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An intelligent battery management system (BMS) with end-edge-cloud connectivity – a perspective

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The widespread adoption of electric vehicles (EVs) and large-scale energy storage has necessitated advancements in battery management systems (BMSs) so that the complex dynamics of batteries under various operational conditions are optimised for their efficiency, safety, and reliability. This paper addresses the challenges and drawbacks of conventional BMS architectures and proposes an intelligent battery management system (IBMS). Leveraging cutting-edge technologies such as cloud computing, digital twin, blockchain, and internet-of-things (IoT), the proposed IBMS integrates complex sensing, advanced embedded systems, and robust communication protocols. The IBMS adopts a multilayer parallel computing architecture, incorporating end-edge-cloud platforms, each dedicated to specific vital functions. Furthermore, the scalable and commercially viable nature of the IBMS technology makes it a promising solution for ensuring the safety and reliability of lithium-ion batteries in EVs. This paper also identifies and discusses crucial challenges and complexities across technical, commercial, and social domains inherent in the transition to advanced end-edge-cloud-based technology.

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1 Introduction

The recent strides in battery technology and electric vehicle (EV) systems demand advancements in technology supporting their operation. The crux lies in the imperative need for effective battery management to ensure safety, extend battery life, and enhance overall battery performance. The characteristics of individual cells used in a battery pack are not similar even if they are produced by the same manufacturer in same production line. The differences are due to the differences in manufacturing tolerances, the post manufacturing process, and usage. During vehicle operation, if a battery pack discharges or charges without any internal management system and algorithms, cells within a battery pack experience phenomena such as cell-to-cell imbalance, over or under-voltage, overcharge or deep discharge and unequal temperature rise. The phenomenon leads to concerns related to the safety operation of battery packs. Hence, a typical BMS was conceptualised in the early 1990s with functionalities to monitor and control operation by measuring and estimating parameters and states at the cell, module, and pack level to ensure safe usage and prolonged life. Since then, BMSs have become an integral part of battery packs for mobility, large-scale energy storage, and other applications.[1–7]

In due course of time, as per the use cases, various developments in BMS design have been made with sensitive functionalities such as cell balancing, state estimation, and thermal management.[8,9] Given the electrochemical and non-linear nature of batteries, precise state estimations become challenging. However, precise measurement and estimation is paramount to ensure safe and reliable operation. Furthermore, each use case of battery demands specific functionalities with desired accuracy, specific to the application. This surge necessitates further refinement of functionalities and their applications, with a pivotal focus on the battery unit. The perspective BMS in this article, also called an IBMS, will disrupt the existing concepts by utilising cloud and artificial intelligence technologies to provide advanced functionalities such as fault prognosis, battery diagnostics and predictive maintenance while maintaining the aspects of scalability and commercial viability. However, the development of such a sophisticated system necessitates a deep understanding of battery behaviour under different operating conditions. This understanding forms the foundation upon which the IBMS architecture is built.

At the base of this pyramid of knowledge lies the complicated behaviour of individual battery cells as shown in Fig. 1. Expanding on the complexity of battery pack characteristics, it becomes evident that their performance is intricately linked to the behavior of individual cells. The behavior of these cells, in turn, is influenced by a multitude of factors such as driving patterns, recharging habits, and environmental conditions like temperature. This alters the cell internal electrochemical

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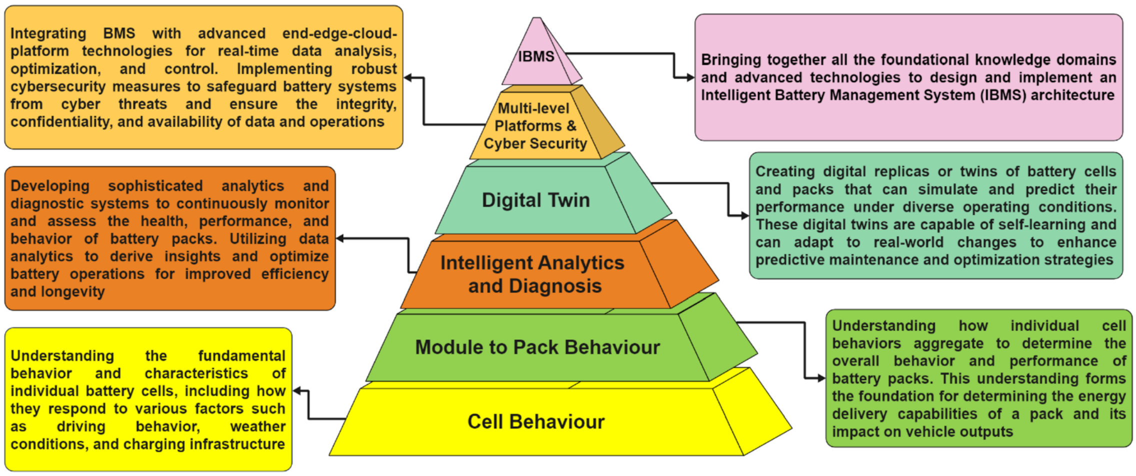

Fig. 1 Pyramid of hierarchy levels involved in building a sophisticated intelligent battery management system (IBMS) architecture.

properties affecting diffusion and reaction rates, transport properties and cell internal impedance and ultimately leading to cell degradation. This interplay of variables results in highly nonlinear relationships, making the task of measurement and understanding exceptionally challenging. To effectively understand the behavior of EVs, it is vital to comprehend the pack behavior, which is a reflection of individual module and cell behavioral characteristics. This understanding forms the foundation for determining how much energy a pack can deliver and the corresponding vehicle outputs it results in, such as acceleration profiles and range. Hence, it becomes apparent that vehicle behavior is essentially a manifestation of pack behavior, which, in turn, is a culmination of cell behavior as shown in Fig. 2.

1.1 Article organisation

This perspective aims to propose an advanced BMS architecture by discussing the requirements for intelligence and the technological innovations necessary to upgrade existing conventional BMS topologies. Following this, in Section 2, we provide an overview of conventional BMS systems and the transition to cloud-based BMS technologies. This section further includes a detailed review of the current advancements in BMS technologies, helping the reader understand the state-of-the-art developments in this field. Next, in Section 3, we present the necessary recommendations and innovations that can be introduced to BMS architecture. This section outlines the specific technological enhancements and design considerations that can elevate the capabilities of BMS systems. Within this section, we propose our potential IBMS architecture, which integrates cutting-edge technologies to ensure seamless and safe performance. This proposed architecture aims to be both scalable and advanced, addressing the needs of modern EV systems.

In Section 4, we explore the challenges inherent in this transition. This includes discussing commercial, social, and

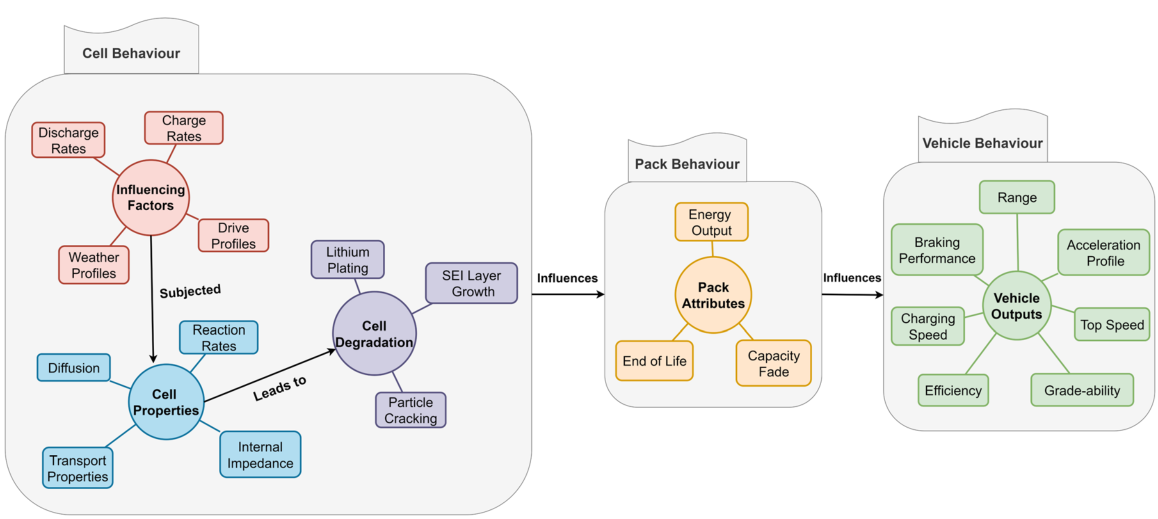

Fig. 2 Influence of cell behavior on vehicle performance through pack dynamics.

technical challenges, providing a comprehensive view of the hurdles and considerations involved in implementing this new BMS architecture. Through this perspective, we aim to offer a clear and thorough understanding of the potential and challenges of advanced BMS technologies. In Section 5, we summarize the key points of this perspective, highlighting the standout features of the proposed IBMS architecture. This perspective concludes with Section 6, which encapsulates the key ideas discussed and highlights the potential impact of the proposed BMS architecture on advancing the future of electric vehicles.

