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Digital twin technology in electric and self-navigating vehicles: Readiness, convergence, and future directions

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ABSTRACT

Digital Twin (DT) technology, which creates digital replicas of physical systems, significantly enhances the lifecycle of complex items, systems, and processes. It is especially important in the automotive industry for improving the design, construction, and operation of Electric Vehicles (EVs). Digital Twins make EVs safer, more comfortable, and more enjoyable to drive, thereby enhancing user experience. As mobility systems evolve to become more intelligent and eco-friendlier, electric and self-navigating vehicles are increasingly replacing internal combustion engine vehicles by leveraging technologies such as IoT, Big Data, AI, ML, and 5G. Significant contribution of transportation to global CO2 emissions underscores the need for sustainable practices. Smart EVs, capable of significantly reducing emissions, require innovative architectures like DTs for optimal performance. The advancement of data analytics and IoT has accelerated the adoption of DTs to increase the efficiency of system design, construction, and operation. EV batteries, being the most expensive components, necessitate thorough analysis for State of Charge (SoC) and State of Health (SoH). This review examines the application of DT technology in Intelligent Transportation Systems (ITS), addressing challenges with particular attention on issues regarding monitoring, tracking, battery and charge administration, communication, assurance, and safety. It also explores current trends in EV energy storage technologies and the crucial role of Digital Twins in optimizing battery systems. This technology enables comprehensive digital lifecycle analysis, enhancing battery management efficiency through optimal models for SoC and SoH assessments. Additionally, this review provides insights into various models, future challenges, and discusses DTs for EV battery systems, highlighting case studies, characteristics, and technological opportunities.

1. Introduction

The electric vehicle (EV) industry is currently transforming the transportation manufacturing sector. Many features and services in EVs are powered by advanced smart technologies. In contrast to traditional internal combustion engine vehicles, which rely on fossil fuels and emit harmful gases such as hydrocarbons and carbon oxides, EVs offer a more sustainable solution. Recent advancements in EV technology aim to address these environmental concerns. Numerous industries are integrating Internet of Things (IoT) technologies to enhance the intelligence and efficiency of electromobility. Vehicles are increasingly becoming smart devices by using sensors that form the backbone of IoT networks. These sensors, which monitor everything from charging to engine performance and internal components, generate valuable data that can transform EV management systems. The collected data must be synchronized, analyzed, and processed to improve the quality of EV services and aid in decision-making. While physical sensors have advanced considerably, challenges persist, leading researchers to explore the potential of virtual sensors (VS) in electromobility. VSs can assess vehicle behavior, predict battery state of charge (SoC), and track charging point availability [1–10].

Improving the electric vehicle (EV) user experience relies on three key elements: physical components, virtual models, and the data these models produce. To effectively integrate these aspects, a simulation framework is required that can model large-scale traffic scenarios. This framework is crucial for the efficient and safe management of charging infrastructure, the growing number of EVs, and the dynamic operations within the EV network [11]. Simulation platforms help replicate the

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components of the EV ecosystem and their interactions, enabling a better understanding of each stage of the physical product and its characteristics, which supports the development process. Many of these platforms use the concept of a digital twin (DT), a virtual representation of a real-world object, allowing for the analysis of physical object development in a digital environment [12]. By 2019, the DT concept had been recognized as one of the ten most strategic innovations globally, fostering advancements in autonomous technologies like self-driving vehicles and immersive systems such as virtual reality (VR), augmented reality (AR), and quantum computing [13]. The core idea behind this technology is to replicate the behavior of physical objects in a virtual space, generating outputs that closely mirror those of their real-world counterparts [14].

The Digital Twin (DT) concept offers substantial benefits to both industrial and academic sectors. By utilizing digital data, DT enhances engineering system intelligence, enabling advanced analytics, predictive diagnostics, and performance optimization. These insights can then be applied to improve efficiency in physical products or processes. Academically, Grieves et al. introduced the DT concept in 2002 at a product lifecycle management summit at the University of Michigan Lurie Engineering Center. The first practical application of DT technology was by Tuegel et al. who developed a digital framework replicating the structural behavior of aircraft [15]. Today, DT technology is widely employed across various industries to streamline maintenance operations and predict failures, enabling seamless human-machine interaction. DT applications span fields such as transportation, manufacturing, healthcare, business, and education, with mechanical, electrical, and computer systems being simulated in virtual environments. In EVs, for instance, DT technology facilitates continuous performance optimization, enhancing efficiency, intelligence, and effectiveness.

DT technology is characterized as a comprehensive, integrated simulation that encompasses multiple physics, scales, and probabilistic factors of a complex product. It replicates the entire lifecycle of its physical counterpart, providing a detailed digital representation of real-world entities. Unlike Internet of Things (IoT) or Computer-Aided Design (CAD) systems, DT technology focuses on the bilateral connection between virtual and physical systems, enabling real-time adaptation and precise replication of physical conditions [16]. The integration of Big Data analytics, IoT, and Artificial Intelligence (AI) with DT technology unlocks new opportunities, poses unique challenges, and highlights its significance. The development of intelligent DT models relies on advanced AI techniques for in-depth data analysis [17]. These fusion addresses critical manufacturing challenges such as improving process stability, diagnosing faults, reducing downtime, and optimizing logistics. AI further enhances DT technology by transforming raw data into valuable insights through analytical models. In EVs, machine learning (ML) algorithms are increasingly used, and their effectiveness is boosted when combined with predictive testing tools and DT technology [18]. DT also plays a vital role in security and monitoring systems. For instance, Lu et al. introduced an anomaly detection system using DT technology for asset monitoring, tested in a case study on HVAC systems, demonstrating its efficiency in building asset management.

To achieve a true cyber–physical system, DT must dynamically connect with physical models using real-time sensory data. This technology is particularly crucial in the automotive sector, especially for electric vehicles, as it enhances vehicle design, construction, and operation. EVs benefit from DT technology by improving user experiences, making driving safer and more comfortable, and reducing emissions to help mitigate climate change. Different types of EVs are battery EVs, plug-in hybrids, hybrids, extended-range EVs, and fuel cell EVs that have experienced significant progress, driven by IoT, Big Data, AI, ML, and 5G technologies. These innovations are transforming EVs into smart devices, with sensors monitoring and optimizing various components. While physical sensors have limitations, virtual sensors (VS) can analyze, predict, and estimate vehicle behavior, battery state of charge (SoC), and charge point availability [19,20]. DT technology enables the digital replication of physical processes and products, allowing simulations that enhance the original system. Although not necessary for every product, DT is particularly valuable in niche sectors with complex items. The expanding DT market reflects its growing industrial use, providing realistic digital models that improve understanding, design, simulation, and optimization of physical objects. This, in turn, enhances decision-making in EV management systems by predicting behavioral patterns and improving overall system performance.

1.1. Digital twin in EVs

EVs have become a vital solution for combating climate change and enhancing quality of life. Their growing popularity over the past decade is driven by their high operational efficiency, zero emissions, and economic advantages. There are several types of EVs, such as Battery EVs, Plug-in Hybrid EVs, Hybrid EVs, Extended-Range EVs, and Fuel Cell EVs, each utilizing distinct propulsion methods and energy sources. One of the major challenges in EV development is improving battery performance, capacity, and affordability, which continues to be a primary focus of research. Digital Twin technology plays a pivotal role in the development and optimization of EVs, offering innovative ways to enhance performance and address these challenges. The following sections will provide an in-depth exploration of the various aspects of this integration.

1.2. Evolution and application of DT technology

Since its introduction in 2003, the concept of the DT has evolved and found applications across various industries. A DT is defined as a digital representation of an active, unique product or product-service system, capturing its characteristics, conditions, and behaviors through models, data, and information across all phases of its life cycle. In the realm of energy storage systems (ESSs) and electric vehicles (EVs), DTs have proven valuable in enhancing the design, construction, and operation of these systems. One notable advancement is the development of Battery Management Systems (BMS) that leverage DT technology for diagnostics related to the state-of-charge (SOC) and state-of-health (SOH) of batteries. This highlights the powerful integration of data, artificial intelligence (AI), and DTs in optimizing system performance.

1.3. Challenges and technological advances in EVs

Battery performance, including bulk, weight, charging time, and driving range, poses significant challenges for EVs. Current research and development efforts are centered on improving battery models, which are essential for understanding and optimizing EV performance. Electrochemical, electrical, and mathematical models offer various approaches to simulate battery behavior, each with distinct advantages and limitations. The integration of Digital Twin technology with these models presents an innovative solution to enhance EV performance by enabling real-time monitoring and optimization of battery systems.

1.4. Smart electric vehicles and digital twin integration

The integration of IoT, AI, and ML technologies with DT models is transforming the EV industry. Sensors embedded in EVs generate vast amounts of data, which, when processed and analyzed, can significantly improve vehicle performance and user experience. Virtual Sensors (VS) complement physical sensors, providing predictive analysis and behavioral estimations that enhance EV management systems. Simulation frameworks incorporating DT concepts are essential for managing large-scale EV networks, optimizing the distribution of charging points, and ensuring safe and efficient operations [21–24].

1.5. Broader implications and future directions

The widespread use of DT technology extends beyond the electric vehicle market, offering substantial benefits across various sectors, including Production, medical care, and mobility. In production., DTs improve process stability, fault diagnosis, and logistics optimization. In healthcare, they enable predictive maintenance and operational efficiency of medical devices. The ongoing development of DT technology, combined with advancements in AI and ML, holds the potential to revolutionize these industries further, enhancing their intelligence, efficiency, and sustainability [25,26].

Finally, DT technology represents a transformational approach in several industries, particularly in the context of EVs and energy storage systems. By enabling real-time monitoring, predictive analysis, and optimization, DTs address significant challenges in battery performance and EV management. As innovation develops further, its integration with AI, ML, and IoT will further enhance its capabilities, driving innovations and improvements across multiple sectors. The future application of robust, data-driven DT models promises to significantly advance the performance and sustainability of EVs and other critical systems.

1.6. Publication searching and screening procedure

To ensure a thorough review of relevant research, a well-structured approach was employed:

- *Search Databases:* Extensive searches were carried out using platforms such as IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar.
- *Keywords:* Key terms included “Digital Twin Technology”, “Electric Vehicles”, “Battery Management Systems”, “Energy Storage”, and “Autonomous Vehicles”.
- *Selection Criteria:* The focus was on peer-reviewed studies published in the past decade that specifically explored the application of Digital Twin technology in electric or autonomous vehicles. Papers without empirical data or unrelated to the topic were excluded.
- *Screening Process:* Titles and abstracts were initially reviewed, followed by an in-depth evaluation of the full text for relevance and quality.

1.7. Publication analysis

The selected studies revealed important trends and areas of focus:

- *Research Distribution:* Out of 92 studies reviewed, 45% concentrated on battery management systems, 30% on predictive maintenance, and 25% on smart transportation systems.
- *Technological Emphasis:* Significant attention was given to integrating IoT and AI into Digital Twin frameworks to enable real-time analytics and decision-making.
- *Regional Trends:* Research activity was predominantly concentrated in North America, Europe, and East Asia, showcasing these regions as innovation leaders in EV technology.
- *Performance Metrics:* Several studies highlighted enhancements in energy efficiency, predictive diagnostics, and lifecycle cost savings through the implementation of Digital Twin applications.

1.8. Knowledge gaps and challenges

Despite the progress, several critical gaps in the literature were identified:

- *Scalability and Deployment:* There is limited research on the large-scale implementation of Digital Twin technology in real-world electric vehicle ecosystems.
- *Cybersecurity:* The potential vulnerabilities in data exchange within Digital Twin systems remain underexplored.
- *Integration Standards:* A clear, standardized framework for incorporating Digital Twin technology into existing vehicle and industrial systems is lacking.
- *Sustainability Considerations:* Few studies address how Digital Twins can be leveraged to optimize resources and minimize environmental impacts.

