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Recent Advances and Future Prospects in Digital Twin Technology for Battery Management Systems of Electric Vehicles

Bhushan Chavan[1], Manish Pokharna[2], Sameer Nanivadekar[3], Amol Shinde[4,*]

Abstract

Digital twin technology in battery management systems (BMS) for electric cars (EVs) represents a major development in the automotive industry. Digital twins provide predictive maintenance, modelling, and real-time monitoring by creating virtual copies of real-time monitoring, actual battery systems. This paper describes the functional components, architecture, and design of Digital Twin technology along with how it may be included into BMS. Emphasizing how consistent data flow from sensors improves battery safety and performance, it looks at the benefits of merging and gathering data in real time. The paper emphasizes the use of modern machine learning techniques for predictive maintenance, which may identify any issues early on and resolve them to extend battery life and save money. The report also addresses the prerequisites for high computational needs, robust data integration systems, and data security concerns. By means of case studies and practical results, the paper demonstrates how well Digital Twin technology addresses heat control, battery management, and guarantees of effective energy consumption. The results show that digital twin technology has great power to revolutionize EV BMS and inspire innovation in the electric car sector by means of efficiency. This study reviews existing research status as well as future perspectives for the integration of Digital Twin in BMS for EVs.

Keywords: Digital twin, battery management system, electric vehicles, predictive maintenance, data acquisition

***Author for Correspondence**
Amol Shinde
E-mail: amolshinde01991@gmail.com

[1]Research Scholar, Department of Mechanical Engineering, Pacific Academy of Higher Education and Research University, Udaipur, Rajasthan, India
[2]Professor, Department of Mechanical Engineering, Pacific Academy of Higher Education and Research University, Udaipur, Rajasthan, India
[3]Associate Professor, Department of Information Technology, A.P. Shah Institute of Technology, Thane, Maharashtra, India
[4]Assistant Professor, Department of Mechanical Engineering, A.P. Shah Institute of Technology, Thane, Maharashtra, India

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INTRODUCTION

Advanced lithium-ion battery technologies are in more demand as electric cars (EVs) and renewable energy systems rapidly expand. Reliable, safe, and efficient functioning of modern battery systems depends on advanced battery management systems (BMS) able to precisely monitor and regulate battery performance [1]. Digital twin technology has been a potent technique for improving BMS capabilities in recent years by means of high-fidelity virtual models reflecting practical battery systems, therefore reflecting their capabilities. A digital twin is a virtual model of a real-time monitored, analysable actual item or system that supports optimization. Within the framework of battery management, digital twins combine machine learning, data analytics, and multi-physics modelling to provide a comprehensive understanding of battery states and future behaviour [2]. In EVs and other uses, this technique might dramatically improve battery lifetime, safety, and performance [3]. With an eye on improvements from 2023–2024, this article offers a thorough overview of current breakthroughs in digital twin technology for battery management systems. Important elements include modelling strategies, state estimate methods, predictive maintenance powers, and new trends are under examination. Furthermore covered are possibilities and research initiatives for battery digital twins.