2 Defining conventional and cloud-based BMSs

With the current market pushing the limits of the operation of EVs, BMSs have become a keystone of innovation. Along with functionalities such as cell balancing, protection, state estimation, and isolations, which are features of a conventional BMS, additional advanced functionalities are required for performing advanced monitoring and fault prevention. The advanced functionalities include prevention of thermal runaway, self diagnostics, fault prevention, and prognosis, and use of cutting-edge technologies and advanced cyber-physical security features, which are needed to ensure safe, efficient, and reliable performance.[10–12] Few new technologies include advanced sensing of temperature and charge states within the battery pack,[13] and advanced embedded systems capable of hosting complex and computationally extensive algorithms for fault diagnosis and prognosis.[14–16] These algorithms, when supported by robust communication between components within the BMS,[16–21] and computing and embedded systems, enhance the functionalities required for large-scale EV deployment. For increasing scalability and adaptability, leveraging advanced technologies, such as cloud-computing resources,[22,23] multi-layer computing architectures,[24–26] digital twin technologies,[27–31] blockchain technology,[32,33] and IoT technologies[34] is highly beneficial.

Cloud computing in BMS technology offers scalability and enhanced computational power, enabling deployment of computationally intensive models capable of accurate and efficient fault diagnosis, lifespan evaluation, and predictive maintenance.[10] Cloud computing generally refers to the availability of on-demand computing services, physically located far from the user but which can be accessed by virtually connecting using specific user interfaces provided by the operators. These services generally include servers for computational power, storage and database creation and management for remote data storage, analytics, computation and communication. For BMS applications, vast datasets containing vital parameters of the battery pack,[14,15] such as real time current, voltage, temperature, and states of each component are generated which require data storage capabilities. These datasets can be stored for analysis and performing computational studies in remote cloud servers. However, considering latency, bandwidth limitations, and connectivity issues associated with cloud computing, BMSs with multi-layered computing architectures have been proposed.[24] These architectures have local computing layers deployed within the vehicle, which ensure time-sensitive actions and functions that require quick decision-making to be performed effectively despite limited computational capability. Typically, these multi-layer computing architectures include cloud, edge, and end computing layers, each with predefined functions based on priority and performance needs.[25,26]

To seamlessly transmit all relevant battery data to the cloud, IoT technologies are integrated.[34] The massive datasets stored on cloud servers are then used to develop computationally intensive but highly accurate models, algorithms, and systems, such as the digital twin of the battery.[23,32] The battery digital twin is a virtual representation of any physical battery pack that simulates its real-time behavior and performance. For batteries, the digital twin can be used to visualise the internal states of the battery and replicates the real-time behavior virtually within the cloud platform using already available datasets or by communicating in real-time. This enables continuous monitoring and diagnosis of battery systems in vehicles, simplifying the implementation of complex but critical functionalities which require detailed physics, data or hybrid modelling, such as early fault prediction, advanced diagnostics, and analytics. Blockchain technology has emerged as a very reliable solution to manage the entire dataset history and lifecycle management of battery packs. Blockchain offers superior security and privacy through encrypted and secure indices for data management, ensuring the integrity and confidentiality of battery pack information.[11] Significant research and development efforts have been dedicated to integrate these technologies into BMSs, resulting in innovative solutions that address the critical challenges associated with managing large-scale battery energy storage systems.

2.1 Cloud-based technologies

Cloud based systems and technologies are revolutionizing the scalability, efficiency, and remote management capabilities of BMSs.[11] Cloud technologies provide a wide range of possibilities to use computationally costly algorithms and methodologies. These include computationally intensive mathematical solvers for physics based models and equations, data based machine learning models, and hydrid models. Dapai *et al.*[35] discussed the key components and technologies of cloud-based BMSs, emphasizing the power of machine learning in enhancing BMS capabilities, particularly in handling large datasets for battery state prediction. Cloud-BMS offers a digital solution by processing and analyzing data more efficiently, allowing for remote monitoring, diagnostics, and predictive maintenance. This system enables fleet management, optimizing energy consumption and maintenance schedules across multiple vehicles or energy storage systems. Additionally, cloud-BMS supports over-the-air updates for onboard BMS firmware and algorithms, improving battery performance and extending the lifespan. Machine learning algorithms, transfer learning, and deep learning play a critical role in predicting battery behavior and addressing complex spatio-temporal challenges.

Studies to distinguish local and cloud functionalities are also presented in the literature defining a cloud-based smart BMS, such as that by Tran *et al.*[15] The design involves slave units for real-time data acquisition, a master unit for basic safety functions, and cloud components such as IoT, cloud infrastructure, application programming interface (API), and user interface (UI). Local functions encompass real-time data acquisition, cell balancing, charge control, thermal management, and fault detection. Meanwhile, cloud-based features include enhanced cell monitoring, SOC and SOH estimation, and fault prognosis through historical data and machine learning.

A similar cloud-based framework is introduced by Dominic *et al.*[36] for storing and analyzing data from stationary and mobile measurements in a battery research platform. The architecture enables real-time and historical data analysis, automating measurements and allowing remote monitoring without additional local hardware infrastructure. The system incorporates both laboratory measurements and real-world data from an electric-powered buggy's inverter. The cloud architecture, utilizing Amazon Kinesis for data streaming, is divided into sections for data collection, storage, processing, and visualization. It facilitates detailed condition monitoring of electric vehicles, early anomaly detection, and seamless comparison of measurements in different environments. A framework that combines a BMS with a big data platform for EVs was proposed by Rui *et al.*[37] It involves transferring constant data, including voltage and temperature, to a cloud-based big data platform during EVs' daily driving. Machine learning methods are then trained on this data to enhance prediction accuracy, with cloud computing handling computation-intensive tasks. The results are sent to a battery monitoring center for recording and storing lifetime battery state and fault information.

2.2 Multi-layered computing technologies

Multi-layered computing technologies open another wide horizon to significantly enhance the performance, efficiency, and adaptability of BMSs. A multi-layered BMS architecture can leverage edge and cloud computing for enhanced functionality.[24] The architecture includes end sensing for local data acquisition, edge computing for time-critical monitoring, and cloud computing for scalable, real-time data analysis. The integration of a digital twin and deep learning enables complex functions like detection, prediction, and optimization. The knowledge repository employs the monitor-analyze-plan-execute over shared knowledge (MAPE-K) loop for automatic and self-adaptive control.

Data transmission cost is a crucial factor for large scale deployment. A solution can be to use a cloud-end collaboration BMS (CEC-BMS) framework to address the high data transmission costs associated with a cloud based BMS (CBMS).[25] In a CEC-BMS, simple calculations are performed in the end BMS, while complex calculations are handled in the cloud BMS, reducing the need for extensive data transmission. A low-cost SOC estimation algorithm based on a CEC-BMS is proposed, utilizing a gated recurrent unit (GRU) neural network and transfer learning for accurate SOC estimation in the cloud. The end BMS uses the obtained accurate SOC for real-time SOC estimation of battery cells using the Ah-counting method. The collaboration between an end BMS and cloud BMS enables cost-effective real-time monitoring of numerous battery cells. The framework involves three components: the battery system, end BMS, and cloud BMS, where simple data processing occurs in the end BMS, and complex processing takes place in the cloud BMS. The cloud BMS, with enhanced computing power and storage, communicates with end BMSs *via* 5G communication protocol, processes massive battery datasets, and implements advanced algorithms for health management and remaining useful life prediction. Transfer learning is employed to construct neural networks using data from different battery systems.