1.9. Research perspectives

To address these gaps, future research should prioritize:

- *Enhanced Battery Digital Twins:* Developing sophisticated models for monitoring battery health, managing thermal performance, and enabling second-life applications.
- *AI-Driven Analytics:* Creating advanced predictive algorithms for real-time diagnostics and optimization.
- *Standardization Efforts:* Establishing universal frameworks to ensure compatibility and seamless integration of Digital Twin technologies across diverse platforms.
- *Sustainability Integration:* Exploring how Digital Twins can improve energy efficiency and reduce ecological footprints.
- *Data Security:* Implementing robust cybersecurity measures to protect the integrity of interconnected Digital Twin environments.

This paper is structured into several key sections. Firstly, Section 2 delves into the application of DT technology in transportation systems, highlighting its modus operandi and showcasing case studies within the various sectors. Following this, Section 3 analyses the key technologies integral to DT implementation in electromobility, focusing on the interplay between physical and virtual entities through architectures. Section 4 provides a comprehensive overview of battery modeling frameworks with their respective advantages and drawbacks. Section 5 addresses current designs and challenges in EV batteries, particularly in Energy Storage Systems (ESS), offering insights into scientific contributions related to various battery types for EVs and discussing potential DT solutions for these challenges. Finally, the paper concludes with a discussion of outcomes and future directions, emphasizing the need for continued research and development in the evolving field of DT technology within the automotive and electromobility domains.

2. Category, process functions and domain applications of digital twins

DT technology spans a wide array of applications and has already made significant strides in various technological fields. As it continues to evolve, its influence is expected to grow across even more sectors. This makes the Digital Twin concept increasingly vital for numerous business industries. To more thoroughly understand and comprehend how DT technology works, it can be categorized by its potential applications and relevant process functions. This classification highlights its diverse uses and the growing importance of Digital Twin in modern business practices [27–29].

2.1. Category

DTs are categorized as three types depending upon the nature of the applications namely product twins, process twins and systems twins. Before establishing the real production line, product twins construct a virtual prototype of an item. This allows for testing its performance under different conditions and identifying possible malfunctions. Consequently, any needed adjustments can be made to achieve an optimized design. Process twins are digital replicas that simulate the performance and outcomes of processes under various conditions. By developing these virtual models for each piece of equipment, it becomes possible to optimize production planning and predict potential issues, thereby

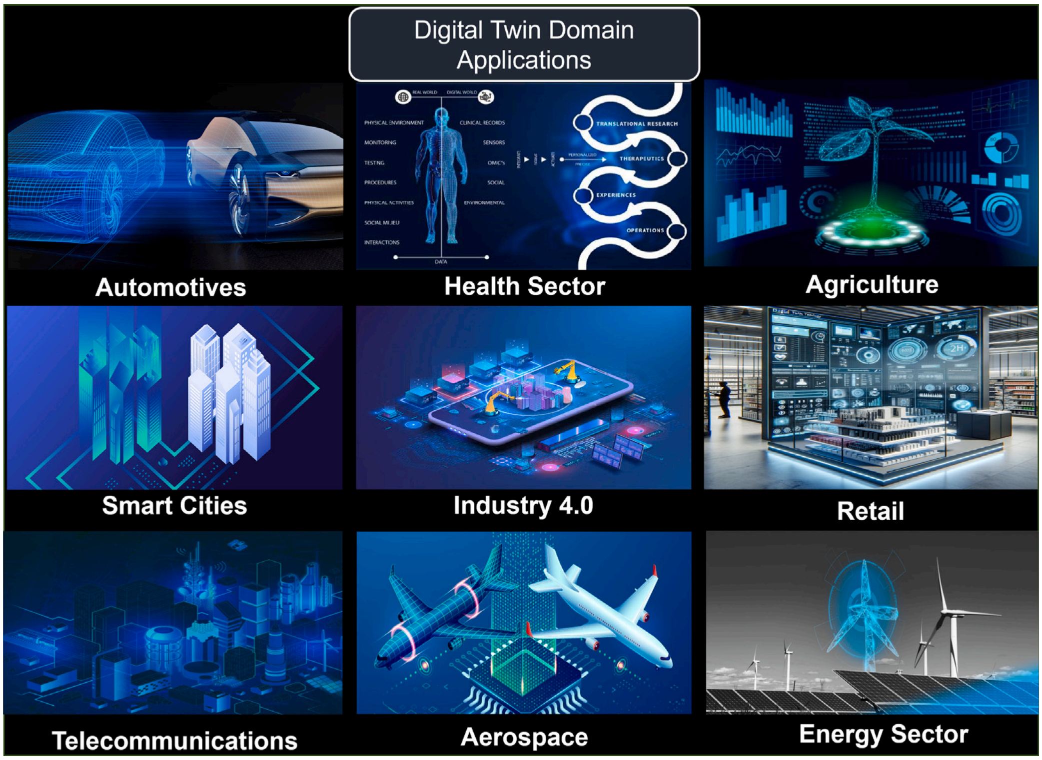

Fig. 1. Digital Twins Domain Applications.

enhancing overall efficiency and productivity. System twins are digital counterparts of actual integrated systems. They collect extensive systemic data produced by these systems, which allows for the extraction of valuable insights [30]. This data can be utilized to refine processes and boost the overall performance of the broader system [31].

2.2. Process functions

Digital Twins process functions are design, Diagnostics, prediction and maintenance. Design involves the use of visualization techniques to evaluate and inspect the complete 3D assembly of a product. These processes help ensure that all components fit together correctly and meet the intended specifications, allowing for verification and refinement before final production. Diagnostics encompass the use of simulations paired with sensor data to evaluate aspects of a product that are otherwise difficult to measure directly. By examining the simulations and sensor data, it becomes feasible to evaluate factors such as the forces and stresses acting on various components of the product. Prediction relies on the combination of engineering methods and advanced deep learning algorithms to provide accurate and timely forecasts. This approach is crucial for extending the operational life of machinery or equipment. Furthermore, the continuous availability of real-time data supports the development of strategic maintenance plans. These plans are designed to effectively reduce the risk of unplanned operational disruptions by ensuring that potential issues are addressed proactively. Maintenance involves examining performance data gathered over specified time periods and under different operating conditions. By analyzing this data collectively, users can obtain essential insights needed to make informed decisions about the necessary maintenance actions. This comprehensive analysis helps ensure that maintenance activities are both appropriate and effective.

2.3. Domain applications

The DTs are utilized in automotives, health sector, smart cities, industry 4.0, agriculture, retail, energy sector, aerospace and telecommunications given in Fig. 1.

2.4. Automotives

These tools are essential not only in the design of new automotive products but also throughout the entire production process. During the design phase, they help refine and optimize the vehicle's features. Once manufacturing is complete, these tools continue to be valuable by analyzing specific performance patterns and functional details of the vehicle. This analysis supports efforts to enhance the vehicle's performance and ensure it meets desired standards [32,33].

- *Vehicle Testing and Design:* DTs make it possible to simulate how a car would behave in a variety of scenarios, which helps with safety testing and design improvement. With the use of this technology, engineers can assess and improve car systems and parts virtually, producing designs that are safer and more effective [34,35].
- *Fleet Management:* Digital twins are essential for route optimization, charging session scheduling, and maintenance demand prediction for electric and self-navigating. This guarantees fleets run smoothly, cutting downtime and raising overall effectiveness [11].

2.4.1. Health sector

DTs are transforming the field by improving clinical practices and hospital administration. This is achieved through digital monitoring and sophisticated modeling of human body systems. These advanced tools offer significant benefits to researchers, facilitating the investigation of different diseases, the development of new drug formulations, and the innovation of medical devices [36–39].

- *Personalized medicine:* DTs of individual patients allow for more accurate simulations of how different treatments will affect them. By leveraging this technology, healthcare providers can tailor treatment plans to the unique needs of each patient, enabling more personalized and effective care [40].

- *Medical Device Testing:* By testing medical devices virtually using digital twins, development times are sped up and hazards related to in-person trials are minimized. With this method, devices are made sure to be fully assessed and optimized before being employed in practical applications [41,42].

2.4.2. Smart cities and building design

In smart cities, the integration of DTs with the Internet of Things (IoT) enhances the overall design and functionality of urban environments. This synergy helps optimize financial metrics, improve resource management, and minimize the environmental footprint of residents. Through these technologies, cities can operate more efficiently and sustainably [43–45].

- *Urban Planning:* Digital twins can help with strategic planning and development by modeling the needs for infrastructure and urban expansion. City planners can make well-informed judgments to control urbanization and resource allocation by simulating various growth scenarios.
- *Traffic Management:* DTs enhance traffic management by simulating various strategies to optimize flow and reduce congestion. With the use of this technology, various strategies may be tested in a virtual setting, resulting in more effective and seamless transportation systems [46].
- *Utility Management:* By using DTs, cities can track and optimize the consumption of resources such as water and energy. This guarantees the effective use of resources, cutting down on waste and enhancing the administration of urban services as a whole [47].
- *Building Design:* In order to enhance design, digital twins mimic building performance by evaluating elements like structural integrity and energy efficiency. This allows architects and engineers to identify and address potential issues early, resulting in the development of more resilient and sustainable buildings [48].
- *Facility Management:* Predicting maintenance requirements and optimizing facility management are made possible by using digital twins to monitor building systems. Through the ongoing analysis of data from several building systems, DTs guarantee prompt maintenance and efficient operation, which lowers operating costs and improves occupant comfort [49].

2.4.3. Industry 4.0 and manufacturing

DTs play a crucial role in streamlining industrial operations by enabling effective monitoring, coordination, and management of production systems. Their primary purpose is to minimize errors and shorten the time required for production and delivery, thereby enhancing overall efficiency and reliability in manufacturing processes [50–53].

- *Predictive Maintenance:* DTs can predict equipment failures in advance, enabling a proactive approach that significantly lowers maintenance costs and minimizes downtime. Predicting failures allows maintenance to be planned during convenient times, preventing unanticipated production disruptions [54–58].
- *Process Optimization:* By simulating multiple production scenarios, digital twins make it easier to identify the manufacturing procedures that are most efficient. This feature helps manufacturers identify the most effective procedures and practices for their operations, which helps them improve productivity, decrease waste, and optimize workflows [59–63].
- *Quality Control:* Digital twins allow for timely modifications and uniformity by monitoring product quality in real-time. DTs assist maintain high standards and promptly rectify any deviations by continuously monitoring and analyzing quality factors. This helps guarantee that products match the necessary specifications [64].

2.4.4. Agriculture

DTs are employed to oversee land resources by deploying a range of tools and sensors that track factors such as water levels, temperature, and humidity. This monitoring is essential for protecting crops, optimizing yields, and minimizing potential failures, ultimately contributing to increased profitability and more efficient farming practices [65–67].

- *Precision farming:* By modeling crop growth and identifying the ideal planting and harvesting periods, digital twins optimize agricultural techniques. By leveraging this technology, farmers can make data-driven decisions to boost crop yields, enhance resource efficiency, and operate more profitable and sustainable farming practices [68–70].
- *Resource Management:* Sustainability is ensured by tracking and controlling the usage of resources like water and fertilizers using digital twins. DTs help farmers use resources more wisely, cutting waste and lowering the environmental effect of agricultural operations by offering real-time data and predictive analytics [71–73].

2.4.5. Aerospace

- *Aircraft Design:* By simulating systems and parts of an aircraft under varied circumstances, digital twins improve the aircraft's safety and design. Before physical manufacturing, engineers can find possible problems and make the required adjustments by virtually testing various scenarios [74].
- *Upkeep and Repair:* By predicting when parts will require servicing or replacement, predictive maintenance with digital twins minimizes downtime. By taking a proactive stance, maintenance is carried out effectively, prolonging the lifespan of aircraft components and averting unplanned failures [75,76].