Usually referred to as a Li-ion battery, a lithium-ion battery is a kind of rechargeable battery in which energy is stored via reversible reduction of lithium ions. Based on a titanium disolyte cathode and a lithium aluminium anode, M. Stanley Whittingham invented the first rechargeable lithium-ion battery in the 1970s. He also pioneered the idea of intercalation electrodes. While lithium-ion batteries (LIBs) were first commercially developed for portable electronics, they are now widely used in a wide range of applications, including electric cars, power tools, medical devices, smart watches, drones, satellites, and utility-scale storage[4]. The proper regulation of lithium-ion cell functioning will be provided by BMS. Few studies on improving the battery balance index exist as most present research hotspots are on balance topology. Most studies presume that the BMS will turn on when the voltage or SOC difference between the battery cells exceeds the predefined level and turn off when it falls below it [5]. These assumptions might decide whether a BMS is switched on or off. [6] Consequently, when voltage serves as the index, the eventual equalizing effect is somewhat poor. This method based on the SOC of the battery cell is very interesting as the aim of cell balancing is to have all the battery cells in the battery pack to have the same SOC [7]. Unlike the easily measured voltage of the battery cell, each battery cell in the battery pack must be estimated for SOC. Only by observing variables like voltage, current, and temperature can one ascertain the state of charge (SOC) of a battery cell [4, 8]. It is impossible to believe that reaching a necessary BMS technology, precise battery pack SOC, would be simple [9]. Whereas in the latter a model is utilized to estimate the OCV of the battery cell, in the former fluctuations in voltage and current are used to deduce the SOC of the battery cell [10]. Whereas the former ignores the error resulting from the battery polarization factor, the second depends on the correct SOC of the battery pack [11]. Although model predictive control is among the most innovative control systems ever tried, it is very complex and calls for a lot of time and computer capacity [12]. Actually, a 10-minute or longer balancing period is usually necessary for lithium-ion batteries to be effectively in a constant state [13]. Li-ion batteries' chemistry makes them especially prone to severe drain and overcharging, both of which limit their usable life and cause their destruction, therefore generating safety concerns [14].

LITERATURE REVIEW

The theory of Digital Twin technology, which involves generating a digital clone of a real thing, has acquired substantial popularity across a wide range of businesses [15]. This technology enables real-time monitoring, simulation, and optimization, which leads to increased operational efficiency and lower maintenance costs. In the realm of electric vehicles (EVs), integrating Digital Twin into Battery Management Systems (BMS) presents a good way to enhance battery performance, longevity, and safety [16]. This review shows a growing corpus of studies on the integration of Digital Twin technologies into BMS for EVs [17]. Leading studies show how Digital Twin might allow real-time diagnostics and predictive maintenance, therefore reducing defects before they become major failures [18]. Longer battery life and improved vehicle performance would follow from the Digital Twin models' anticipatory battery deterioration and optimizing of charging techniques [19]. Showed that Digital Twin could sustain ideal temperature levels and stop overheating, therefore helping with thermal management of batteries [20].

Moreover, developments in Internet of Things (IoT) and sensor technologies have greatly raised the feasibility of the Digital Twin use in BMS. These technologies provide smooth connection between physical and digital entities as well as reliable data collecting [21-23]. Stress the need of data quality and integration for the success of Digital Twin models. They provide strong data processing frameworks to ensure the accuracy and reliability of digital reproductions.

Despite the obvious benefits, the research cites many obstacles and limits connected with implementing Digital Twin in BMS for EVs [24]. Data privacy, cybersecurity, and the high processing needs for real-time simulation are widely discussed [25]. Researchers argue for the development of improved encryption techniques and efficient algorithms to address these issues.

BATTERY MANAGEMENT SYSTEMS: CONCEPTS AND FUNCTIONS

Battery Management Systems (BMS) have a significant impact on the performance and safety of electric cars [26]. Basically the brain of the battery pack, a battery management system (BMS) monitors and controls the battery's condition to guarantee best performance, lifetime, and safety [27]. A BMS's primary tasks are to estimate state-of-charge (SoC), monitor state-of-health (SoH), regulate thermals, and balance cells [28]. State-of-charge estimation is crucial since it notifies the user about the remaining battery capacity, similar to a fuel gauge in a conventional vehicle [29]. Range prediction and avoidance of overcharging or deep draining—both of which may affect battery life—depend on accurate SoC estimate. State-of- health monitoring, on the other hand, assesses the battery's capacity to over time distribute and store energy [30]. Tracking traits like capacity fading and internal resistance development helps one to learn about the battery's remaining usable life [31]. Another crucial ability of BMS is thermal management as batteries are very sensitive to temperature variations. Good thermal management systems maintain the battery running within a safe temperature range, therefore reducing overheating and the possibility of thermal runaway—which may cause disastrous failures. Active or passive cooling and heating systems maintaining suitable temperature conditions help to achieve this. Providing constant performance across all of the cells in a battery pack depends on cell balancing. Manufacturing defects and operational considerations may cause variations in the charge states of cells over time. By spreading charge throughout all the cells, a BMS guarantees that each one of them is balanced, so preventing individual cells from overcharging or discharging too deeply, thus damaging the whole battery pack. Overview of digital twin technology for smart electric vehicles is shown in Figure 1.