Multi-layered computing can also be leveraged for state estimations in large scale energy systems. By coordinating edge and cloud computing, Wu *et al.*[26] presented a method for SOH estimation in distributed battery energy storage systems (DESS). Initially, a 3-round feature selection (TRFS) approach is proposed for extracting features from charging data on the edge side, reducing network traffic and cloud platform resource consumption. A noise sensitivity degree to mitigate the impact of measurement noises from a BMS on SOH estimation is proposed. Subsequently, a networking cloud platform collaborates with a BMS to estimate SOH using a random forest regressor (RFR).

2.3 Digital twin technologies

Research in digital twin technologies has advanced significantly, offering innovative solutions for real-time monitoring, predictive maintenance, and optimization in BMSs. Wang *et al.*[28] introduced a four-layer networked architecture for cloud-side-end collaboration in BMSs. Leveraging the computing and storage capacity of cloud-based servers, the framework overcomes limitations in a conventional BMS, enabling high-performance algorithms like deep learning. The BMS's 5G transceiver module collects real-time battery data, used to create a digital twin model in the cloud. This dynamic mapping allows continuous learning and model updating, addressing the fixed parameter issue in a traditional BMS and enabling refined and safe battery management throughout their life cycle. The intelligent on the air (OTA) remote program upgrade technology utilizes accumulated data to optimize system performance upgrades. The collaboration between the embedded system's real-time processing and the cloud platform meets the growing demands for sophisticated battery management.

Approaches to safely operate batteries were discussed by Wu *et al.*,[27] highlighting the limitations of conservative controls and advocating for model-driven methods focusing on SOX estimation, including SOC, SOP, and SOH for RUL prediction. Model-driven approaches face challenges in parameterization, leading to interest in data-driven methods like ML. The integration of model-driven and data-driven approaches, along with the concept of a digital twin, is proposed for more intelligent battery management. Functional requirements, performance factors, modeling, control, sensing, diagnostic techniques, and the application of AI to LIBs, presenting a roadmap for creating a battery digital twin are also proposed.

In a similar study, a novel cloud-connected battery management approach is introduced by Michael *et al.*[30] for optimizing the second-life use of retired EV batteries. This approach continuously estimates electric parameters through an equivalent circuit model and electric-thermal co-simulation, serving as a 'digital twin.' Furthermore, the method eliminates the need for post-operation state estimation, providing reliable predictions of the remaining lifetime for both vehicular and second-life applications. By combining this model with a net present value evaluation, the system facilitates economically sound decisions, offering advantages compared to current practices in terms of cost efficiency and accurate lifetime predictions.

2.4 Blockchain technologies

Research is also advanced in blockchain technology and it has been demonstrated to be a game changer to support battery prognosis, data security, and management across battery management systems. Wang *et al.*[32] discussed the integration of digital twin technology with a BMS for advanced battery monitoring and control. They outline the data flow from in-vehicle sensors to a cloud-based BMS for data cleaning and mining. The collaboration between a cloud-based BMS and in-vehicle BMS aims to create a new generation of battery management systems. Challenges include the need for historical data for digital twin model establishment and the use of smart algorithms for transfer learning when dealing with new battery types lacking sufficient data. The role of AI algorithms in overcoming data limitations and discussing the potential of blockchain technology in battery full life cycle management is highlighted. The ultimate goal is to establish a virtual world corresponding to the real world, connecting the battery digital twin with vehicle, road, and traffic digital twins through a distributed blockchain system. Several functions and opportunities for a battery digital twin in BMSs, including continuous battery state monitoring, real-time optimization of management strategies, establishment of a comprehensive fault diagnosis system, and integration with vehicle and road digital twins for coordinated development are envisioned in this study.

A system that integrates blockchain with vehicular cloud computing (VCC) technology is introduced by Xiaosong *et al.*[33] for collaborative sharing of battery data among EVs. VCC involves recording travel history through in-vehicle sensors and a broadband wireless communication system, with data transferred to a cloud *via* vehicle-to-vehicle and vehicle-to-infrastructure communication models. Idle resources in participant vehicles are used to form a data center or local computer cluster. Blockchain technology ensures data safety and privacy by using private and consortium blockchains. Each EV receives a token upon registration, allowing secure sharing of battery data within a league. The system enables collaborative training of RUL prediction algorithms across EVs while maintaining data privacy through encryption and secure indices.

2.5 IoT technologies

Exploring the integration of IoT technologies and battery systems allowed for advanced technology redefining connectivity and data exchange. Santhosh *et al.*[34] presented an IoT-BMS for EVs to enhance battery monitoring and prevent issues related to current and voltage uncertainties. The proposed framework uses lasso regularization (LR) parameter estimation and ORMeshNet gateway topology, achieving accurate SOC and SOH estimates. The IoT-based approach addresses challenges like data loss and message delivery delay.

By leveraging IoT and cloud computing, Amit *et al.*[38] proposed a cloud-based BMS for large-scale Li-ion battery energy storage systems. The system comprises wireless module management systems (WMMS) equipped with IoT devices and a cloud battery management platform (CBMP) featuring cloud storage, analytics tools, battery algorithms, and visualization methods. The CBMP's cloud components include storage for battery data, analytics tools for parallel computing, data mining, machine learning, and optimization algorithms. These tools present data in accessible formats, enabling comprehensive monitoring of battery health conditions, optimizing power management, and enhancing the scalability of large battery energy storage systems. The platform offers cost reductions and operational improvements, though challenges remain in integrating application software tools within the cloud platform.

2.6 Reconfigurable battery pack technologies

Studies and advancements in reconfigurable technologies have opened new avenues for a flexible BMS, enabling dynamic pack operations. Zhongbao *et al.*[39] explored advancements in smart battery technology, focusing on the concept of smart cells and their role in addressing issues related to inconsistency among LIB cells. It classifies smart batteries into self-reconfigurable multicell batteries and self-regulated smart cells. The former relies on a central controller for pack-level coordination, while the latter features independent cells with extensive autonomous capabilities. The classification, advantages, and future outlooks of smart cells, emphasizing the benefits of local optimization at the cell level for fault tolerance and reliability are discussed in this study. Self-regulated smart cells exhibit precise control over individual cells, enhancing system performance.

2.7 Integrating advanced technologies

The convergence of cutting-edge technologies such as cloud computing, digital twins, IoT, and cyber-physical platforms within battery management systems is explored by recent studies enabling seamless optimization and control. Weihan *et al.*[31] introduced a cloud BMS leveraging cloud computing and IoT for revolutionary advancements. It proposes a digital twin for battery systems in the cloud, enabling continuous monitoring, diagnostics, and advanced prognostics. The system enhances lifetime predictions, fault detection, and system optimization through machine learning algorithms. Two prototypes validate the cloud BMS, offering superior computation power, extensive data storage, and reliability compared to a traditional onboard BMS.

