research emphasizes the potential of incorporating IoT, cloud technologies, and vehicle-cloud collaborations. These technological advancements can improve operational efficiency, optimize traffic flow, improve fault detection mechanisms, and enable comprehensive health monitoring systems. Additionally, the use of machine learning and edge computing in these systems shows promise for addressing challenges such as latency and the efficient handling of diverse driving scenarios. However, there are still several areas that have not been explored, which provides a rich opportunity for further research.

5. Challenges of implementing IoB in electric vehicles

Implementing the Internet-of-Batteries (IoB) in electric vehicles (EVs) presents a number of challenges alongside potential opportunities. The innovative integration of Internet-of-Things (IoT) technologies within the battery management systems (BMS) of EVs presents a wide range of challenging issues that need to be thoroughly addressed for the technology to achieve a reliable state and widespread use. Fig. 6 illustrates the various challenges associated with the implementation of IoB in EVs.

One of the most prominent concerns in the IoB domain is the security of battery data. As the IoB system becomes increasingly interconnected, data about battery health, state of charge, and usage patterns becomes

Table 4
Summary of literature on vehicle-level opportunities presented by cloud, IoT, and wireless technologies.

Paper	Year	Main discussion	Gaps
Zhang et al. [158]	2020	Discussed the role of cloud computing in self-driving vehicles and highlighted the potential cost reductions and simplified on-vehicle systems that could result from offloading automated driving intelligence to the cloud.	Limited analysis on how cloud-based offloading affects real-time decision making in self-driving vehicles.
Zhang et al. [159]	2019	Explored the potential of the IoV and proposed the edge information system (EIS) as a solution for low-latency services and localized data acquisition, aggregation, and processing.	Limited exploration of edge-based solutions for data latency in IoV.
Chu et al. [160]	2021	Proposed the cloud control system (CCS) as a solution to overcome the data acquisition limitations of autonomous vehicles and improve operational efficiency, safety, and traffic flow optimization.	Insufficient discussion on data ownership and the implications of centralized control in cloud-based systems.
Ji et al. [161]	2020	Discussed the potential of IoV in the automotive industry, emphasizing cloud-based vehicle management and vehicle fault detection through service applications.	Inadequate exploration of fault detection mechanisms for cloud-based vehicle management systems.
Abbas et al. [162]	2020	Explored the use of IoT and cloud-based applications to reduce traffic accidents caused by driver fatigue.	Limited exploration of the integration of multimodal sensing for driver fatigue detection in cloud-based systems.
Mei et al. [163]	2023	Proposed a novel RDR prediction method based on vehicle-cloud collaboration, leveraging cloud computing and machine learning to address challenges in RDR prediction.	Little focus on how vehicle-cloud collaboration can be leveraged to handle prediction challenges in varied driving scenarios.
Devi et al. [164]	2016	Discussed how the integration of IoT, connected vehicles, and cloud technologies can help to improve vehicle management, fault detection, and driving assistance.	Lack of attention to data synchronization and topology changes in the context of mobile cloud computing.
Yang et al. [165]	2023	Investigated the potential of vehicular communications in alleviating traffic congestion, air pollution, fuel wastage, and car accidents.	Insufficient exploration of the implementation and design of vehicular cloud systems.
Iqbal et al. [166]	2019	Explored the potential of using IoT devices in vehicles to create a SVMS that can monitor health conditions of drivers.	Limited discussion on the integration of IoT with cloud technologies for real-time health monitoring systems.
Qureshi et al. [167]	2020	The authors highlighted the emerging importance of IoV, which aims to provide safe and secure networks for vehicle users, benefiting from services that range from network maintenance to security systems. The paper proposed various models for IoV, including a cloud-based model.	Limited analysis of the real-time implementation challenges and complexities of a fully integrated cloud-based IoV model.