2.4.6. Energy sector

- *Power Grid Management:* DTs monitor and enhance power grid performance, enabling the efficient integration of renewable energy sources. By managing supply and demand, this technology maximizes the use of sustainable energy while ensuring a stable and reliable power supply [67,77].
- *Oil and Gas:* The oil and gas industry utilizes DTs to simulate drilling processes and monitor equipment health, helping to minimize downtime and enhance productivity. DTs assist in preserving optimal performance and lowering the possibility of expensive downtimes by offering real-time data and predictive analytics.

2.4.7. Retail

- *Supply Chain Optimization:* By anticipating demand and improving inventory management, digital twins improve supply chain operations. Retailers may manage their supply chains and make sure that products are accessible when and where they are needed while decreasing extra inventory and cutting costs by modeling various scenarios.
- *Consumer Experience:* Better service delivery is fostered by employing digital twins to simulate and improve consumer encounters in retail settings. Retailers may improve the shopping experience and customize their goods by researching customer behavior and preferences. This increases customer happiness and loyalty.

2.4.8. Telecommunications

- *Network Management:* By anticipating possible problems and enhancing network performance, digital twins raise service quality and dependability. DTs support excellent performance levels and prompt problem resolution by continually monitoring network conditions and simulating various situations [78].
- *Infrastructure Planning:* Using digital twins to plan and implement new network infrastructure increases productivity. Telecommunications firms can save costs and maximize coverage by making well-informed judgments by modeling the effects of new infrastructure on the current network [79].

3. Introduction to electric vehicle digital twin layout

With the rise of Big Data, IoT, and AI, effectively managing modern information, technology, geographic, and global positioning data has become critical. The integration of these technologies with DT systems is playing a key role in shaping digital trends, especially in transportation, for uses such as planning, maintenance, and security. The DT concept is particularly valuable in the transportation sector by providing digital identities, synchronized visualizations, and seamless interactions between the virtual and physical world. DT technology harnesses advanced capabilities to improve traffic monitoring, issue real-time road warnings, and respond to emergencies. It also introduces innovative transportation solutions, like intelligent driving systems, enhancing both efficiency and safety, while streamlining traffic management. For instance, Wang et al. developed a DT framework for connected vehicles, utilizing an advanced driver assistance system (ADAS). They integrated vehicle-to-cloud communication, allowing sensors to compute advisory speeds to help drivers manage speed more intelligently. Similarly, Alam and Saddik presented a DT model for a cloud-based cyber–physical system (C2PS), highlighting key features of C2PS and showcasing a driving assistance application based on telematics for vehicular systems [80–82]. Furthermore, Bhatti et al. reviewed DT technology in the context of smart electric vehicles (EVs). They categorized smart vehicle systems into areas such as self-navigation control, advanced driver assistance, vehicle power electronics, health monitoring, battery management systems (BMS), and electric power drives. Their work provides insights into the theoretical impacts of integrating DT technology with smart EVs, outlining potential future developments.

In today’s technological landscape, digital twin models have become valuable tools for bridging the gap between the physical and digital worlds. These virtual replicas of real-world objects, systems, or processes offer a comprehensive and interactive view, enabling more effective management and optimization of their real-world counterparts

3.1. Structural representation

3.1.1. Geometry and dimensions

A digital twin layout begins by capturing the intricate geometry and dimensions of the physical entity it represents. This includes detailed 3D models that accurately depict the object’s shape, size, and spatial arrangement. For complex systems like buildings or machinery, this level of precision is crucial for understanding their physical structure [83–85].

3.1.2. Components and parts breakdown

Going deeper, the digital twin layout breaks down the entity into its components and parts. Each component is meticulously detailed, showcasing its specifications, materials, and connections within the larger system. This breakdown provides a holistic view of the entity’s composition and functionality [86–88].

3.2. Prospects of digital twin technology in the electromobility

Digital twin technology is becoming more common in the field of electromobility, where it integrates with technologies such as IoT, 5G, Big Data, ML, virtual systems, and advanced communication interfaces. This integration supports essential features like real-time monitoring, predictive analytics, and cloud-based computing. Despite the variety of technologies, the core concept and architecture of digital twins remain consistent, as illustrated in Fig. 2, which highlights key technologies like IoT, virtual sensors, and self-navigating vehicles.

The integration of DTs with modern technologies for EV is depicted in Fig. 3.

3.2.1. Sensors, dynamic data analysis and digital twins

A key feature of digital twin layouts is their integration with sensors and dynamic data streams. These sensors act as the entity’s sensory network, capturing real-time data on various parameters such as temperature, pressure, performance metrics, and more. The layout visually represents the sensor placements and data flows, enabling continuous monitoring and analysis. EVs rely on numerous environmental sensors to perceive their surroundings and respond accordingly. This section explores the role of VSs within a DT framework, functioning as digital replicas of physical sensors. VSs provide innovative services for smart transportation, including optimized battery charging and route planning for EV drivers through data forecasting and parameter estimation. For example, Roccotelli et al. developed virtual sensors to improve the EV charging process [17], while Gruosso et al. developed a method to estimate the state of charge in EVs using VSs and other vehicle measurements like speed and battery voltage. Overall, the integration of VS technology with EVs enhances user experience and optimizes vehicle services, addressing complex issues like battery and energy management.

3.2.2. IoT integration and digital twins

Recently, IoT technology has been utilized in smart and electric mobility applications enabling advanced data analytics and DT technology applications. In the realm of electromobility, IoT connects physical devices, allowing for intelligent access and data transmission to the cloud or local servers, while DT manages this information and integrates it with AI for enhanced real-time analysis and decision-making [29]. By combining IoT and DT, electromobility benefits from improved performance, monitoring, analytics, and predictive capabilities Digital twin layouts often leverage the Internet of Things (IoT) technology, connecting the virtual model with physical sensors and devices in the real world. This integration enables seamless data exchange, remote monitoring, and control, enhancing the digital twin’s capabilities and real-time responsiveness [89,90].

3.2.3. Internet of Vehicles (IoV) and digital twins

EVs are gaining a larger market share due to their greenhouse gas reduction and fuel efficiency benefits. However, the current battery technology presents a challenge for the EV industry, making a comprehensive charging infrastructure with fast-charging poles and battery swapping stations essential DT models can accurately simulate EV behavior and interactions, aiding in the evaluation of charging efficiency from both demand and supply perspectives [91–93]. These models enable real-time monitoring and decision-making by creating virtual representations of vehicles and traffic systems. For instance, a DT simulation platform can replicate EV charging and discharging processes, helping to optimize the deployment and management of charging infrastructure and its impact on the smart grid. DT technology for the IoV creates virtual models of vehicles and traffic systems, connecting the physical and virtual worlds [94,95]. This integration allows for real-time monitoring, improved situational awareness, predictive analysis, and informed decision-making through detailed, multidimensional simulations.

3.2.4. 5G networks and digital twins

The 5G network supports a diverse array of applications across various industries, significantly influencing sectors within Industry 4.0, including smart cities, military operations, healthcare, and IoT-driven transportation. By advancing wireless communications, 5G boosts capacity, reliability, and speed while reducing latency, thereby enhancing overall network performance. Unlike earlier cellular technologies dependent on fixed infrastructure, 5G leverages small and mobile cell sites to improve network access in densely populated areas. This network is vital for electric vehicles (EVs), facilitating component communication, enabling self-navigating functions, and supporting the exchange of traffic data autonomously [96–98]. Integrating 5G with digital twin

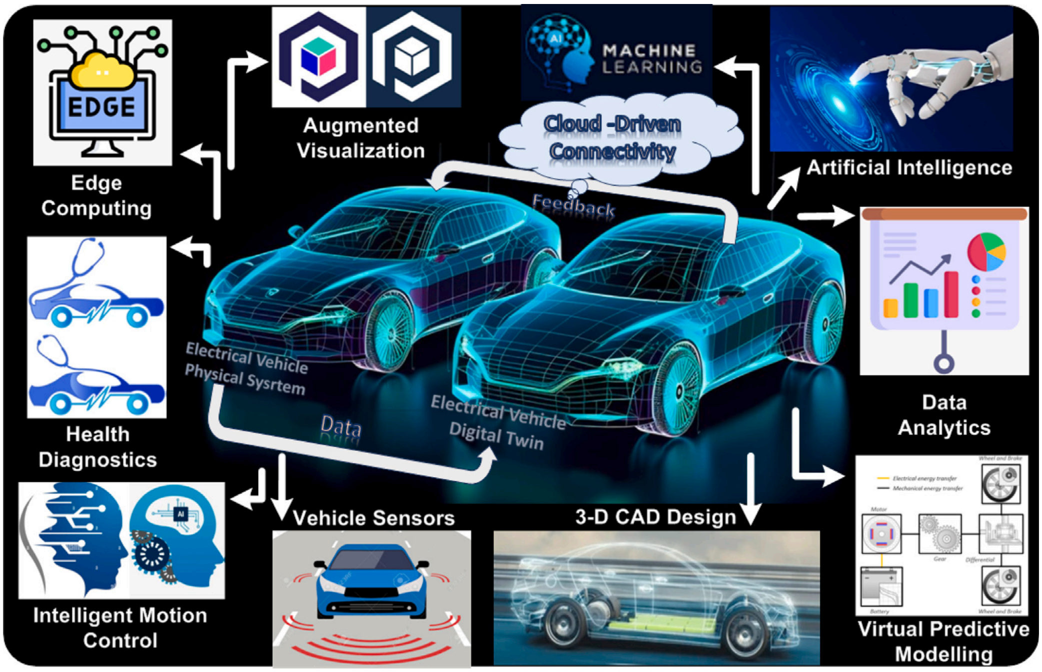

Fig. 2. Electric vehicle digital twin layout.

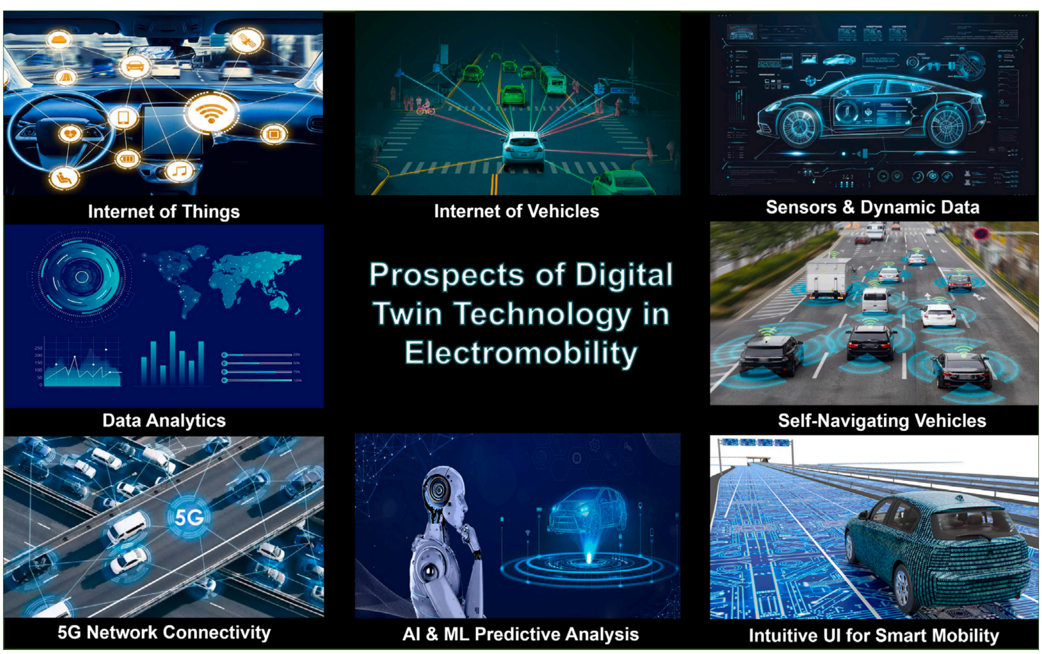

Fig. 3. Integration of digital twins with modern technologies for EV.