The challenges of a traditional BMS in ensuring the safety and long life of batteries in electric vehicles were discussed by Bragadeshwaran *et al.*[29] The limitations of existing BMSs were

Table 1 Comparing a conventional BMS and Cloud-based BMS

Dimension	Conventional BMS	Cloud-based BMS
Monitoring and protecting functions	Primarily focuses on basic monitoring tasks such as tracking current, voltage, and temperature, and triggers safety protocols when these parameters deviate from safe operational ranges	Offers advanced monitoring capabilities, including detailed diagnostics and prognostics, utilizing cloud computing for enhanced accuracy and reliability
State estimation algorithms	Relies on simpler, often model-based algorithms to estimate the state of charge (SOC) and state of health (SOH), but struggles with accuracy due to the inherent complexity and uncertainty of operating conditions	Utilizes sophisticated, data-driven and physics – based algorithms for precise state estimation, capitalizing on the vast computational power and storage capabilities of cloud platforms
Predictive fault diagnosis and Remaining Useful Life (RUL) prediction	Lacks the capability for predictive fault diagnosis and Remaining Useful Life (RUL) prediction, often failing to detect early signs of battery issues and unable to forecast the remaining lifespan of batteries	Implements advanced, data-driven predictive fault diagnosis techniques, enabling early detection of potential issues and accurate estimation of RUL. This capability enhances safety and performance by identifying battery anomalies before they escalate and predicting the battery lifespan
Computational capability and data storage	Constrained by limited computational power and data storage capacity, makes it challenging to integrate with large-scale lithium-ion battery (LIB) systems and implement advanced algorithms	Provides high computational power and unlimited data storage, facilitating the utilization of complex battery management algorithms and seamless integration with large-scale systems
Hardware and software efficiency	Requires additional hardware for local computing, which can impede system efficiency and scalability	Reduces the need for local hardware while harnessing superior computing power from the cloud, resulting in more efficient and scalable systems
User Interface (UI) and data visualization	Provides limited data visualization and user interaction features, offering minimal support for maintenance and repair scheduling tasks	Features advanced user interface components for real-time system monitoring and historical data analysis, improving user experience and facilitating system maintenance and repair scheduling
Optimization and control	Limited in terms of system optimization and control due to computational constraints	More effective in system control and optimization thanks to the extensive computational resources available on cloud platforms

highlighted and an intelligent BMS using advanced technologies such as IoT, cloud computing, AI, and data science to address these issues was proposed. The focus is on data-driven models, including neural networks, regression models, support vector machines, and fuzzy logic, to improve accuracy and speed in estimating battery states and diagnosing faults. The integration of IoT and cloud-based communication enhances fault tolerance and allows for efficient data handling. The use of a cyber-physical platform and digital twin technology in the cloud further contributes to fault diagnosis and analysis, ensuring secure and private data transmission.

A cyber-physical system (CPS) integrating physical, networking, and computational elements for monitoring and controlling battery operations was presented by Nitika *et al.*[23] The development of a digital twin through AI-based methods and data-driven frameworks, including cloud computing is emphasized. The CPS incorporates sensors, microprocessors, WiFi, and wireless sensors for estimating, evaluating, simulating, and optimizing battery parameters. The cloud-based digital twin utilizes real data from EVs for optimization and prognostics through ML-based hybrid intelligent learning control methodologies. The paper discusses existing methodologies for determining battery life and introducing dynamic battery models within the CPS framework.

As summarised in Table 1, a cloud-based BMS offers several improvements and advantages and opens multiple new horizons to monitor and control battery packs compared to a conventional BMS in different dimensions. Based on the discussions presented in the sections so far, the next section will introduce the perspective IBMS.

3 Motion for a new-fangled BMS architecture

3.1 Recommendations

The sophistication of cloud-based BMS design has reached commendable levels, yet further enhancements are required. The expected functionalities to be performed by a BMS can be categorised into time-critical and those which are not time-sensitive. Critically time-sensitive functionalities require instant actions and should have the least latency in estimating and control loop implementation, such as basic state estimations, cell monitoring and balancing, and thermal monitoring and protection. The non-time-sensitive functionalities, such as prognosis, do not require instant actions. Hence, edge computing devices can handle the former and be placed within the vehicle. In contrast, the latter must be deployed in cloud-based platforms where advanced diagnosis and big data analytics can be performed.

Interlinking cloud-based platforms with the local BMS *via* edge computing can provide huge benefits to the users. The results from the advanced diagnosis and big data analytics can also be used to complement time-sensitive functionalities. A significant advantage in terms of scalability, computational power and requirements, advanced data studies, increased collaboration, root cause analysis determination based on data, *etc.*, is visible. Furthermore, integrating the digital-twin technology concept can be brought into reality from theory for industrial applications by an enhanced cloud-based BMS. The integration of digital twins will enhance diagnostics and prognostics using advanced algorithms inside the cloud platform, ensuring intelligent control and monitoring of both mobile and stationary battery systems. An extensive cell-level electrochemical analysis must be performed in real-time by developing a fault prognostics unit inside the cloud platform that monitors all the critical electrochemical parameters while charging and discharging at different C-rates. An IBMS that can actively monitor thermal performance across the module and the cell to mitigate battery degradation could address the primary drawback of range anxiety in electric vehicles.

Although the definition of using cloud services appears simple, intensive work to perform data management in a centralised/decentralised manner will require privacy protections, transparency, and accountability. Blockchain technology has emerged as a game-changer in BMS applications,[11,40] offering a secure, transparent, and immutable platform for storing comprehensive battery usage history. This enables informed decision-making, extending to second-life applications or recycling, ensuring optimal resource utilization. However, implementing blockchain IoT platforms for smart EV battery management entails high initial investments and maintenance costs, with scalability limitations arising from increasing data volume.

Interoperability challenges hinder seamless data exchange across networks, while security vulnerabilities and concerns regarding data privacy pose significant risks to system integrity and user confidentiality. Utilizing blockchain, we store comprehensive historical data on battery usage, including drive patterns, regional climatic conditions, and charge–discharge profiles, linking them to individual users. Maintaining an immutable record of the battery's entire life cycle facilitates easier monitoring of battery performance, usage, and health, enhancing overall management efficiency and reliability. This enables us to identify specific instances where a user has previously misused a battery. In such cases, dynamic pricing strategies are implemented, applying different rates for users with a history of battery abuse. Repeat offenders of harsh usage can then be subjected to appropriate penalties, ensuring responsible usage and prolonging battery life. Moreover, leveraging this data allows us to enhance algorithms to minimize or prevent instances of abuse on the batteries. The geographical history of battery usage further enriches this dataset.

Another new dimension in battery management is the ability to control reconfigurable connections through the BMS within a reconfigurable battery pack.[39] Reconfigurable packs differ from conventional fixed-configuration packs, featuring multiple switches between cells that can be controlled to connect cells in series, parallel, or various combinations. This flexibility allows for optimized performance, fault mitigation, and dynamic voltage output. Advancements in BMSs can enable seamless control of these switches by facilitating dynamic adjustments at the cell or module level, optimizing performance and mitigating potential faults. The synergy of cloud, edge, and end computing layers optimizes decision-making processes, enabling multi-layer computing. The end BMS conducts immediate data sensing and acquisition from strategically placed sensors within the physical battery pack, detecting changes and transmitting critical and additional valuable data to the edge unit for further processing and eventual storage on cloud servers. While edge computing facilitates real-time, rapid decisions, cloud computing handles tasks such as state estimation and blockchain utilization, aiding in decisions regarding second life or recycling.

3.2 Potential architecture

The previous paragraph and sections discuss the current challenges in existing BMS architecture. Hereby, we propose an advanced IBMS to safeguard battery operations in electric vehicles, ensuring safety and reliability. The system incorporates cutting-edge technology, powerful embedded electronics, and software that elevate its technological superiority. The range of functionalities and features it offers is extensive. The potential architecture and its functionalities are described below.

The design adopts an optimized approach, introducing a multilayer parallel computing architecture incorporating end-edge-cloud platforms, each dedicated to specific vital functions. Active communication is maintained among the reconfigurable battery pack, smart BMS, user, and charge devices and stations for enhanced battery management. The overall architecture of the proposed IBMS is illustrated in Fig. 3. To delve into the multi-layer hierarchy of this intelligent BMS, it consists of three components: end, edge, and cloud.

3.2.1 End BMS. The end BMS performs immediate data sensing and acquisition from sensors within the physical battery pack. Sensors are strategically placed in remote locations inside the battery packs to detect any changes and notify the IBMS of the occurrences. These changes are then captured and pushed to the edge unit of IBMS. Critical data, including cell/module/pack voltage, current, and ambient temperature, and additional valuable data like relative humidity, pack pressure, and vibration, are actively monitored and processed further. The data from the sensors are then acquired by the data acquisition unit, comprising state-of-the-art acquisition chipsets and devices, in which data are temporarily stored before being communicated to edge and cloud servers for storage purposes.