Fig. 6. Major challenges in implementing the IoB in EVs.

vulnerable to cybersecurity threats. Faika et al. [168] discussed the security risks of wireless battery management systems (WBMS). They point out that lightweight IoT protocols, such as MQTT, are efficient but have weak encryption, access control, authorization, authentication, and identification mechanisms. This weak security configuration leaves the system vulnerable to attacks, such as man-in-the-middle attacks, where hackers can secretly relay and potentially alter communication between two entities. The research also shows that data privacy, confidentiality, and integrity can be easily compromised in this scenario. The paper concludes by recommending the investigation of blockchain-based IoT networks as a potential solution to these issues. Kumbhar et al. [169] identified six types of cybersecurity threats that can arise from vulnerabilities in IoT devices: unauthorized software updates or source code modifications, unauthorized access to data storage, man-in-the-middle attacks, insecure network protocols, unauthorized cloud access from unauthorized IoT devices, and SQL Injection attacks on cloud databases. Particularly concerning is their observation about IoT networks often using lightweight IoT protocols that might be insecure, giving rise to multiple forms of attacks. Kim et al. [170], investigated the cybersecurity vulnerabilities of BMS in cyber-physical environments. They found that cyber and physical attacks on these systems could cause explosive battery failure, damage to physical systems, threats to human safety, and economic loss. They categorized the attack vectors into three layers: communication and supervisory, control, and hardware. Each layer has unique vulnerabilities, including network, software/firmware, data storage, on–board interface, and hardware component security vulnerabilities. The authors emphasized the need for a thorough investigation of these vulnerabilities and the development of robust security standards and regulations. They proposed blockchain technology as a promising solution to mitigate these cyber-physical security vulnerabilities and recommended further research into developing a blockchain-based security framework for BMS. Fraiji et al. [171], discussed the need for security in EVs, which communicate with the internet using different modes, such as Wi-Fi, Bluetooth, and cellular networks. While this communication provides beneficial services, it also exposes the system to potential threats like DoS attacks, eavesdropping, and false data injection. They proposed developing an adaptive security strategy that considers factors like the type of sensor, available energy, available charging stations, type of available network, and energy level of the battery. This adaptive strategy would relax or tighten security measures depending on the situation to mitigate these threats. A study by Li et al. [172] argued that the integration of EVs and IoT requires real-time data analytics, which raises privacy and security concerns. The authors suggested that a balance must be found between the utility of data sharing and privacy protection. They identify three key privacy and security concerns in the context of IoB: data collection and sharing, data security, and data integrity. The authors argued that these concerns can be addressed through a combination of technical and policy solutions. They concluded that the successful implementation of IoB will require a concerted effort to address privacy and security concerns.

In comparison to the traditional BMS communication network, IoB technologies face additional cybersecurity challenges due to their increased connectivity and data exchange capabilities. The integration of battery systems into an interconnected network exposes them to a wider range of potential threats. One significant concern is the vulnerabilities inherent in lightweight IoT protocols commonly used in IoB systems. These protocols, such as MQTT, while efficient for data transmission, often lack robust encryption, access controls, authentication mechanisms, and identification protocols [173]. This weak security configuration leaves IoB technologies susceptible to unauthorized access and compromises of data integrity and confidentiality. Furthermore, the integration of IoB technologies with EVs and other IoT devices introduces additional attack vectors and potential security threats. The use of various communication modes like Wi-Fi, Bluetooth, and cellular networks in EVs exposes the IoB system to potential risks such as DoS attacks, eavesdropping, and false data injection [174]. These interconnected networks require comprehensive security measures to protect against unauthorized access, data manipulation, and potential disruptions to the system's functionality.