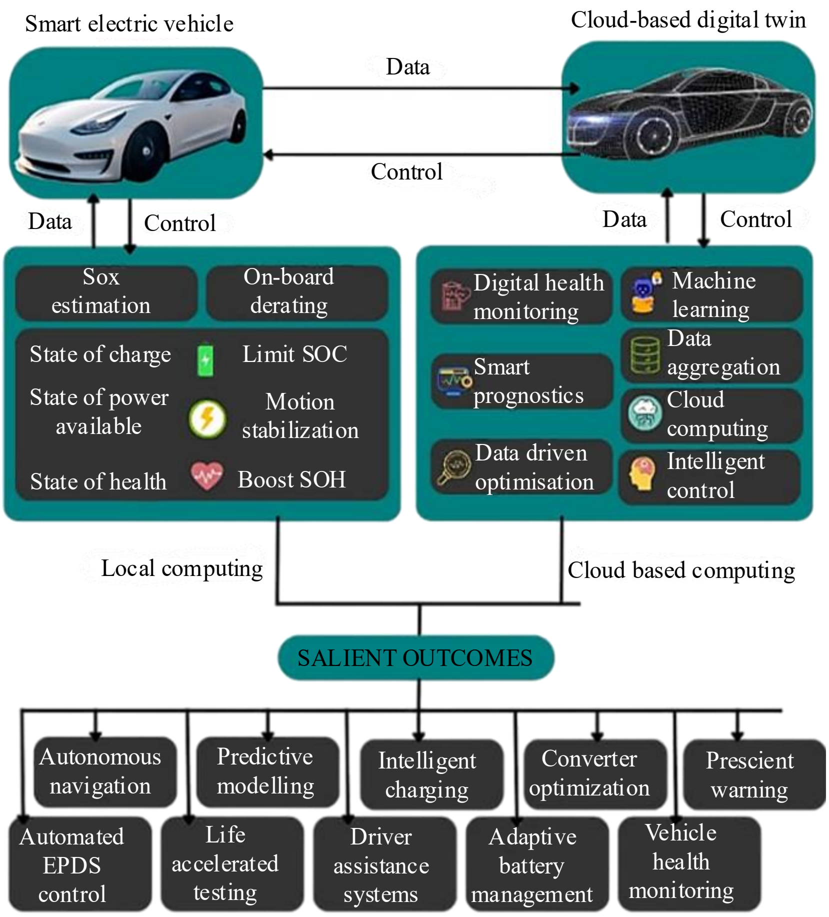

Figure 1. Overview of Digital Twin Technology for Smart Electric Vehicles.

Apart from these basic tasks, contemporary BMS include advanced features such data recording, communication interfaces, and failure detection. These capabilities enable predictive maintenance and quick interventions by means of real-time monitoring and diagnostics. Digital Twin technology is causing BMS to change even more as it adds advanced simulation models to increase predictive capabilities and maximize battery performance in real-time.

IMPLEMENTATION OF DIGITAL TWIN IN BMS FOR EV

Conceptual Framework

In Battery Management Systems (BMS), digital twinning for Electric Vehicles (EVs) is the process of producing a virtual copy of the actual battery system. To provide exact monitoring, management, and optimisation, this digital twin integrates real-time battery system data with potent analytics and predictive modelling [32]. While tuning to changes in the battery's condition over time, the framework is meant to explain dynamic battery behaviours including thermal, electrochemical, and mechanical characteristics. Combining IoT, machine learning, and cloud computing, the digital twin acts as a dynamic, self-learning system bridging the physical and digital spheres and sending actionable data to enhance battery performance and safety [33]. To build a digital twin required framework is shown in Figure 2.