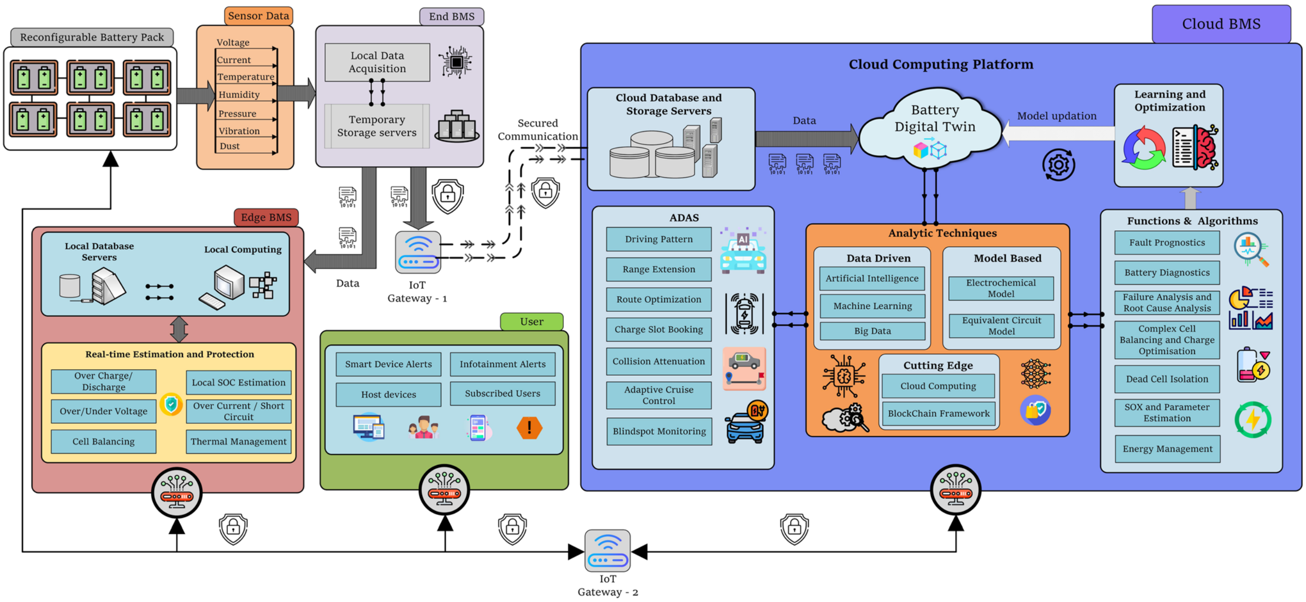

Fig. 3 Comprehensive architecture of the intelligent battery management system (IBMS) illustrating real-time multilayer (end-edge-cloud) communication. The three-layered structure (end-edge-cloud) employs hierarchical sensing and processing, with an adaptive digital twin-based cloud platform featuring an advanced analytic toolbox and blockchain technology. This setup ensures accurate prediction, prognostics, and cybersecurity for large-scale battery systems (Few icons from ref. 41).

3.2.2 **Edge BMS.** Data from the end BMS are directly sent to the edge BMS, where real-time state estimations, critical and time-sensitive operations, and safety measures are attended to. Local SOC estimation, primary cell balancing, and essential safety functions, such as overcharge/discharge protection, over-current protection, over/undervoltage short circuit protection, and thermal management, are monitored. Overlooked high temperatures may lead to significant battery lifetime depletion and eventual thermal runaway. The servers and database required here would not be storage extensive, as only crucial operations are performed. These can be executed over minimal storage databases, and local computing facilities can achieve efficient edge computational efficiency. All bulk data processing and storage are not possible on edge servers. Computationally extensive functions and algorithms executed over the cloud due to scalability and reliability. The edge BMS enables stable and real-time data processing and protection by running the safety algorithms locally.

3.2.3 **Cloud BMS.** The cloud-based framework is a sophisticated platform where distributed programs executed using state-of-the-art analytic techniques. Data from the edge BMS are securely transmitted to cloud servers within the cloud BMS over a secured communication line with IoT-based encrypted protocols such as Wi-Fi, Zigbee, and message queuing telemetry transport (MQTT), ensuring privacy and protection from cyber-physical attacks. The cloud BMS enhances data storage capability and computational power, enabling the simultaneous performance of multiple applications while actively monitoring the battery pack's status, thereby achieving robust execution. The proposed cloud BMS platform architecture comprises six critical components:

(1) Cloud storage

The data storage capability and computational power are improved by the cloud BMS, comprising large storage servers with extended storage to realize the scalability of the cloud platform. The data collected by the end and edge BMSs using different sensors are transmitted to the cloud based on various communication protocols, including wired (controller area network (CAN), RS485, or Modbus), wireless (Bluetooth, Zigbee, or proprietary RF solutions), and IoT gateways (Wi-Fi, cellular (3G/4G/5G), or LPWAN, LoRaWAN, NB-IoT). The data are stored by categorizing them into time series, relational, and semi-structured data. Each database is interconnected for use as required by the algorithms. The processing of the data can be performed either in a batch manner or in real-time.

Currently, the industry offers various technologically advanced solutions for establishing cloud storage and data processing. Examples include InfluxDB, Amazon Timestream, and Google Cloud Bigtable, which are optimized for storing time-series data. MySQL and PostgreSQL can be used for relational databases, while MongoDB, DynamoDB, and Azure Cosmos DB can store semi-structured data. For data processing, Apache Hadoop, Spark, and AWS Glue are examples used for batch processing, whereas Apache Kafka, AWS Lambda, and Azure Functions are used for real-time processing. Additional tools for analytics, such as Grafana, Kibana, PowerBI, or Tableau, can also be integrated. Data security for access and usage is a concern when bulk data are stored and used in servers. Role-based access control (RBAC) and fine-grained permissions can be employed for access control, while standards like AES 256 can be used for data encryption at rest and TLS for data transfer. Furthermore, regular security audits and compliance checks can be performed to ensure data integrity and confidentiality, maintaining a high level of organization and security for the cloud infrastructure.

(2) Digital twin

Within a cloud BMS lies the critical component of the IBMS platform – the digital twin. The digital twin although deployed in cloud requires information from the physical entities. This information is made available for usage from the cloud storage or can be collected in real time. The operational process and safety parameters are also communicated along with necessary parameters for operation of the end BMS. As depicted in Fig. 4, multiple parameters and data within and outside the pack are transmitted to the digital twin *via* secured wireless communication. These data from within the pack include sensor and actuator data, operations and processes occurring within the pack, as well as safety parameters of modules and cells.[42] Additionally, data from outside the pack, such as ambient conditions – whether sunny, rainy, windy, or dusty – are incorporated.[43] All these data, both internal and external to the pack, are sent to the digital twin, where data analytics is performed. The analysis helps to reveal information leading to advanced prognosis and diagnosis of the physical pack. Further suggestions for the optimisation of the operation are also possible based on the requirement of the user.

The digital twin serves as the foundation, a crucial component of the intelligent BMS in the cloud server. To model this digital twin, various performance-based models are employed, including EEC models,[44–46] EM models,[47–50] data-driven machine learning models,[51–53] or fusion models.[54,55] Fusion models, which utilize a combination of equivalent cell models, electrochemical and data-driven ML models, are referred to as hybrid models. BMSs have traditionally relied on EEC models, empirical models, or lookup tables to estimate battery states such as SOC and SOH.[56,57] These models are computationally efficient and straightforward to implement[58–65] but often lack accuracy, particularly as batteries age and undergo repeated cycles.[66,67] This limitation has driven the development of more sophisticated, physics-based models that incorporate continuum-level equations to simulate charge and mass transport, enabling a deeper understanding of degradation mechanisms and capacity fade under various operating conditions.[47–50] Such models allow for more precise control and optimization, paving the way for the design of more efficient and durable battery systems.

Electrochemical modeling represents a significant advancement in BMS design, as it offers detailed insight into the complex interactions within a battery.[68,69] These models simulate physicochemical processes, such as SEI-layer formation, stress–strain effects, and material degradation, at different scales.[70,71] While highly accurate, they are computationally intensive and require iterative refinement to balance model complexity and predictive accuracy. Techniques such as reduced-order modelling,[72–77] adaptive solvers,[78–81] and numerical optimization[82–84] have been developed to enhance simulation speed and efficiency. Nevertheless, experimental validation remains crucial, as many internal variables are not directly measurable, requiring parameter estimation through comparison with experimental data.