To address these cybersecurity challenges, robust security measures must be developed and implemented in IoB technologies. This includes enhancing encryption protocols to ensure secure data transmission and storage. Access controls and authentication mechanisms should be strengthened to prevent unauthorized access to the IoB system. Additionally, the implementation of comprehensive identity management systems and authentication protocols can help verify the integrity and authenticity of data sources and ensure the trustworthiness of the system. Blockchain technology emerges as a promising solution for addressing the security concerns of IoB technologies. Its decentralized and immutable nature offers enhanced data privacy, integrity, and security [175]. By utilizing blockchain technology, IoB systems can establish secure and tamper-proof data exchange mechanisms, protecting against unauthorized modifications and ensuring the authenticity of battery-related information. Furthermore, an adaptive security strategy is crucial in mitigating the unique risks associated with IoB technologies. This strategy should consider contextual factors such as sensor types, available energy, charging stations, network types, and battery energy levels to dynamically adjust security measures based on the situation [176]. By applying adaptive security measures, IoB systems can respond to changing threat landscapes and ensure a proactive defense against potential attacks. Comprehensive vulnerability assessments and ongoing security audits are also essential to identify and mitigate potential risks [177]. By conducting regular investigations into the system's vulnerabilities, potential security weaknesses can be identified and addressed promptly. This includes evaluating network security, software/firmware vulnerabilities, data storage practices, on–board interfaces, and hardware component security vulnerabilities. A thorough understanding of these vulnerabilities will inform the development and implementation of effective security measures.

Another significant challenge lies in the compatibility between different systems. The diversity of EV models, battery technologies, and BMS makes it difficult to establish an IoB network that seamlessly integrates these distinct elements. There are a wide variety of EV models on the market, each with its own unique battery technology and battery management system. This diversity makes it difficult to develop a single IoB network that can support all EVs. There are also a variety of battery technologies available. BMS plays a critical role in ensuring the safety and reliability of EV batteries. However, there is no single standard for BMS, and different manufacturers use different BMS [178]. This lack of standardization makes it difficult to develop an IoB network that can communicate with different BMS. The lack of standardized protocols and interfaces further complicates the challenge of compatibility [179]. Protocols are sets of rules that govern how data is exchanged between different systems. Interfaces are the physical connections between different systems. Without standardized protocols and interfaces, it is difficult for different systems to communicate with each other. Habib et al. [180], discussed the need for standards and regulations to ensure the safe and efficient operation of EVs. The authors argue that current standards are not sufficient to address the unique challenges posed by the incompatibility of EV systems and that new standards are needed to ensure the safety and reliability of EV systems. The authors identified a number of key areas where new standards are needed, including battery management, charging infrastructure, and grid integration. It requires the establishment of universal protocols and standards to ensure smooth interoperability. For example, the battery data from an EV manufactured by one company should be interpretable and useable by the charging infrastructure of another company. Effective solutions should allow for seamless data exchange, interoperability, and future scalability to accommodate advancements in EV and battery technologies.

Lastly, the large-scale application of IoB in EVs comes with its own set of technical complexities. Designing and deploying an IoB system that can handle vast amounts of data from millions of EVs worldwide requires sophisticated data management and processing capabilities. Furthermore, managing the real-time data transmission from and to moving EVs can pose significant challenges in terms of bandwidth and latency. Network congestion could result in delayed data transmission, affecting the performance of the IoB system. Kaleem et al. [181], highlighted some of the key challenges including latency and scalability issues in the case of cloud-based BMS. The real-time processing of large amounts of data, as required by sophisticated machine learning algorithms, introduces potential latency issues. This could impact the timely assessment and communication of battery states, which is crucial for the efficient operation and management of EVs in an IoB setup. In terms of scalability, as more electric vehicles come online and are integrated into the IoB, the volume of data that needs to be managed increases exponentially [182]. Managing and processing this data efficiently presents a significant scalability challenge. This is further complicated by the need to share and update data and models across multiple vehicles, which requires robust and scalable communication and data management protocols [183]. Overall, these challenges present key areas of focus in the ongoing development and optimization of IoB. Similarly, the system must be capable of handling different network conditions, as the quality of internet connectivity can vary significantly across different regions. Therefore, to achieve reliable and efficient large-scale application of IoB in EVs, it is necessary to overcome these technical challenges.