(DT) technology optimizes traffic resource management, alleviates congestion, and enhances real-time traffic data prediction, underscoring 5G's significance in modern IoV frameworks for safer, more efficient transportation [99–101].

3.2.5. AI and ML predictive analytics for self-navigating vehicles and digital twins

Recent studies on EVs are increasingly examining self-navigating vehicles (SNVs), also known as self-driving vehicles, which function without human control. These SNVs are usually electric because electric propulsion is easier to manage autonomously. Advanced technology allows SNVs to perceive their surroundings, plan routes, and navigate safely using AI and ML [102]. Although still in testing and not yet widely popular, SNVs are expected to become prevalent due to their significant advantages. However, they face challenges in achieving full safety, particularly with varying road, traffic, and weather conditions, as well as the need for better communication systems. Rassolkin et al. created test platforms that utilize DT technology and ML to enhance the efficiency of electric propulsion systems in autonomous EVs [103]. Venkatesan et al. proposed an intelligent DT for pre-estimating service requirements of EV motors in SNVs, using artificial neural networks and fuzzy logic for monitoring and prognostic [104]. DT layouts incorporate AI algorithms and predictive analytics [105,106]. These technologies analyze data from the DT and external sources to generate insights, predict future trends, and recommend actions. This data-driven approach empowers stakeholders to make informed decisions and drive continuous improvement. Beyond static representation, digital twin layouts incorporate dynamic behavioral models. These models simulate how the entity operates under different conditions, predict its performance outcomes, and simulate responses to various scenarios. This dynamic aspect allows stakeholders to assess performance, identify potential issues, and optimize operational strategies.

DTs are a promising invention for Intelligent Transportation Systems (ITS), as shown by the evaluation that was undertaken. However, the application of DT in conjunction with other cutting-edge technologies in EVs or SNVs is not well explored in the academic literature that is currently available. While there are studies discussing about EVs and DT technology in general, there is not a thorough analysis of all the technical aspects involved in using this technology for electromobility. It is clear that critical technologies for electromobility are not being discussed enough in DT, especially when it comes to the next generation of self-navigating vehicles. For instance, there is a lot of promise in this field for using data analysis because, in the age of artificial intelligence (AI), data is essential for improving security and performance optimization. The investigation uncovered a dearth of studies that recognize the significance of ITS data and its possible application in DT to produce value-added electromobility services. Our intention was to close this gap by providing a more comprehensive study. We conclude that technical breakthroughs can be fueled by connecting DTs of EVs and SNVs with other technological solutions, like Iot, IoV, Vehicle-to-Everything (V2X) and 5G. Through this integration, the technology of individual vehicles may be optimized, and EV companies can operate more efficiently in terms of transportation and battery charging.

3.3. Intuitive user interface and interaction for smart transportation

3.3.1. Intuitive user interface

DT frameworks are generally accessed through intuitive user interfaces or dashboards, providing a seamless platform for stakeholders to interact with the system. These interfaces offer a user-friendly environment where users can visualize real-time data streams, conduct simulations, and utilize advanced analytical tools. This accessibility enhances usability, allowing stakeholders to derive actionable insights from complex data sets with ease, thereby facilitating efficient and informed decision-making. The ability to simulate various scenarios and predict outcomes through these interfaces is particularly valuable in optimizing operations and planning.

However, alongside these benefits, DT systems face significant security challenges. As they integrate various data sources and interact with numerous devices, the risk of cyber threats and data breaches increases. Ensuring the integrity and confidentiality of the data processed by digital twins is paramount, requiring robust cybersecurity measures. This includes implementing encryption, regular security audits, and real-time monitoring to detect and mitigate potential threats. Additionally, access control is crucial to prevent unauthorized users from manipulating the digital twin or accessing sensitive information. As digital twins become more complex and widespread, developing comprehensive security frameworks to address these challenges is essential. By prioritizing security, stakeholders can confidently leverage the full potential of digital twin technology, knowing that their data and systems are protected against malicious activities.

3.3.2. Interaction for smart transportation

A digital twin network (DTN) signifies the advancement of digital twin technology in the modern world. It consists of several digital replicas of physical objects, all linked through a high-speed communication network to create an integrated virtual system. In a typical DT data flows in one direction, with updates in the physical entity influencing the virtual model, but not the other way around. In contrast, a DTN facilitates multidirectional data exchange between digital twins and physical assets [107]. This capability makes DTNs particularly effective for addressing complex urban transportation issues like traffic congestion and accidents, offering innovative solutions such as traffic information services and enhanced vehicle security.

The DTN architecture is structured into three layers: physical, network, and virtual. The physical layer consists of EVs, charging stations, roads, and other infrastructure, all linked to the network layer through sensors that transmit data on vehicle locations, traffic conditions, and charging station status through 5G or WiFi is Shown in Fig. 4. This information is then sent to the virtual layer, where digital twins and servers work together using advanced technologies like AI, AR, and ML for decision-making, analysis, and maintenance tasks [108].

3.4. Maintenance and optimization

3.4.1. Predictive maintenance

DT designs are essential for predictive maintenance strategies, as they enable the analysis of sensor data and behavioral models, they can predict potential equipment failures, schedule maintenance activities proactively, and optimize asset performance. This proactive approach minimizes downtime, reduces maintenance costs, and extends asset lifespan.

3.4.2. Performance optimization

Furthermore, digital twin layouts facilitate performance optimization by identifying inefficiencies, analyzing operational data, and recommending improvements. Through continuous monitoring and analysis, stakeholders can fine-tune processes, optimize resource utilization, and enhance overall efficiency. In conclusion, digital twin layouts offer a multifaceted approach to understanding, managing, and optimizing complex systems. By combining structural representation, data integration, behavioral modeling, and user interaction, they provide a powerful framework for digital transformation across industries. From predictive maintenance to performance optimization, digital twin layouts drive innovation and efficiency in the digital age. The analysis underscores DT as a promising technology for intelligent transportation systems (ITS), noting that current literature inadequately addresses its deployment in EVs and SNVs. Although some articles discuss DT technology in relation to EVs, they often lack comprehensive coverage of its technical applications in electromobility. Critical technologies in DT for next-generation self-driving systems, particularly data analytics, remain underexplored despite their potential for optimizing performance and enhancing security [109]. Our research revealed a scarcity of reviews on the importance of data generated by ITS and its utilization in DT for value-added electromobility services, prompting us to fill this gap with broader analysis. Combining DTs with other technologies like the IoV, vehicle-to-everything systems (VSs), the IoT and 5G can drive technological advancements and optimize EV and SNV operations, including travel and charging [110].

The energy management system (EMS) influences the EV driving range, battery lifespan, and vehicle acceleration. Typically implemented onboard EVs, the EMS often faces limitations due to restricted processing power, making it challenging to integrate advanced strategies like global optimization methods, stochastic algorithms, and machine learning. Conversely, DT provide ample computational power to run sophisticated EMS algorithms, enhancing EV performance under various driving conditions by optimizing power limits during acceleration and regenerative braking [111].

4. Overview of digital twin battery and challenges

In the context of EVs, DTs can model and manage various components, including the battery, drivetrain, and energy management systems. By leveraging data from sensors and advanced analytics, DTs provide insights into the performance and health of these components, allowing for predictive maintenance and operational optimization. Battery challenges in EVs are significant due to factors such as energy

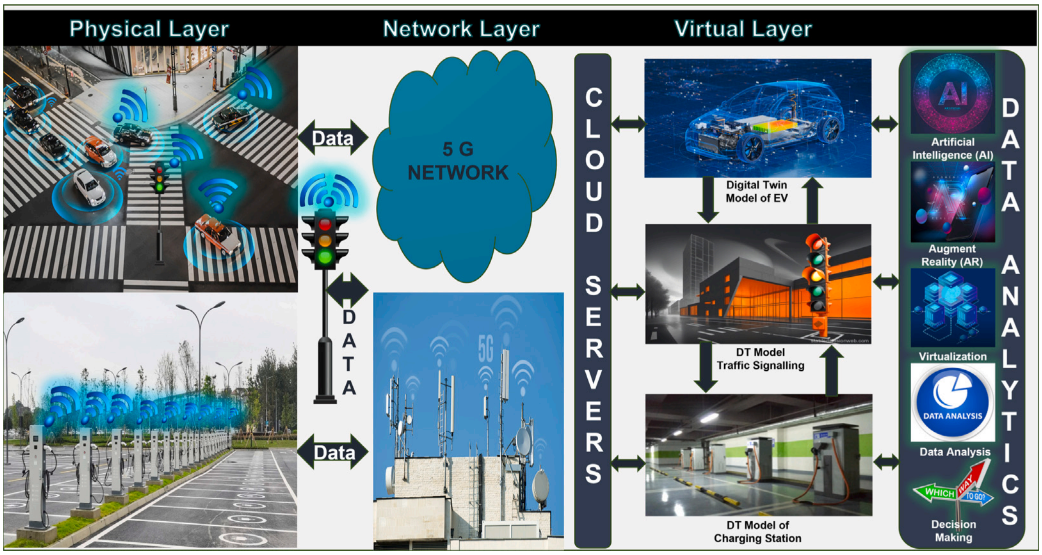

Fig. 4. Structural diagram digital twin network for EV smart transportation.

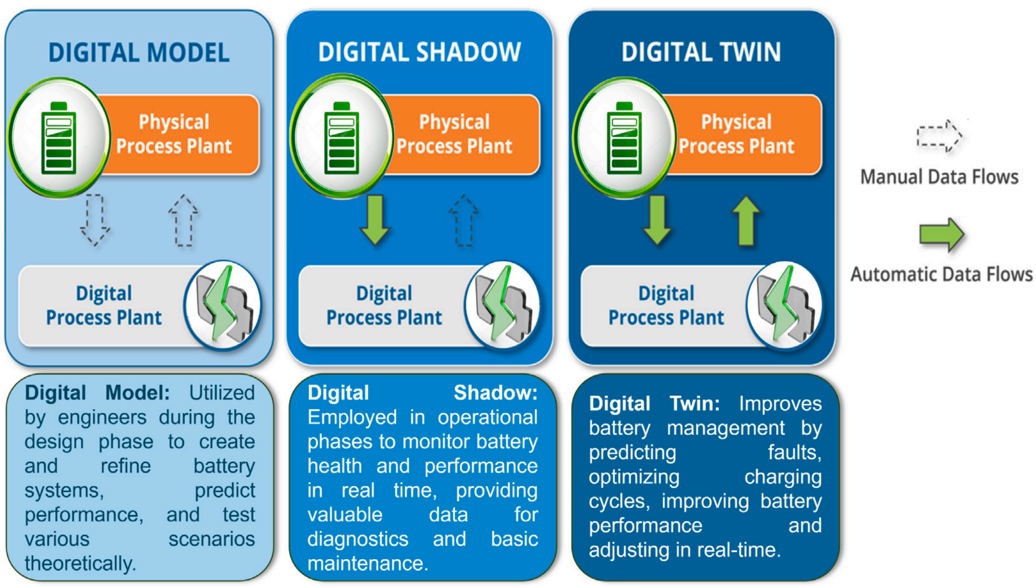

Fig. 5. Digital representations of EV batteries: Models, Shadows, and Twins.

density, charging time, lifespan, and thermal management. Efficiently managing these aspects is critical to improving the driving range, reliability, and overall performance of EVs. DTs address these challenges by enabling detailed simulations and analyses of battery behavior under different conditions. This helps in optimizing charging cycles, predicting potential failures, and enhancing thermal management strategies, ultimately extending battery life and improving EV performance.