Despite their advantages, electrochemical models pose unique challenges, including issues related to initialization,[85,86] nonlinearity,[87] and solver robustness.[88–90] The dynamic nature of battery operation introduces steep gradients in key variables like concentration and potential, which can cause solver convergence issues and increase simulation times.[91,92] Furthermore, uncertainties in underlying physicochemical mechanisms, such as capacity fade and lithium loss, limit the accuracy of these models. To address these challenges, adaptive solvers, efficient event detection algorithms, and the integration of molecular and mesoscale simulations with continuum models have been explored. These efforts aim to enable real-time simulation and optimization, making electrochemical models more applicable for advanced BMS design and control.

All these models must adapt based on the specific application requirements. While EEC models accurately estimate

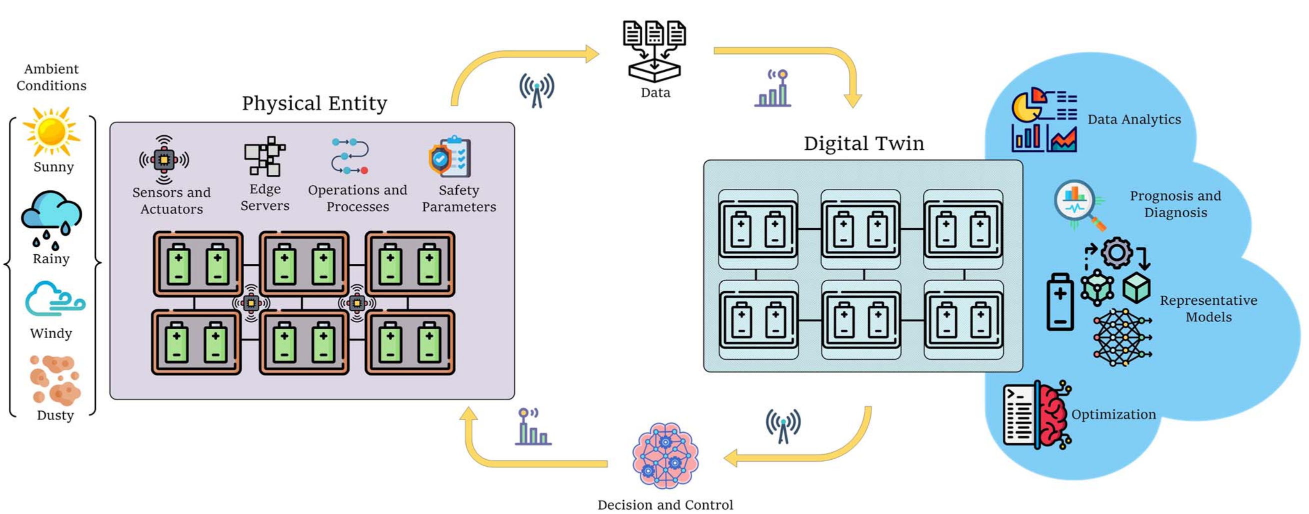

Fig. 4 Battery pack digital twin modeling for a cloud platform to enhance battery diagnosis and prognosis.

parameters like SOC, diffusion, and hysteresis voltages, the intricate electrochemical properties necessitate the use of electrochemical models and fusion techniques. Hybrid models, integrating both data-driven and model-based approaches, are vital for precise diagnosis and prediction.

(3) Analytical toolbox

The analytical toolbox component incorporates data-driven and model-based methods for accurate prediction and prognosis of large-scale battery systems. AI-powered and machine learning techniques, along with big data methods, electrochemical models, and equivalent circuit models, utilize cloud computing tools based on the application.[38] These tools may comprise algorithms and functions responsible for multiple operations across the battery pack. Model based methods are conducted to capture the degradation dynamics that are used to describe the dynamic properties of a battery, such as electrochemical,[93] equivalent circuit,[94] and empirical models.[95] These estimation methods are often implemented by using advanced filtering techniques, such as particle filtering (PF),[96] extended Kalman filtering (EKF),[97,98] sliding mode observer,[99] and Lyapunov-based adaptive observer.[100,101]

Benefitting from the massive historical data and no request of an explicit physical model, data-driven methods have been widely used in the field of battery SOH and RUL dynamics in recent years. These modelling methods are usually conducted by using a large amount of offline data to train and establish nonlinear approximate models between the input and the output features. By extracting features from the monitoring data and mapping them into the degradation model for the SOH, the data-driven prediction approach can describe the inherent degradation relationship and trend of the battery.[102] Data-driven methods such as artificial neural network (ANN),[103,104] support vector machine (SVM),[105–107] and correlation vector machine[108] have been widely used for lithium-ion battery prognostics. Along with prognosis, the identification of fault occurrence during the potential stage with rapid accuracy is of utmost importance. If not addressed, there is a possibility of critical faults leading to thermal runaway and eventually irreparable damage.[109] Over time, uncertainties within a battery pack occur among the cells with respect to charge or voltage, causing imbalances within the pack. Similar minor anomalies cumulatively become major anomalies, leading to bigger faults and potentially catastrophic failure. Advanced data-driven methods, due to their superior non-linear fitting capabilities and lower requirement of domain expertise, are employed for performing anomaly detection techniques in the field of battery packs.[110] Another important aspect of the analytical tool box is to make use of state-of-the-art safety techniques to safeguard the operations occurring within the entire IBMS architecture. The cybersecurity of the entire IBMS is improved by using blockchain technology, managing and encrypting all critical operations, activities, and communications among the nodes of end-edge-cloud platforms, the battery pack, and the user within the blockchain framework, and authenticating the validity of any transaction or communication.[111]

(4) Functions and algorithms

The techniques and computing tools aid in the diagnosis and prognosis of large-scale battery systems, estimating accurate parameters of the battery pack, deciding optimal charging patterns for the vehicle, robust estimation of SOC/SOH/SOP/SOE, effective cell balancing, isolating dead/aged cells from the battery pack, and overall energy management.[112,113] One significant functionality is to utilize historical data of the battery pack, analyze the most frequently occurring failures, and perform root cause analysis to determine the fundamental reason behind the occurrence of that failure. As discussed earlier, model based methods and data-driven methods are widely used in the field of state estimations and prognosis of battery systems. However, model based methods require precise mathematical models. This is very difficult to satisfy in actual industrial processes due to lack of sufficient physical insights into aging dynamics. Similarly, if there is not enough high-quality training data, the data-driven approach will not yield satisfactory results. Considering the aforementioned challenges in both data-driven and model-based approaches, a data-model fusion framework of algorithms can be employed for enhancing prognosis.[114]

The methodology uses data-driven approaches to map the relationship between direct observations and state values of complex systems and predicts the measured values of systems. Currently, widely used fusion data-driven methods can be divided into two categories. One is regression methods. For example, Liu *et al.*[115] and Song *et al.*[116] combined particle filtering with the auto regression (AR) method and proposed a fusion prediction method based on AR and nonlinear degradation AR respectively. Wang[117] studied the AR method and support vector regression (SVR), in order to solve the unreliability of the particle filtering method for long-term prediction, and fused them with particle filtering to provide a fusion prediction method with higher robustness. Zhang *et al.*[118] proposed the combination of relevance vector machines (RVMs) and particle filtering, and proposed a fusion prediction method under the condition of small samples. Another approach is based on neural networks, such as ANNs[119] and adaptive neuro fuzzy (ANF) systems.[114] Huang *et al.*[120] integrated the advantages of deep learning in feature extraction and proposed a fusion prediction method based on bidirectional long short-term memory (BLSTM), which can automatically provide features and fusion. Deng *et al.*[121] adopted gated recurrent units (GRUs) to fuse with particle filtering. Compared with LSTM, GRUs have a simpler structure and fewer parameters, but they exhibit quite a good performance. Cadini *et al.*[122] proposed a fusion prediction method based on multilayer perceptron (MLP) networks and verified it on lithium-ion battery life. Only model based or only data-driven algorithms can be extended to these fusion algorithms to include more degradation, life estimation, and capacity fading estimation processes, making it a robust diagnostic unit.