6. Discussions and future perspectives

The Internet-of-Batteries (IoB) is an emerging technology that has the potential to revolutionize the electric vehicle (EV) industry by offering opportunities for greater efficiency, optimization, and intelligent management of EV batteries. Through the integration of Internet-of-Things (IoT) and cloud technologies, IoB enables continuous battery prognosis, real-time data monitoring, and improved battery management, leading to enhanced vehicle performance, extended battery lifespan, and optimized energy utilization.

The necessity of IoB in the electric vehicle industry is driven by several key factors.

- *Enhanced battery management*: IoB enables continuous battery monitoring, real-time data analysis, and predictive maintenance. This capability allows for precise monitoring of battery health, state of charge (SoC), state of health (SoH), and remaining useful life (RUL). With this information, EV owners and fleet operators can optimize battery usage, schedule maintenance proactively, and extend battery lifespan. IoB's advanced battery management contributes to increased reliability, safety, and cost-effectiveness of EVs;
- *Optimized energy utilization*: IoB facilitates intelligent energy management, optimizing the utilization of stored energy in EV batteries. Through sophisticated algorithms and real-time data analysis, IoB can determine the most efficient charging and discharging patterns, considering factors like energy demand, grid conditions, and user preferences. This optimized energy utilization not only enhances the driving range of EVs but also ensures efficient use of electricity and reduces energy costs;
- *Integration of renewable energy*: As the world shifts towards renewable energy sources, IoB can play a crucial role in integrating EV batteries with renewable energy systems. IoB-enabled EVs can act as energy storage devices, absorbing excess renewable energy during peak generation periods and discharging it when needed. This capability contributes to grid stabilization, load balancing, and reduces dependency on fossil fuels, making the EV ecosystem more sustainable and environmentally friendly;
- *Advancements in battery technology*: IoB's continuous monitoring and data analysis provide valuable insights into battery performance and behavior. This feedback loop enables researchers and battery manufacturers to identify areas for improvement and drive advancements in battery technology. By identifying limitations and optimizing battery designs, IoB accelerates the development of more efficient, safer, and higher-performing batteries, benefitting the entire EV industry.

However, as the IoB framework expands and EV fleets become increasingly interconnected, new vulnerabilities and threats emerge, necessitating robust security measures and protocols to protect battery data. With batteries becoming interconnected nodes in a network, they are susceptible to cyber attacks that can compromise not only individual vehicles but also potentially impact the entire fleet or grid. Ensuring the security and integrity of battery data is of great importance to maintain user trust and safeguard critical infrastructure. The development of encryption algorithms, authentication mechanisms, secure communication protocols, and intrusion detection systems becomes imperative to mitigate these risks and protect against unauthorized access or manipulation of battery information.

Another critical challenge associated with IoB is interoperability and cross-platform functionality. The EV industry covers a wide range of battery technologies, models, and manufacturers, making it challenging to develop a universally applicable IoB architecture. Seamless communication and interaction within the IoB framework require standardized protocols, common data formats, and interoperable systems. Collaborative efforts between automakers, battery manufacturers, and technology companies are crucial to developing aligned standards, facilitating data exchange, and establishing a unified ecosystem for IoB implementation. These collaborations will encourage interoperability and ensure that IoB can effectively integrate with diverse EV systems and infrastructure.

Looking ahead, as the world increasingly focuses on renewable energy and smart technologies, the potential of IoB to improve energy management and battery optimization positions it as a technology with widespread adoption prospects. IoB is likely to become an integral part of the EV infrastructure in the near future, contributing to the development of a smarter, more responsive, and energy-efficient transportation system.

The implementation of IoB will have a profound impact on the existing battery technology system in several ways.