4.1. Digital representations of EV batteries: Models, shadows, and twins

4.1.1. Digital model

A digital model is a computerized depiction of a battery based on theoretical principles and simulations. It employs mathematical equations and algorithms to describe the battery's behavior under various conditions. Digital models are typically utilized in the design phase to predict performance, optimize parameters, and evaluate different scenarios without the need for physical prototypes. Shown in Fig. 5 and Table 1. However, these models do not incorporate real-time data from actual batteries [112,113].

4.1.2. Digital shadow

A digital shadow builds upon the idea of a digital model by integrating real-time data from the physical battery. This allows the digital shadow to constantly adjust its parameters using live information like temperature, voltage, and state of charge. As a result, it offers a more precise and dynamic representation of the battery's current condition compared to a static digital model. However, the interaction is one-way: the physical battery sends data to the digital shadow, but the shadow does not influence or interact with the physical battery [114].

4.1.3. Digital twin

A digital twin represents the most sophisticated form of a digital replica, offering a dynamic, real-time counterpart of the physical battery. Unlike a digital shadow, the digital twin enables a two-way exchange of data. It not only receives live information from the battery but can also send feedback and interact with it. This interaction supports ongoing monitoring, predictive maintenance, performance enhancement, and real-time decision-making. Additionally, digital twins

Table 1
Comparison of digital model, digital shadow, and digital twin.

Digital Model	No real-time data; based on theoretical and simulation data. Lacks real-time monitoring and updates. Simplest, used for initial design and simulation. **Use Case:** Design, simulation, and theoretical analysis
Digital Shadow	One-way data flow from the physical battery to the digital shadow. Real-time monitoring without interaction. More complex due to integration of real-time data for monitoring. **Use Case:** Real-Time Status Monitoring And Diagnostics
Digital Twin	Two-way data flow; real-time interaction and feedback. Real-time monitoring and interaction, enabling predictive and adaptive functionalities. Most complex, enabling real-time interaction, predictive maintenance, and optimization. **Use Case:** Predictive maintenance, performance optimization, and advanced analytics

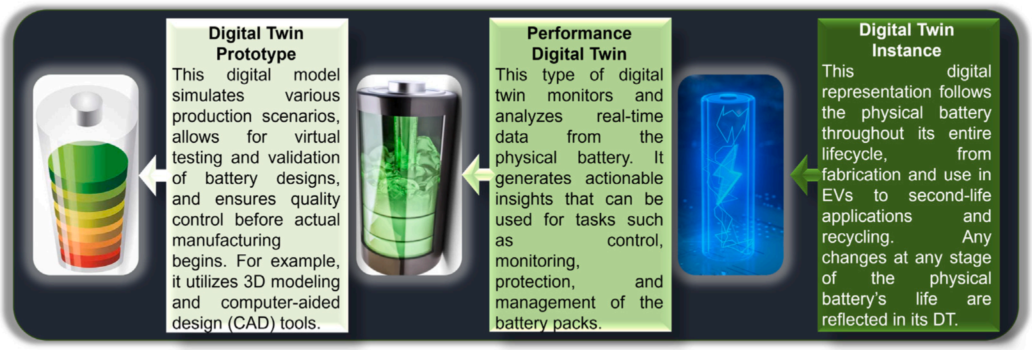

Fig. 6. Battery DTs types.

can simulate future conditions and modify operations to optimize the battery's performance and extend its lifespan [115].

4.2. Digital twin battery types

The concept of a DT differs based on its application, with various terms like mega-model, avatar, mirrored system, digital shadow, and synchronized virtual prototype often used to describe it. As a result, there is no universally agreed-upon definition of DTs. Recent progress in battery digital twins has introduced new capabilities, thanks to advancements in IoT, AI, big data, and cloud computing. Digital twins can address challenges at each stage of the battery lifecycle and bridge different phases to improve performance and lower overall costs. The following sections explore both existing and potential applications of battery digital twins. This research classifies DTs into three categories based on their applications, as illustrated in Fig. 6. Each category addresses specific needs at different points in the battery lifecycle: the Digital Twin Prototype (DTP) focuses on battery manufacturing, the Performance Digital Twin (PDT) oversees battery operation during its first and second life, and the Digital Twin Instance (DTI) spans the entire lifecycle from production to recycling. Below is an in-depth look at the Digital Twin Prototype (DTP), Performance Digital Twin (PDT), and Digital Twin Instance (DTI).

4.2.1. Digital twin prototype (DTP)

The main objective of DTP is utilized in the design and development stages to simulate and validate designs before creating physical prototypes [116].

- *Simulation and Testing:* DTP allows extensive testing of various design iterations in a virtual environment, significantly reducing costs and time compared to physical prototyping.
- *Design Enhancement:* It assists in identifying design defects and optimizing the design for better performance.
- *Virtual Verification:* Offers a platform to verify the functionality and performance of a design virtually, ensuring that it meets the required specifications before physical implementation.

4.2.2. Performance digital twin (PDT)

PDT's primary goal is to monitor and improve the performance of a physical asset during the operational phase [31,45,64].

- *Real-time Monitoring:* Continuously gathers and analyses data from the physical asset to keep track of its performance.
- *Predictive Maintenance:* Uses data analytics to predict potential failures and schedule maintenance activities proactively.
- *Operational Optimization:* Assists in optimizing operational parameters to enhance efficiency and performance.
- *Feedback Mechanism:* Provides feedback to the design and manufacturing teams for ongoing improvements based on real-world performance data.

4.2.3. Digital twin instance (DTI)

The main objective of DTI represents a specific instance of a digital twin, corresponding to a unique physical asset [28,117].

- *Individual Representation:* Each DTI is a digital replica of a specific physical asset, capturing its unique characteristics and operational data.
- *Lifecycle Management:* Manages the asset's lifecycle from commissioning through operation to decommissioning.
- *Data Integration:* Integrates data from various sources, including sensors, maintenance records, and environmental factors, to provide a holistic view of the asset.
- *Tailored Analysis:* Facilitates detailed analysis and decision-making based on the specific conditions and performance of the individual asset.

These types of digital twins work in synergy to enhance the overall lifecycle management and optimization of assets from design to decommissioning.

Fig. 7. Challenges in the making process of EV batteries.

4.3. Battery challenges

In EVs, DTs are employed in various areas, including autonomous driving, power converters and inverters, digital design and manufacturing, health monitoring, advanced driver assistance systems, and battery management. These applications are designed to improve the performance and safety of various EV components and subsystems. Battery systems, however, face significant challenges throughout their value chain, from raw material sourcing and cell manufacturing to pack assembly, operation (both in EVs and second-life applications), and recycling. Major issues include identifying sustainable and abundant materials, ensuring quality control during manufacturing, maintaining battery durability and safety in EVs, and addressing the complexities involved in repurposing and recycling batteries, as illustrated in Fig. 7. Additionally, the value chain suffers from a lack of interoperability, limiting collaboration between stakeholders and the standardization of technologies. A universal framework is urgently needed to evaluate battery technologies and track advancements in sustainable design.

4.3.1. Sourcing and processing raw materials

The first challenge in the battery value chain involves the sourcing and processing of raw materials such as lithium, cobalt, nickel, and graphite. The extraction and refinement of these materials pose several problems, including supply chain vulnerabilities, geopolitical tensions, and significant environmental and social impacts. Sustainable mining practices, alternative materials, and improved recycling methods are critical areas of current research to address these challenges [118,119].

4.3.2. Component fabrication and production

Creating the components of a battery, such as cathodes, anodes, separators, and electrolytes, involves complex and costly manufacturing processes. These processes need to ensure high purity, consistency, and performance. Scaling up production while maintaining quality and reducing costs remains a significant challenge. Advances in materials science and manufacturing techniques, including solid-state batteries and innovative coating technologies, are key research areas [120,121].

4.3.3. Battery cell and pack assembly

The assembly of individual battery cells into modules and packs presents several technical challenges. Ensuring uniformity and reliability across thousands of cells is critical to avoid performance issues or safety hazards. Key considerations include thermal management, mechanical stability, and efficient cell interconnection. Innovations in design, materials, and assembly techniques are the focus of current research to improve the durability, safety, and performance of battery packs [122,123].

4.3.4. Integration into electric vehicles

Integrating batteries into electric vehicles (EVs) involves challenges related to energy density, charging times, and overall vehicle performance. Consumers demand longer driving ranges, faster charging, and lower costs, which place high demands on battery technology. Ensuring safety and reliability under various operating conditions is crucial. Research focuses on improving battery chemistries, developing fast-changing technologies, and enhancing battery management systems to meet these demands [124,125].

4.3.5. Secondary use and repurposing

Batteries reaching the end of their useful life in EVs often retain substantial capacity and can be repurposed for secondary applications, such as energy storage systems. However, efficient and cost-effective methods for testing, refurbishing, and repurposing used batteries are needed. Standardized protocols and technologies for second-life applications are a major research focus, aiming to extend battery lifecycles and reduce environmental impact [126,127].

4.3.6. Recycling and end-of-life management

Recycling batteries to recover valuable materials and minimize environmental harm is the final stage in the battery value chain. Current recycling processes are often inefficient, costly, and environmentally damaging. Efficiently separating and extracting materials, handling hazardous components, and scaling up recycling infrastructure are key challenges. Research focuses on developing more sustainable recycling methods, such as hydrometallurgical and direct recycling techniques, to improve material recovery rates and reduce the environmental footprint of battery disposal [128,129].

Through these challenges addressed in innovation and collaboration, the battery industry aims to create more sustainable, efficient, and cost-effective solutions that can support the growing demand for energy storage and electric mobility.

4.4. Review of DT battery implementations and functions

In recent years, research into battery Digital Twins (DT) has surged. With the progression of IoT, AI, big data, and cloud computing technologies, battery DTs are acquiring new features and capabilities. These advancements enable DTs to address challenges throughout the battery's life cycle, leading to enhanced performance and lower life cycle costs (LCC). The following sections explore the current and potential applications of battery DTs.

4.5. Estimating SoX and equalizing battery cells

In the Battery Management System (BMS), the state-of-X (SoX) variables-state-of-charge (SoC), state-of-health (SoH), and state-of-power (SoP)—are essential because they inform various algorithms that monitor, control, and protect the battery pack. The SoC functions similarly to a fuel gauge in a non-electric car. The SoH of a battery is often reflected by its internal resistance or capacity. During normal operation or regenerative braking in an EV, the SoP determines the safe power limits for the battery [130,131]. These algorithms typically run on the onboard BMS, which operates with a microprocessor having a few hundred megabytes of RAM [132]. However, deploying top-tier SoX estimation algorithms is challenging due to the CPU and memory constraints of the BMS. Several studies have explored state-of-X (SoX) estimation using digital twins. Particle swarm optimization and the adaptive H-infinity filter are applied for SoC and SoH estimation, respectively, within a cloud-based digital twin framework. As illustrated in Fig. 8 from [131], voltage, current, and temperature (VIT) data is transferred from the slave battery management system (BMS) to a Raspberry Pi through the controller area network (CAN) protocol. The data is then transmitted to the digital twin using the MQTT protocol. An uninterruptible power supply setup was used to validate these SoX methods, achieving a mean absolute error (MAE) of 0.5% for SoC estimation [133].