(5) Advanced Driving Assistance System (ADAS). A conventional ADAS technology ensures the safe operation of vehicles by interacting with and assisting vehicle drivers through a human–machine interface (HMI). Utilizing cameras and sensor information, ADAS detects obstacles or eliminates driver errors in real-time. These ADAS functionalities can be further enhanced

by integrating them with cloud technologies. The data from cloud storage can be utilized by the driving assistance component through the digital twin, along with state-of-the-art techniques from the analytics toolbox, to provide smart support to the user/vehicle driver.[123]

Based on the SOH and previous driving pattern data from the cloud, range estimation is performed, and optimal charging patterns are suggested to the charger. Optimal driving patterns are presented to the user to minimize battery degradation and extend battery life. Smart assistance in booking charging stations nearest the vehicle location is provided to the user. Additionally, features such as collision attenuation, adaptive cruise control, and blind spot monitoring are also offered by the ADAS unit.

(6) Learning and optimization

The significant importance of the digital twin is that it realizes feedback from the algorithms and processes reflecting the physical battery pack, continuously learning and optimizing within the cloud server. This way, our digital twin model gets re-trained in real-time and updated for further improvement.[124] Learning and optimization can also be performed using the already generated data from the components. For instance, the output from the analytics toolbox can be used to optimize the ML models used in digital twins to improve performance and efficiency, such as reducing bias and decreasing error. With usage over time, complex and computationally expensive algorithms can be replaced by simpler ones, such as rule-based algorithms.

Overall, our study proposes the IBMS architecture with several key features designed to enhance battery management and user experience as illustrated in Fig. 5. The intelligent BMS facilitates real-time multilayer communication among the reconfigurable battery pack, smart BMS, user, and charge devices through a multilayered parallel computing architecture. This ensures dynamic battery management. The system employs a hierarchical sensing and processing structure with three layers: end-edge-cloud. Remote sensors within the physical battery pack provide data to local edge processing units for real-time state estimations and safety functions, while cloud-based analytics offer extensive data-driven modeling and predictions. This hierarchical approach, combined with adaptive digital twin modeling techniques that include electrical equivalent circuit models, machine learning models, and fusion models, provides an accurate virtual representation of the physical battery pack's behavior in real-time.

Moreover, the system incorporates a comprehensive analytical toolbox that combines data-driven and model-based methods, AI, machine learning, big data analytics, and blockchain technology to ensure precise predictions, prognostics, and cybersecurity for large-scale battery systems. Intelligent driving assistance is provided through cloud-stored data,

Fig. 5 Key features of the proposed intelligent battery management system (IBMS).

offering optimal charging and driving patterns, range estimation, and features like collision attenuation and blind spot monitoring. This enhances user experience and optimizes battery performance. The intelligent BMS also oversees the dynamic adjustments of modules and cells within a reconfigurable battery pack, enhancing adaptability and overall efficiency.

4 Caveats and complexities

While the shift to advanced end-to-cloud-based technology promises significant advantages, it also introduces a spectrum of complex challenges. These issues span across technical, commercial, and social realms, presenting multifaceted obstacles for adopting and effectively implementing such systems.

4.1 Technical challenges

In a battery pack within an EV, every cell needs to be monitored for issues such as cell-to-cell imbalance, over/under-discharge/charge, over/under-voltage, and internal temperature rise. The critical data from each cell to pack need to be aggregated and analysed for prognostics and fault detection. Furthermore, the aging in the cells in the pack is not even; rather, they are unequal between each cell.[125,126] The current state-of-the-art BMS technology misses a few features, such as ineffectual individual cell and module monitoring in a pack and also locating and/or isolating a dead/aged cell within a battery pack.[127–129] Advanced algorithms and system development, integration and implementation are required to cater to such specific requirements. Considering the computational requirements and cost issues, these wide ranges of requirements cannot be fulfilled by a BMS within the vehicle itself. Furthermore, adding more complex computation can lead to added latency to the real-time responses.

Shifting to a cloud-based BMS presents a significant technical challenge in implementing battery prognosis effectively, as it necessitates sensing every critical parameter from each cell and module within an electric vehicle battery pack. Prognosis often involves analysing various critical parameters and factors such as voltage, current, C-rates, charge–discharge cycles, temperature and capacity degradation, *etc.*[130,131] While battery prognosis includes predicting future battery behavior and identifying faults or degradation mechanisms, it's a complex process that requires advanced electrochemical cell models, data-driven algorithms, and diagnostic techniques.[132,133] Ensuring precise data collection and analysis seamlessly over the cloud platform is essential for reliable prognostic outcomes. Furthermore, implementing battery prognosis on a local BMS poses limitations due to scalability and reliability issues. Local systems may lack the computational power and data storage capacity required to handle the complex algorithms and models necessary for accurate prognosis, making it essential to migrate to a cloud-based BMS.

While focusing on predicting battery life cycles and ensuring safe operation within predefined limits is necessary, understanding degradation phenomena within the pack is significant, which requires advanced electrochemical modeling of batteries within the pack.[134,135] By utilizing state-of-the-art electrochemical models within a cloud platform's digital twin, it becomes possible to understand the intricate degradation processes occurring within the battery over time. Phenomena such as LLI and LAM in positive and negative electrodes, thermal runaway, and other degradation mechanisms are challenging to model accurately within IBMS architecture.[136,137] However, cloud-based solutions offer the computational power and flexibility needed to implement sophisticated degradation modeling, providing deeper insights into battery health and aging processes.

Conventional BMS systems rely on established protocols like CAN, Modbus, I2C, and SPI to facilitate seamless communication with ECUs within vehicles.[138] These protocols ensure cross-compatibility, interoperability, and ease of communication between various components. Additionally, they have substantial libraries and tools for development and debugging, making them widely adopted in the industry. However, for advanced features hosted on cloud platforms, such as advanced battery diagnostics and predictive fault prognosis, wireless secured communication is necessary. Protocols like Zigbee, Bluetooth, and Wi-Fi, along with IoT-based encrypted protocols, ensure privacy and protection against cyber-physical attacks.[138]

Cloud-based solutions offer large computational environments, which is an opportunity. Cloud-based solutions also open another dimension of increasing computational efficiency by using methodologies such as big data and distributed computing. However, a critical aspect of using and integrating cloud-based systems with BMSs lies in the versatility and compatibility of algorithms used for a wide array of battery technologies. Each BMS is tasked with managing battery packs that may vary significantly in terms of chemistry and geometry. Therefore, when these systems are linked to a cloud platform, they require a flexible and adaptable framework. In addition, the scalability for different sizes of battery packs and applications, keeping the performance and reliability intact, is another critical challenge when performing cloud integration to BMSs.

A possible solution is to develop an advanced, versatile, physics-informed machine learning model that blends the relevance of empirical equations based on physics and data-based models.[139,140] Using an integrated approach of physics and data-based models offers the opportunity to perform online calibration of models based on real-time inputs and feedback. In a way, the digital twin of the battery systems can be developed within the cloud in a way that is adaptable and versatile enough to accommodate these diverse battery technologies and use cases. The digital twin has emerged as one of the promising methodologies for safe and reliable electric vehicle operation.[141] It involves developing models that take real-time inputs to monitor, diagnose, and predict the performance and health of the entire battery system within the cloud platform. However, the challenge lies in optimising the digital twin's performance over time by studying the battery pack performance in real-time and upgrading continuously.[124,142]

4.2 Social challenges

The existing landscape of BMSs prioritizes safety and reliability as critical features, but with the introduction of cloud systems, data security will be an additional challenge.[17] However, to support these aspects, there is a pressing need for advancements in encryption, augmented with cybersecurity measures.[143] The amount of data generated to perform real-time monitoring of the battery will be massive, and the vehicles are not equipped with large data storage systems. Hence, transferring the data to a central or distributed cloud infrastructure, which enables complex computations using readily available resources and supports distributed programs and functions, will pose a data security challenge.[144] The massive amounts of data extracted for real-time monitoring that include driving profiles of individuals increases data privacy issues that are not handled appropriately during communication or use within the cloud servers. This demands a robust encryption system and advanced cybersecurity, ensuring the data are handled securely over the cloud architecture.[145,146]

Another critical social challenge in adopting a cloud-based BMS lies in building and maintaining user trust in this advanced technology. It is essential to ensure that these systems are accessible and beneficial across various economic sections, thereby preventing the rise of a new digital divide in transport electrification. Additionally, the environmental impact of the large-scale computational servers required for a cloud-based BMS cannot be overlooked. While essential for handling complex computations and vast data, these servers contribute to a notable carbon footprint due to the high energy consumption.[147] Addressing these challenges is crucial for ensuring the sustainable and justifiable adoption of cloud integrated BMS solutions.