- *Data-driven design*: IoB's real-time data collection and analysis will drive a shift towards data-driven battery designs. Battery manufacturers will utilize IoB-derived insights to create batteries tailored to specific applications, optimizing performance and longevity based on real-world usage patterns;
- *Predictive maintenance*: IoB's predictive maintenance capabilities will replace reactive maintenance practices. Battery health monitoring and early fault detection will lead to targeted and timely maintenance actions, minimizing downtime and reducing maintenance costs;
- *Smart grid integration*: With IoB-enabled V2G technology, EV batteries will become an integral part of the smart grid ecosystem. They will actively participate in demand-response programs and grid stabilization, promoting grid flexibility and resilience;
- *Informed battery lifecycle management*: IoB will provide a comprehensive understanding of battery aging and degradation processes. This knowledge will enable more informed battery lifecycle management, ensuring optimal usage and recycling practices;
- *User-centric experience*: IoB will empower EV owners with detailed insights into the battery health, driving patterns, and energy consumption of the vehicles. This user-centric experience will enhance user satisfaction and confidence in EV technology.

The successful development and deployment of IoB will require close collaboration between automakers, battery manufacturers, and technology companies. By working together, these stakeholders can address technical challenges, share expertise, develop common standards, and establish interoperability guidelines. This collaborative effort will drive the adoption of IoB, encourage innovation, and pave the way for a more connected and sustainable EV ecosystem.

Advancements in battery technology will further enhance the potential of IoB. Research and development in areas such as solid-state batteries, advanced energy storage materials, and new electrode chemistries are expected to significantly improve battery performance. These advancements can lead to increased energy density, faster charging capabilities, and improved battery longevity, making IoB an even more valuable tool for optimizing battery performance and extending EV range. The integration of IoB with these advanced battery technologies will enable intelligent battery management, precise energy allocation, and efficient utilization of enhanced battery capabilities. With further research, development, and collaboration, IoB has the capacity to shape the future of EVs, enabling a smarter, more efficient, and sustainable transportation ecosystem.

7. Conclusion

The Internet-of-Batteries (IoB) is a novel concept that brings together batteries, IoT technologies, and cloud server infrastructure to create a networked system for efficient battery and vehicle management. IoB can significantly contribute to enhancing the overall performance and reliability of electric vehicles (EV) by providing continuous monitoring of battery performance, optimizing energy management, and supporting advanced state estimation and fault diagnosis.

Despite these potential benefits, it faces challenges such as data security and system compatibility. Data security is a concern because IoB involves the exchange of sensitive battery data. System compatibility is a challenge because different manufacturers use different systems and communication protocols for their EVs. Addressing these challenges requires the development and application of robust encryption methods, secure communication protocols, and coordinated efforts towards standardization of IoB systems.

Although there have been several studies on battery management systems (BMS), there is a lack of a comprehensive review that brings together the latest advancements in the field, particularly with regard to the integration of cloud, wireless, and IoT technologies. This paper aims to fill this gap by providing an integrated analysis of the IoB concept, its architecture, benefits, challenges, and potential future directions. By comprehensively exploring the current state of IoB in the context of EVs, this paper has highlighted both the advantages and limitations of this technology.

In the future, more research and development will be needed to fully realize the potential of the IoB and optimize battery use in EVs. Future efforts should focus on addressing the challenges identified in this review, such as data security and system compatibility. Additionally, research should explore the potential role of artificial intelligence and machine learning in enhancing the efficiency and effectiveness of IoB systems. The IoB has the potential to transform the EV industry, but realizing this potential will depend on addressing these challenges and seizing the opportunities it offers.

CRediT authorship contribution statement

Heng Li: Conceptualization, Writing-Reviewing and Editing, Supervision. **Muaaz Bin Kaleem:** Methodology, Software, Writing-Original Draft, Writing-Reviewing and Editing. **Zhijun Liu:** Investigation, Software, Writing-Reviewing and Editing. **Yue Wu:** Investigation, Writing-Reviewing and Editing. **Weirong Liu:** Investigation, Project Administration, Supervision. **Zhiwu Huang:** Conceptualization, Supervision.

Data availability statement

The data and materials used to support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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