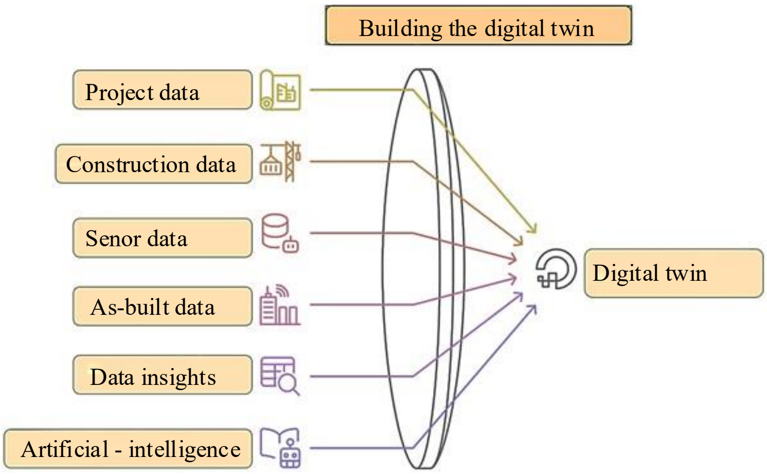

Figure 2. Framework of the Digital Twin.

Architecture and Design

Designing a Digital Twin for Battery Management Systems (BMS) in Electric Vehicles (EVs) means seamlessly integrating the digital equivalent of the physical battery system [34]. Several key components working together provide powerful analytics, precise data representation, and real-time synchronisation in the architecture [35]. The main component of the design is the physical layer, which comprises the data collecting devices, sensors, and battery pack. These sensors continually track critical parameters like voltage, current, temperature, and state of charge (SoC) [15]. Sent to the digital twin via communication connections, the acquired data forms the foundation of the virtual model [36]. Included on the digital layer are computational models and algorithms that replicate the characteristics and behaviour of the actual battery system. These include models for heat control, cell balance, state-of-health (SoH) monitoring, and SoC estimation. Sophisticated machine-learning algorithms examine both historical and current data to enable predictive maintenance and anomaly identification. The digital twin architecture depends critically on the layer of data integration and processing. Combining data from many sources, ensuring data quality, and facilitating seamless connection between digital and physical things fall to this layer. High-performance computing resources satisfy the computational needs of real-time simulation and analysis [37].

The user interface and visual layer provide a comprehensive awareness of the status and capability of the battery system. Part of this layer are dashboards, visualisation tools, and reporting systems providing stakeholders with actionable information. Users of this interface may interact with the digital twin, conducting simulations, retrieve past data, and arrive at well-informed decisions. When creating the digital twin, two very important considerations are capacity and adaptability. The design should help future advancements in analytical algorithms, data processing capability, and sensor technologies [38]. This ensures that the digital twin may grow in concert with the physical system, regularly raising its predictive and optimising capability. Figure 3 shows the six-layer architecture of the digital twin.

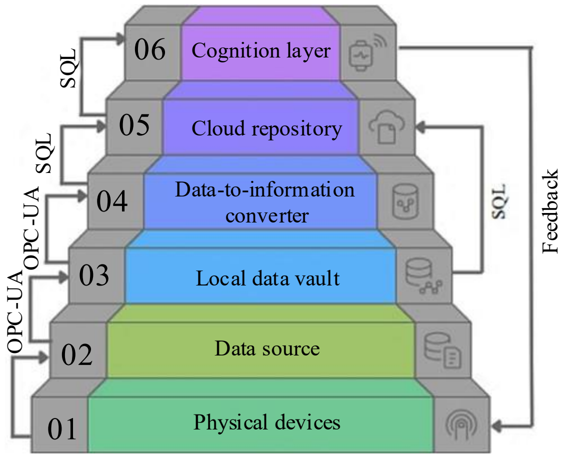

Figure 3. The six-layer architecture of digital twin.