Likewise, the MAE for capacity and resistance estimation using the DT-based SoH estimation was found to be 0.74% and 1.7%, respectively. A battery discharge tester utilizing long short-term memory is developed and used to fully discharge the battery to measure its capacity, resulting in an estimated state-of-health (SoH) mean absolute error (MAE) of 2.86%. Additionally, in [134], the DT-based estimation for both state-of-charge (SoC) and SoH has been successfully implemented. In [135], the battery Digital Twin (DT) was used for cell balancing management and state-of-X (SoX) estimation. For SoX estimation, the particle filter (PF) algorithm achieved mean absolute error (MAE) values of 0.5% for SoC and 0.3% for SoH. DT calculates the time required for each cell to balance based on the estimated capacity and formulates a rapid and implementing an accurate balancing technique [134]. Fig. 8 illustrates the notion of the DT-assisted equalization procedure. The BMS boards monitor important properties of different batteries and transmit this data to the cloud-based DT, which then processes it using balancing algorithms. The DT generates the necessary commands to control the balancing actuators and sends them back to the batteries. Other studies have utilized DT for SoC and SoH estimations using machine learning [136,137], the Kalman filter (KF) combined with the least-squares support vector machine and particle filter (PF) [138], as well as the extended Kalman filter with particle swarm optimization [139]. Battery algorithms can also be integrated into the cloud-based BMS concept proposed in [140]. The battery DT and the cloud BMS differ in terms of their deployment approach and DT concept. When the cloud BMS is considered a physical digital twin of the battery.

4.6. Diagnosis and prognosis of faults

To identify and protect against battery issues such as over-discharge, over-charge, and short circuits, the onboard BMS employs traditional methods. Typically, these methods rely on univariate techniques, diagnosing faults by comparing voltage, current, and temperature variables to set threshold values without considering past used statistics. With extensive computing resources and past battery consumption information, the battery DT can investigate more advanced flaw detection techniques. Given the quantity of sensory information, modern multivariate condition monitoring techniques can be employed to detect and diagnose defects with greater precision. Furthermore, fault prognosis is an interesting field of research that can be investigated within a DT framework. Due to the processing capability of DT technology, advanced multiscale and physics-based models that typically exceed the capabilities of the BMS may now be used online to detect and anticipate mistakes. Battery models combined with DT can monitor processes and mechanisms that might lead to failures. The authors in [141,142] provide examples of model-based strategies include merging the battery's electrical, thermal, and deterioration designs, utilizing basic designs, and adopting data-driven approaches centered around dynamic mode decomposition. The application of DT for intelligent battery monitoring is explored [143].

4.7. Estimation of Remaining Useful Life (RUL)

RUL provides insights into battery's longevity before it reaches the end of its operational life. In contrast to SoH, which reflects the battery's current condition, RUL forecasts future degradation trends. It is typically calculated based on the number of cycles remaining until the battery's end of life. Although considerable academic research has focused on estimating battery RUL, no commercial Battery Management Systems (BMSs) currently offer this feature. However, as illustrated in Fig. 9, estimating RUL using DT and cloud-based approaches presents several advantages. Various methods for predicting Remaining Useful Life (RUL) have been proposed, utilizing battery models, past information or both. A comprehensive review of RUL estimation techniques can be found in [144]. RUL involves in the predictive maintenance, performance optimization, second life planning, guarantee/ warranty and fleet management.

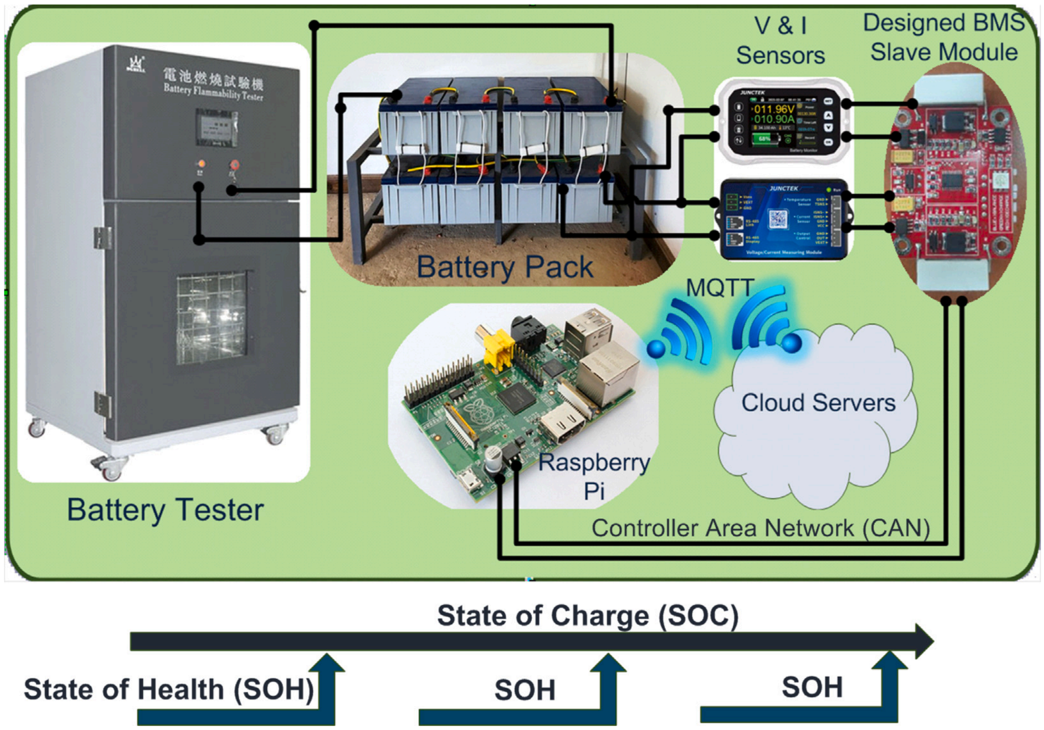

Fig. 8. A cloud-based digital twin (DT) is utilized for State of Charge (SoC) estimation. The State of Charge (SoC) is continuously monitored, while the State of Health (SoH) is periodically updated and fed into the SoC estimation algorithm [131].

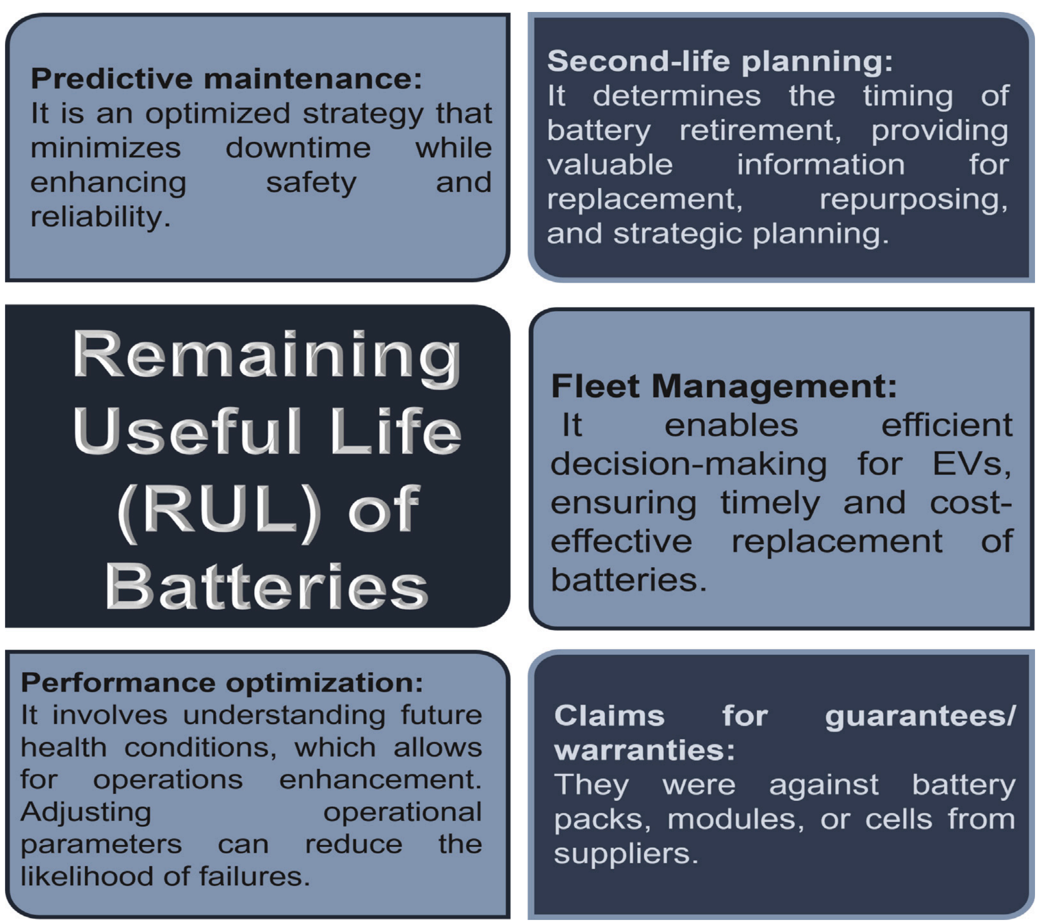

Fig. 9. Remaining Useful Life of batteries.

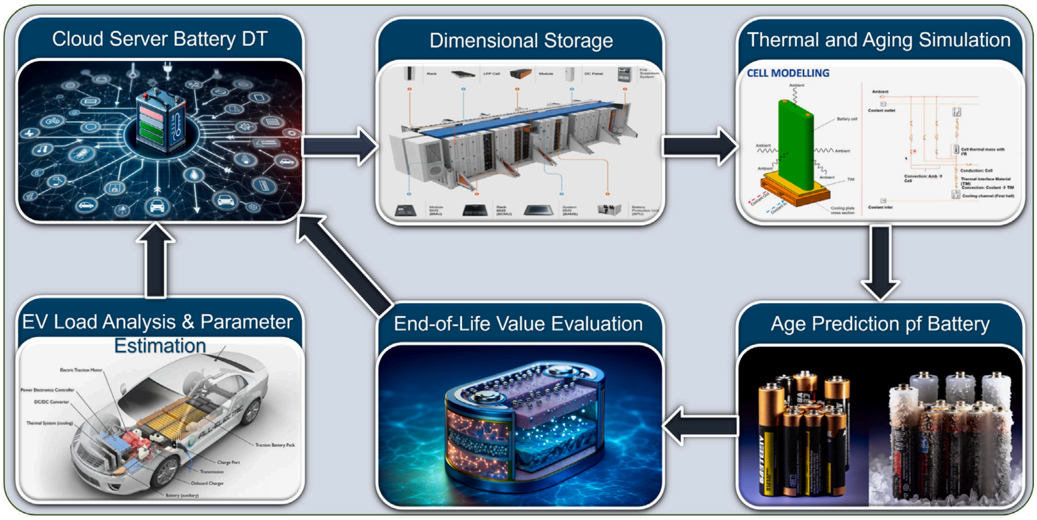

Fig. 10. Depiction of Cloud-integrated decision-making digital twin diagram for reusing second-life batteries.

4.8. Predictive maintenance

EVs require constant upkeep and servicing. Because they are typically applied either too late, when a defect or costly damage manifests itself, or too soon, when the battery pack does not require maintenance, the usual maintenance methods are ineffective and economically unfeasible. The RUL can be tracked in real-time with the battery DT, allowing maintenance to be done only when an issue or service is necessary. This can save costs, extend the life and durability of the battery, and prevent unintentional shutdowns [145]. Likewise, EV owners can save time and money by automating the tedious battery check-up procedure. In [146], researchers employed a Bayesian-based adaptive evolution method to examine the predictive maintenance of battery digital twins (DTs). The study developed algorithms for forecasting battery lifespan and assessing reliability to estimate the Remaining Useful Life (RUL). Implementing this predictive maintenance strategy can reduce battery maintenance costs by up to 62%.