4.3 Commercial challenges

Currently, existing BMSs with basic functionalities cost only 8% of the total battery pack cost. To encourage EV affordability, OEMs aim to maintain this BMS cost at the same level. However, the cost and complexity linked to an end-edge-cloud BMS escalate the overall cost, making it challenging for customers to invest in an EV.

Pursuing sophistication, accuracy, and increased functionality in BMSs involves addressing challenges related to integrating urbane technologies such as cloud platform implementation, effective fault prognosis and diagnosis systems, IoT-based robust encryption, blockchain technology, and reconfigurable battery packs. However, integrating these urbane technologies also adds to the complexity, which in turn increases the cost associated with developing such architectures substantially.[148,149] In addition, some modifications in the vehicle design led to an increase in the overall vehicle and platform costs, accordingly leading to a rise in maintenance costs. Furthermore, operational costs related to cloud services, data management and maintenance are also significant. Considering the market competition, every cloud-service provider needs to introduce continuous innovations and cost reductions to attract customers. The pricing models for these cloud-services can be variable to balance profitability and customer affordability.

Nevertheless, the additional cost can be justified in the long term, as the BMS proves effective in fault prognostics and diagnosis, thereby enhancing the remaining useful life of the batteries. This can significantly reduce the overall maintenance costs of the battery packs and improve system performance. The benefits associated with the proposed BMS for multiple stakeholders are evident. However, the initial investment involved in developing such architectures remains costly. Consequently, countries with lower economies that could not afford such advanced cloud based BMS platforms may not fully realize the associated benefits. These disparities in economic development among nations pose significant challenges to the widespread adoption of IBMS based EV technologies. While some countries with higher incomes are embracing EVs and advanced IBMSs, those with lower per capita incomes struggle to afford such advancements. Factors such as import/export taxes, currency valuation, and limited manufacturing capabilities further contribute to the costliness of EVs in these regions. The persistence of this economic gap could result in a "digital divide" among EV users, where some enjoy the benefits of advanced IBMSs while others lag behind. Additionally, it fosters a sense of social indifference towards EVs, hindering efforts to promote sustainable transportation solutions on a global scale. This could impede the goal of achieving carbon-neutral transportation in such regions.

Overall, the final aspect of an IBMS to be considered is the social imbalance created across continents. The affordability of technology varies in different countries and regions. Although an IBMS will provide advanced outcomes that can help increase safety and longevity, it will demand additional infrastructure for data communication and computation. This additional demand reflects the cost of the technology. Hence, a social technological imbalance will be created across the world, where a few countries will be able to afford it, while others will not find it economically feasible. This imbalance further translates to the promotion and usage of technologies that support sustainability and the overall establishment of a green economy.

5 Discussion

Our proposal integrates a cloud architecture in a structured manner that unifies state-of-the-art technologies and innovative advancements, incorporating software within the cloud platform with diverse programming algorithms for precise battery parameter estimation, such as remaining useful life and SOH. A geographical positioning sensor adds another layer of sophistication, enabling exact determination of the user's vehicle location.

Integrating sensor and control systems, wireless communication, mobile/cellular connectivity, internet interfaces, cloud computing, and various battery technologies into the proposed cloud architecture highlights the necessary infrastructure, promising a more cohesive and efficient BMS. Our proposed IBMS architecture incorporates advanced fault prognosis and diagnosis capabilities, conducting in-depth analyses of frequent faults, their root causes, and subsequent AI-driven solutions. Whether the issue lies in switches within reconfigurable packs, specific cells, or chemical anomalies, the IBMS shall pinpoint, suggest changes, and propose solutions down to the cell level. Blockchain-supported history management for battery swapping services proves helpful in understanding the energy content left in the battery pack and the geographical and usage history (harsher or gentler) of the pack.

The proposed intelligent BMS architecture can ensure intelligent control and monitoring of the large-scale battery system. An IBMS is actively modeled to communicate with the battery pack, charging device, user, and cloud platform. Robust cyber-physical security can be achieved during data transmission and communications between different units within the IBMS by utilizing state-of-the-art IoT devices coupled with secured encrypted communication at both IoT gateways. This entire system is embedded with electronics, software, sensors, and network connectivity, allowing the exchange of a massive volume of data through wired or wireless means. This architecture enables a connected BMS incorporating an accurate monitoring and diagnostic unit and advanced driving assistance unit coupled with machine learning and AI-powered analytics for efficient digital twin technology.

6 Conclusion

The current BMS standards have seen significant technological advancements, with companies employing robust predictive diagnosis, connected platforms, and cloud-based solutions. Our perspective looks beyond the current state of BMS technology and envisions the future trajectory of electric mobility and how the EVs and the associated BMS infrastructure might evolve.

Our proposed IBMS in this smart mobility platform stands out by offering depth and adaptability through digital twin technology. Our proposed end-edge-cloud-based multilayer parallel computing architecture plays a pivotal role, with each layer fulfilling specific vital functions. The IBMS focuses on a reconfigurable battery pack technology that can dynamically adjust the modules and cells within the pack. Moreover, our proposed architecture is characterised by a comprehensive analytical toolbox integrated with a blockchain framework. The proposed architecture ensures safe communication and protects against cyber-attacks and threats that connected systems might face The intelligent driving assistance integrates various communication channels, enabling bidirectional interactions between charger-and-vehicle, vehicle-and-grid, and charging stations and vehicles. This comprehensive communication framework serves as a platform for multiple services, ranging from optimising driving routes through co-optimization with maps, weather services, and traffic conditions to checking the availability of battery charging stations. The navigation system, coupled with an understanding of grid aspects during charging, lays the foundation for an advanced driving assistance system that transcends conventional boundaries.

In this forward-looking perspective, we consider a smart mobility platform which stands out for its integration of key features like adaptive digital twin modeling, intelligent driving assistance, and reconfigurable battery pack control, providing a futuristic and user-centric solution for large-scale battery systems that goes beyond the scope of many existing solutions in the market.

Data availability

No primary research results, software or code have been included and no new data were generated or analysed as part of this review.

Author contributions

Sai Krishna Mulpuri, Bikash Sah, and Praveen Kumar conceptualized the research. Sai Krishna Mulpuri performed data curation, formal analysis, investigation, methodology, resources, software, visualization, writing – original draft, and review & editing. Bikash Sah assisted in the formal analysis, methodology, investigation, software, and visualization processes. Bikash Sah and Praveen Kumar performed supervision, validation, and writing – review & editing.

Conflicts of interest

There are no conflicts to declare.

Abbreviations

ADAS	Advanced driver assistance system
AI	Artificial intelligence
ANN	Artificial neural network
AR	Auto regression
BMS	Battery management system
BLSTM	Bidirectional long short-term memory
CAN	Controller area network
ECU	Electronic control unit
EEC	Electrical equivalent circuit
EKF	Extended kalman filtering
EM	Electrochemical model
GRU	Gated recurrent unit
HMI	Human–machine interface
IBMS	Intelligent BMS
IoT	Internet-of-things
I2C	Inter-integrated circuit
LAM	Loss of active material
LIB	Lithium-ion battery
LLI	Loss of lithium inventory
LoRaWAN	Long range wide area network
LPWAN	Low power wide area networks
ML	Machine learning
MLP	Multilayer perceptron
MQTT	Message queuing telemetry transport
NB-IoT	Narrowband-internet of things
OEM	Original equipment manufacturer
PF	Particle filter
RBAC	Role-based access control

RUL	Remaining useful life
RVM	Relevance vector machine
SOC	State of charge
SOE	State of energy
SOH	State of health
SOP	State of power
SPI	Serial peripheral interface
SVM	Support vector machine
SVR	Support vector regression
ANF	Adaptive neuro fuzzy

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