Data Acquisition and Integration

These techniques provide real-time information for enhanced reliability and performance and ensure that the digital twin accurately replicates the real battery system. Data collecting—the process of compiling data from many sensors included within the battery pack—is High frequencies allow these sensors to track essential characteristics like temperature, voltage, current, and state-of-charge (SoC). The cornerstone of the simulations and analyses of the digital twin is this data, so its quality and accuracy are very important. Accurate and continuous data collecting made possible by IoT (Internet of Things) devices and advanced sensors guarantees that even small changes in the status of the battery are noted. This data has to be delivered straight to the digital twin after being gathered. This requires strong communication interfaces and protocols for seamless data flow between the digital and physical entities. Wireless connection technologies like 5G and edge computing provide fast and consistent data transfer, therefore reducing latency and ensuring that the digital twin operates with the most current data.

Data integration is the method of aggregating and organising data from many sources to generate a coherent and large dataset. This means, in the framework of Digital Twin for BMS, combining sensor data with additional data like consumption patterns, ambient variables, and prior performance data. This vast and diverse volume of data is managed using advanced data processing systems and algorithms. Important for performance improvement and predictive maintenance, patterns and trends can also helped to be discovered by these approaches. Data integration depends critically on maintaining data security and privacy. The sensitive nature of the data involved calls for robust encryption methods and cyber-security policies to prevent illegal access and data breaches. Maintaining the reliability of the digital twin system calls on safeguarding the integrity and confidentiality of the data.

Predictive Maintenance & Failure Prevention

Digital twins provide great potential to enhance predictive maintenance and battery system problem diagnostics [39]. Make use of a digital twin BMS to deliver a cloud-based platform for real-time lithium-ion battery performance monitoring and analysis. Their technology combines advanced data processing and analytics methods to address sensor faults and enhance battery performance prediction. We propose an artificial intelligence-powered digital twin approach for smart lithium-ion battery monitoring in electric vehicles [40]. Their solution mixes a time-series generative adversarial network (TS-GAN) with physical offline modelling and long short-term memory (LSTM) algorithms for SOC predictions to increase predictive skills by means of synthetic data.

PROSPECTS FOR THE FUTURE AND RESEARCH DIRECTION

Enhanced Simulation and Modelling

Future research on battery digital twins most likely will focus on developing more exact and computationally efficient modelling techniques. Hybrid modelling approaches combining data-driven and physics-based methods may be utilised to represent intricate battery behaviour under a range of running conditions. Thanks to advances in multi-scale and multi-physics modelling, digital twins might also be able to provide more complete insights on battery performance at the cell, module, and pack levels.

Advanced Integration of AI and Machine Learning

There are many chances to enhance battery management through the use of digital twins in conjunction with cutting-edge machine learning and artificial intelligence techniques [41, 42]. To improve charging techniques and prolong battery life, future studies might investigate the application of reinforcement learning algorithms [43]. Furthermore, the predictive maintenance capabilities of battery digital twins may be improved by the creation of increasingly complex anomaly detection and fault diagnosis algorithms.

Optimisation and Control in Real-Time

As digital twin technology advances, real-time optimisation and management of battery systems might becoming more deeply entwined [44]. This might include dynamically changing operational settings depending on predictions from digital twins [45] to maximize performance and lower deterioration. Research into edge computing and distributed digital twin architectures might provide faster response times and more efficient battery data processing.