4.9. Reusing batteries, second-life applications, recycling, and swap services

Repurposing an EV battery for secondary use, like in stationary energy storage systems, requires costly and time-consuming dismantling and manual lifespan assessment at the unit or cell level. The DT concept enables continuous monitoring of the battery's SoH. storing this information in a database, and accessing it when necessary. This data can also be shared with stakeholders in the second-life market, such as battery manufacturers, to assist in operational planning and forecasting battery availability after their initial use. Moreover, the monetary worth for different secondary-use applications can be assessed by accurately mapping the energy and power capacities of batteries to determine the best suitable application for their second life. Batteries with greater charging capacity can provide grid ancillary services like power conditioning and frequency regulation, whereas those with higher energy capacity can be utilized in uninterruptible power supply systems. According to [147], DT were used to estimate the residual values of batteries. Fig. 10 depicts the cloud-integrated decision-making digital twin diagram for reusing second-life batteries.

In [148], a DT was utilized to monitor shared batteries and replace them as needed. This allows switching stations to track the battery's health, performance, and degradation during each EV's use. Consequently, EV users can exchange batteries without concern for their condition. Additionally, battery DTs benefit financial and insurance companies by enabling them to adjust rates and strategies based on battery reliability and wear. The online accessibility of detailed EV battery conditions enables stakeholders to create more practical guarantee and warranty programs. This DT-based approach is also applicable to EV rental and leasing companies. It illustrates a use case in which the SoC, SoH and driving distance of EVs are assessed and stored in the DT for shared services.

4.10. Optimization of production and design

Improving battery manufacturing processes is achievable with the battery digital twin prototype (DTP). Traditional quality assurance methods, such as those using Pareto charts or house-of-quality approaches, can take weeks or even months to address a single issue or defect, demanding significant resources from multidisciplinary teams. In contrast, a digital twin can streamline quality assurance, resolving issues within days and simplifying the identification of root causes for production faults [149]. Similarly, by utilizing the battery DT, the operational stage of an EV can access data from the production phase, such as for calibrating specific models and algorithms. Conversely, operational data from the battery can be fed back into the design and optimization processes. This cross-stage data and information sharing offered by the DT enhances flexibility and performance throughout different stages of the battery's lifecycle. This application falls under the Digital Twin Integration (DTI) category. For all-solid-state batteries, DT was built as described in [150] for estimating data that is practically unattainable and hard to get, such as charge distribution, specific contact area, and inactive particles in the 3D domain. This will assist in mapping design and performance parameters for optimizing battery design. The testing of battery using digitization reduces the cost and time associated with battery characterization trials. The authors in [151] also considers the design optimization of the battery thermal management system using the DT. Most of the reviewed works are categorized as DTPs focused on manufacturing processes.

Numerous articles have explored the applications of DT in battery production. The authors in [152] proposed a successful 3D discontinuous scheduling component architecture for the DT of the battery electrode, a crucial component in the manufacturing process. A 3D detailed electrolytic representation of electrodes to assess how production characteristics, like sludge composition, affect the electrode structure and performance of the battery have been discussed in [153]. Further notable works involves the drying model of electrodes the spatial distribution of carbon-binder [154], and the digital twinning of 3D morphologies of active material particles [155]. The use of digital twins (DT) for flexible pouch cell stack construction and rapid, cost-effective battery module assembly to accelerate and scale up manufacturing processes have been discussed in [156,157].

Fig. 11. Illustration of the Battery Global Identification Passport.

4.11. Thermal management, battery passport and optimization of power

The performance of an energy management system (EMS) significantly influences an electric vehicle's (EV) acceleration, battery lifespan, and driving range, among other aspects. Due to limited processing capabilities, EMS is usually integrated into the EV itself. This limitation hinders the implementation of advanced EMS strategies, including those utilizing advanced universal and virtual methods of optimization, dynamic algorithms, and machine learning techniques. Conversely, DTs offer sufficient processing power to run cutting-edge EMS algorithms, enhancing EV functionality under a variety of operating circumstances. These advancements enable the determination of optimal power constraints during regenerative braking and acceleration. For specific examples of such advanced EMS techniques [158,159]. A thorough examination of these algorithms goes outside the reach of this review.

To keep the battery thermal range within limits while minimizing temperature swings and irregularities throughout the unit, the TMS regulates the heating and cooling mechanisms. Generally, the TMS is implemented onboard. However, the integration of DT allows for the application of intelligent control and advanced predictive methods, enhancing the TMS's overall performance and extending battery life. An example of this is BoschTM Mobility Solutions' "Battery in the Cloud" theory, which collects information from the fleet and individual batteries to optimize battery usage predictions. For example, the TMS starts adjusting the thermal limits of battery for small duration before the EV goes to a designated charging station. By manufacturing the battery for greater charging currents, this approach reduces charging time and minimizes battery wear during fast charging. A Battery DT can maintain a battery passport, which allows it to keep track, gather, and aggregate battery data and metadata across the production plant to the recycling phase of the battery's lifecycle. A battery passport is a digital document that communicates the essential social, political, and environmental standards required for regulatory compliance. By implementing efficient lifecycle management through the battery passport system, second-life services can bypass unnecessary battery testing, leading to time and cost savings. Additionally, recyclers can more accurately assess the needs for recycling procedures as specified [160]. Fig. 11 illustrates the proposed Battery Identity Global Passport scheme. Significantly, the Global Battery Alliance has called for the immediate implementation of the battery passport concept to facilitate the transmission of battery data.

The battery passport concept necessitates a comprehensive framework that integrates all stages of operation. A robust DT framework has been proposed in [78], connecting the research and design, manufacturing, after-sales, and post-operation phases using cloud technology and 5G communication. Another framework outlined in [161] focuses on managing the lifecycle of electric vehicle (EV) battery packs. In this model, DTs are applied to various phases such as design, manufacturing, operations, and second-life, encompassing R&D, production, and battery management. These DTs communicate through centralized cloud storage within the IT system. The significance of blockchain in supporting Industry 4.0 lifecycle management and sustainable manufacturing is emphasized in [162,163]. Additionally, the authors in [164] addresses both the challenges and opportunities that digital twins present in product lifecycle management.

4.12. G2V and V2G operations

Battery charging can be carried out using different protocols, including constant current-constant voltage (CC-CV), pulse charging, constant current (CC), and constant voltage (CV). The selected charging method affects battery wear, charging time, cost, and overall efficiency. In this regard, integrating battery health monitoring into the charging process is an ideal use case for digital twins (DT) [165,166]. The DT can reframe the charging process as a multi-objective optimization problem, using a cost function to identify the best protocol and charging parameters, such as the frequency and duration of pulses during pulse charging, while considering factors like degradation, cost, efficiency, and time. For instance, the cost function can be fine-tuned to reduce charging time while extending battery life by minimizing temperature differences and avoiding lithium plating. Additionally, the optimization process can be limited by constraints such as maximum allowable charging power. An example of this method is the convex multiperiod optimization approach discussed in [167], which manages battery charging while accounting for power limits and voltage increases. Similarly, [168] explores the use of artificial intelligence, particularly deep reinforcement learning, for optimizing fast battery charging.

Considering battery aging and thermal safety, this study employs a multi-physics constrained approach to enable rapid charging, resulting in an estimated 15%–20% improvement in battery lifespan at a comparable charging rate. The extensive computational resources of the cloud facilitate the use of advanced algorithms within the DT framework to address large-scale optimization problems. Furthermore, batteries can support the electrical grid through Vehicle-to-Grid (V2G) operations, such as peak shaving, grid stabilization, and providing backup power. By leveraging the DT for optimizing V2G activities, cost functions akin to those used for battery charging can be developed. These functions may aim to minimize battery wear during V2G operations, maximize revenue, and more. In the same way, the DT can store usage profiles and data pertaining to EVs batteries, charging stations, and the grid. This information can then be leveraged to performance optimization of charging stations.

5. EV battery designs and solutions

Modern energy technologies have been greatly impacted by the development of Energy Storage Systems (ESS), especially in the area of mitigating climate change. ESS can be divided into mechanical, electrochemical, electrical, thermal, and hybrid systems according to how much energy they use shown in Fig. 12.

The majority of the energy storage capacity worldwide is accounted for by mechanical ESS, such as flywheel energy storage and pumped hydro storage. Electrochemical energy storage systems (ESS), such as flow and secondary (rechargeable) batteries, provide reversible energy storage and release by converting electrical energy into chemical energy and back. Chemical reactions are used by chemical storage systems, such fuel cells, to store and release energy. Thermal ESS store energy from solar or electric heaters for use in the production

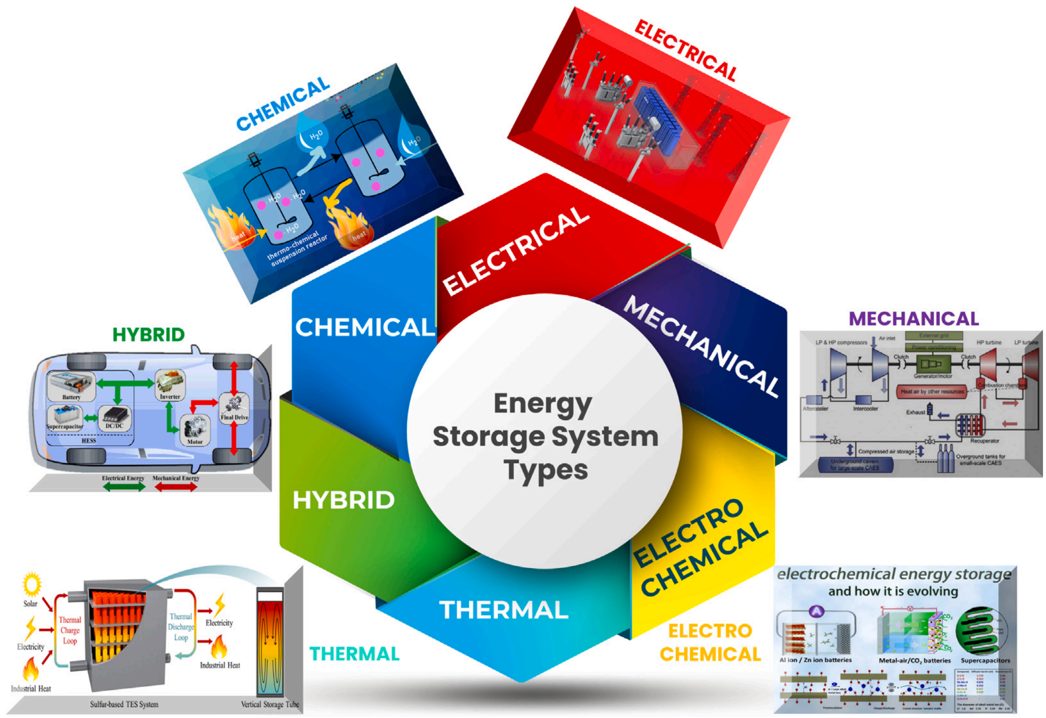

Fig. 12. Summary of the different energy storage system types [178–179].

of electricity later on, whereas electrical ESS, such as ultracapacitors and superconducting magnetic coils, store energy in electrical fields. By combining the best aspects of many ESS types, hybrid energy storage systems balance cost, lifecycle, energy density, and power density to maximize performance.