Interoperability and Standardisation

Standardization and interoperability problems should be the main emphasis of future research to enable the use of digital twin technology in battery management systems more generally. Create common data formats, communication protocols, and modelling frameworks that allow digital twins across many battery kinds and applications to be smoothly integrated. Industry standards for battery digital twins might inspire invention and improve system interoperability.

Security and Privacy Considerations

Dealing with security and privacy issues will become vital as battery digital twins are increasingly linked and data-driven. Future studies should look at strong cyber-security policies to protect private battery information and stop illegal access to digital twin systems. Additionally, investigating privacy-preserving techniques for data sharing and collaborative learning could enable more effective fleet-wide battery management while protecting individual user information.

APPLICATION OF DIGITAL TWINNING IN VARIOUS TECHNOLOGY

Many diverse sectors employ battery banks, which are monitored and controlled by battery management systems (BMS). Since most Lithium-Ion (Li-Ion) batteries represent the great majority of energy storage solutions, BMS is the indispensable tool in terms of security and functionality [46].

Electric automobiles, trucks, off-road vehicles like golf carts, and electric-powered machinery like forklifts are all considered electric vehicles. Usually, the Control Area Network (CAN) is used by the bus, car, and forklift battery banks to communicate with the battery control module. To protect against grid power fluctuations and supply backup power, battery banks are utilised in the grid power infrastructure. A/C power substations, cell phone towers, and Applications consist of distributed energy resources, tower communications, weather stations, internet infrastructure tools, and aviation ground support systems, to mention just a few. The latter use, which encompasses wind and solar power plants, is a substantial industry unto itself [47].

CHALLENGES IN BMS

A critical examination of studies indicates that BMSs are still in their infancy. Even with state-of-the-art algorithms, end users' suspicions about their dependability will remain and monitoring methods were developed and applied to EVs[48, 49]. Because it is more difficult to monitor each cell in a battery pack, BMSs only concentrate on the entire battery pack rather than individual cells, which leads to the entire battery pack's degradation because of the cells' uneven charge [50]. In addition, bridging the gap between laboratory testing and real requirements should be the main goal of future research. In operational scenarios like the vibration from uneven roads and temperature extremes from snow, rain, or summer heat, the effectiveness of BMSs has hardly ever been studied [51, 52].

CONCLUSION

Digital twin technology for electric car battery management systems has a wide range of applications in the future and a great deal of room for innovation. The absence of improvements since 2020 must be addressed in order to utilize this technology effectively. Integrating artificial intelligence and machine learning should be a top priority for future research to improve real-time decision-making and forecast accuracy. Battery performance will be further optimised and lifespan will be increased by creating sophisticated simulation models and real-time data analytics. Establishing accepted procedures and ensuring interoperability would also call for motivating collaboration among regulatory authorities, corporate entities, and academic institutions. Through addressing these challenges and making investments in modern solutions, digital twin technology has the ability to revolutionise battery management systems and open the way for effective and sustainable electric cars.

Future Scope

Definitely a lot of space for future growth and creativity in the context of digital twin technologies for electric car battery management systems. Realizing this promise depends on tackling the stop in technological development since 2020. Future research should focus mostly on the acceptance of innovative technologies such as artificial intelligence and machine learning, which may increase the predictive capacity and accuracy of real-time decision-making of digital twins. Strong simulation models and real-time data analytics should be created to maximize battery performance, extend battery lifetime, and raise general efficiency. Moreover, industry players, educational institutions, and regulatory authorities have to cooperate to create uniform procedures and assure interoperability. Future research may also look at how digital twins may ease their integration into electric automobiles and help to create solid-state batteries and other next-generation battery technologies.

Researchers can expedite the testing and validation procedures for novel battery chemistries and designs by utilising the insights offered by digital twins. Long-term environmental and financial gains will also depend on adopting a comprehensive strategy that takes sustainability factors like battery recycling and second-life applications into account. In conclusion, digital twin technology can transform battery management systems by tackling present issues and funding creative fixes, opening the door for the long-term expansion and broad use of electric cars.

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