With an emphasis on electrochemical devices, different battery technologies are used in applications involving electric vehicles (EVs). Although they are sensitive to operating conditions, lithium-ion batteries (Li-ion) have advantages including low internal resistance, lightweight components, and high charge/discharge cycles [169]. They work by way of reversible chemical reactions with lithium salts. Zinc-bromine batteries (Zn-Br2) are characterized by their low cost of materials, strong energy density, and straightforward chemical makeup [170]. They operate on a zinc-bromine solution. One of the earliest types of rechargeable batteries, lead–acid batteries (Pb-PbO2) are cheap and simple to recycle, but their specific density and energy ratios are poor [171]. Hybrid electric vehicles (HEVs) can benefit from the high self-discharge rates, longevity, and environmental friendliness of nickel-metal-hydride (Ni-MH) batteries, which employ hydrogen as the negative electrode [172]. Although they need high operating temperatures, sodium sulfur (Na-S) and sodium chloride nickel (Na-NiCl) batteries are renowned for having high energy densities and efficiency. Ni-MH batteries are preferred over nickel-cadmium (Ni-Cd) batteries due to the latter's high memory effect and short lifespan [173]. Every battery technology has specific benefits and drawbacks. Li-ion batteries are efficient and long-lasting, although they deteriorate under harsh operating environments. Zn-Br2 batteries have a limited temperature range of operation but are reversible and cost-effective. Pb-PbO2 batteries have a low energy density despite being inexpensive and readily reusable. Although they are environmentally friendly and have a high volumetric energy density, Ni-MH batteries have a high rate of self-discharge. High operating temperatures are necessary for the high energy density and efficiency of Na-S and Na-NiCl batteries. Although Ni-Cd batteries use less energy, they have a large memory effect and a short lifespan.

Artificial intelligence (AI) will be included into ESS technologies to boost performance, charging procedures will be optimized, and manufacturing processes will be improved. To lessen the impact on the environment, green energy and sustainability must be prioritized at every stage of the battery lifespan, from production to recycling. The possibility of advanced battery technologies, such as Magnesium Ion, Aluminium Air, and Sodium Air, to greatly improve sustainability and energy storage capacity is currently being investigated. In example, by maximizing battery performance and enabling wireless connectivity in vehicles artificial intelligence (AI) is revolutionizing the transportation system. Artificial intelligence (AI) technologies, such Artificial Neural Networks (ANN), are being developed to improve battery component efficiency and overall vehicle performance. For example, ANN can optimize energy usage by predicting and managing charging requests based on user habits. In a similar vein, AI techniques are being used to enhance thermal management systems, which lower energy costs and increase vehicle economy. The transportation industry is about to undergo a transformation as a result of the incorporation of AI into mobility systems, making it smarter and more efficient [174,175].

Environmental impact and sustainability are important factors to take into account during the battery lifecycle of electric vehicles (EVs). Because minerals must be mined and processed, the battery production process uses a lot of energy and emits CO2. Because EV batteries require a significant amount of electricity to operate, which is frequently produced from fossil fuels, questions over the total environmental benefits arise. Battery recycling and disposal offer ways to lessen these effects by saving money, reclaiming precious materials, and prolonging battery life. To optimize the environmental advantages of EVs and advance a circular economy, it is imperative to prioritize sustainable practices throughout the EV's production, use, and recycling phases. In conclusion, improving the efficiency and environmental performance of electric vehicles requires integrating AI into battery management and vehicle systems in addition to sustainable battery lifetime methods. Energy storage technologies and electric vehicles of the future will be

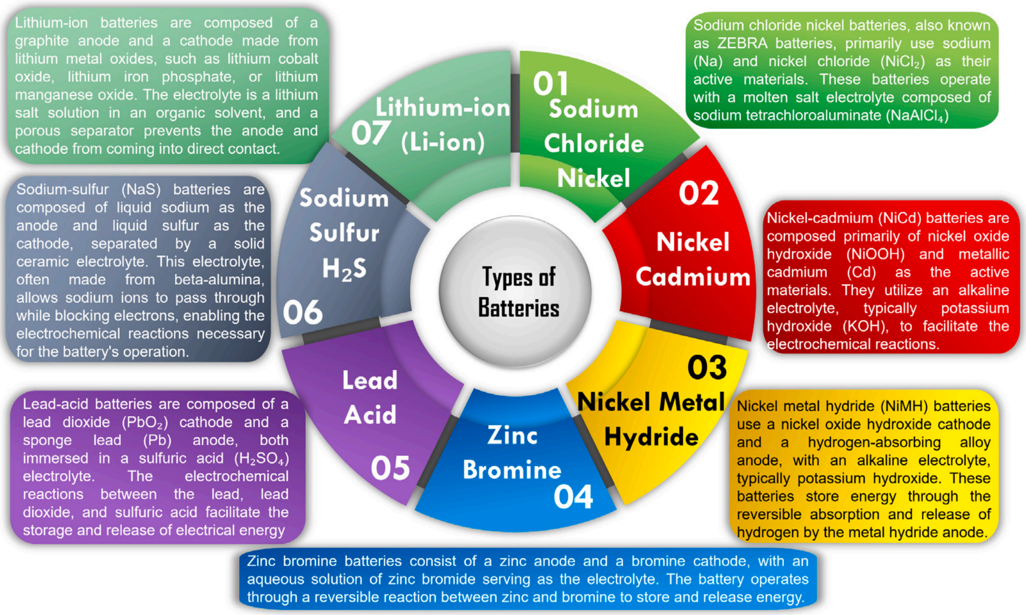

Fig. 13. Battery types based on the composition of elements [169–173].

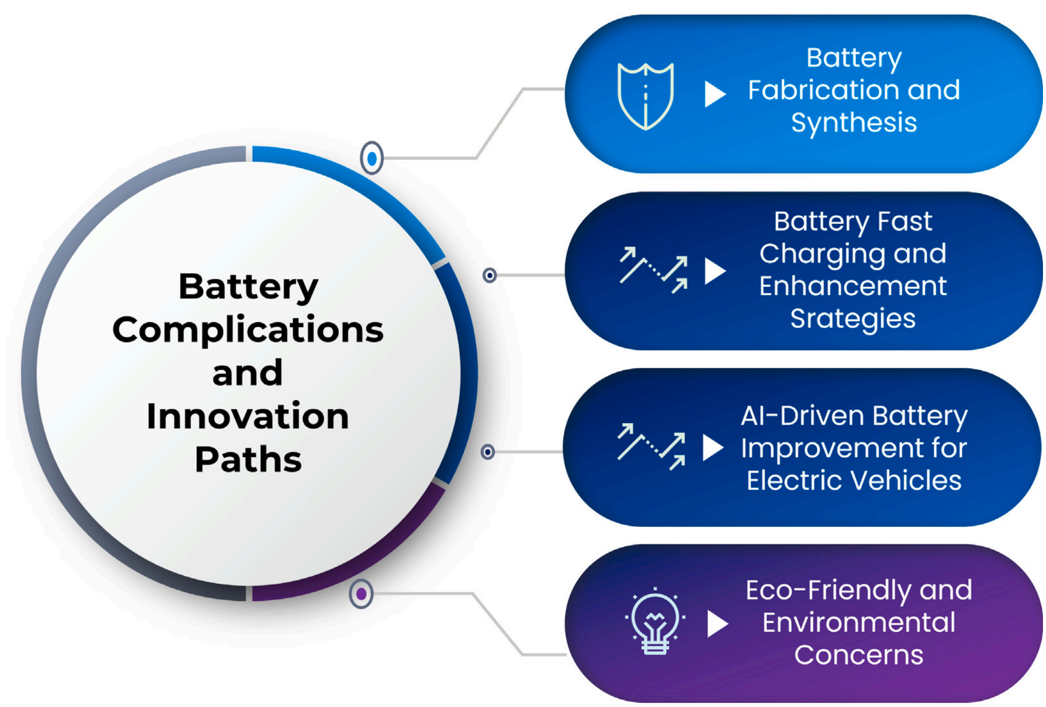

Fig. 14. Battery issues and investigative prospects [176].

driven by this dual focus on technological progress and sustainability. The battery types based on the composition of elements is depicted in Fig. 13.

The battery issues and their investigative prospects was shown in Fig. 14.

5.1. EV battery designs

Based on their level of physical knowing, battery designs can be divided into three primary categories: white, grey, and black box designs. Black box designs integrate artificial intelligence algorithms into a computational framework known as battery mathematical model, white box designs can be exclusively electrolytic. While designs of grey box are put together using the Equivalent circuit Design [177].

5.1.1. Electrolytic design

An electrolytic cell is a chemical apparatus designed to generate or store electrical energy. It consists of two electrodes – one positive and one negative – separated by an electrolyte, as shown in Fig. 15.

The electrolyte facilitates ion movement between the electrodes, even though it itself is an electrical insulator. Both electrodes are immersed in the electrolyte, and the reactive substances are generally

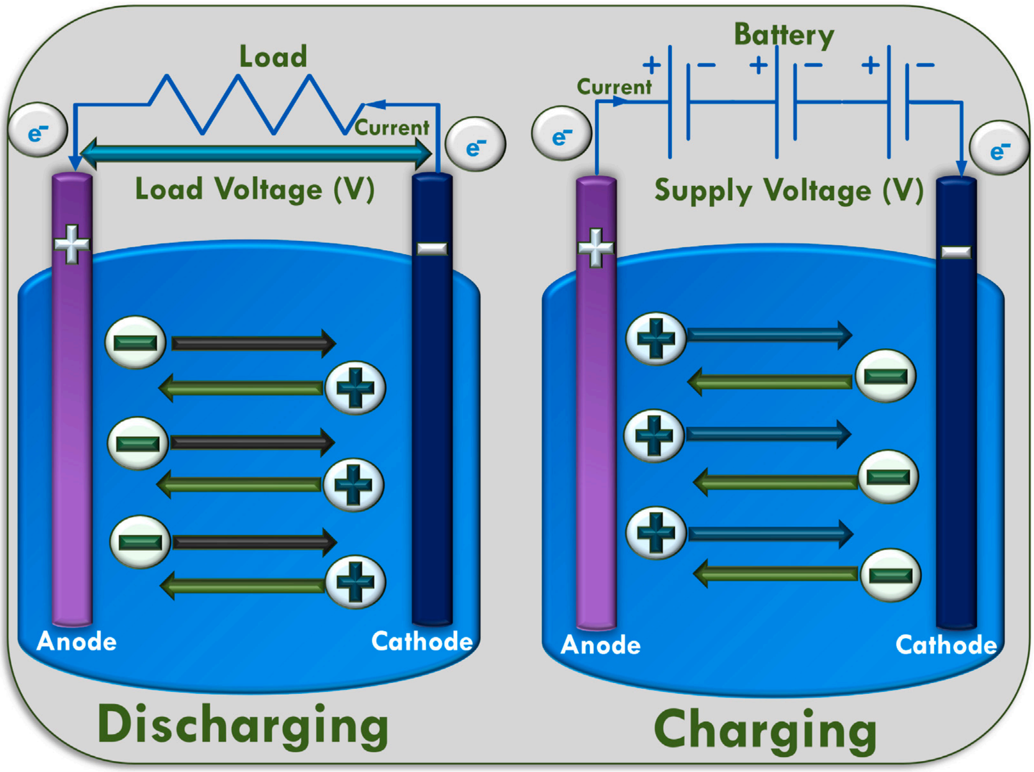

Fig. 15. Charging & discharging of the battery.

housed within the electrodes and sometimes within the electrolyte. Energy-converting chemical reactions occur at the electrodes. The negative electrode contains the material that undergoes oxidation (releases electrons) during discharge, while the positive electrode holds the substance that is reduced (gains electrons). These electrons perform useful work as they move through an external circuit. During charging, the reaction is reversed, requiring the cell to absorb an equivalent amount of energy from an external source [178]. Electrolytic models [177] describe the behavior of chemical reactions occurring within the electrodes and electrolytes. Solving these models involves complex partial differential equations, necessitating advanced computational skills. Recently, new scientific methods have emerged, including the Composite Battery model developed by [179].

In the Composite Battery Model, $Y_{(k)}$ represents the battery's voltage and serves as the output variable, while X_k denotes the state vectors, with the SoC considered as a state variable "x" within the system. The Composite model encompasses the following three electrochemical models. The state equations for Shepherd model, Unnewehr universal model and Nernst model was given in Eqs. (1), (2) and (3) respectively. In this context, the instantaneous current at time 'k' is denoted by i_k the varying OCV by E0, and the internal resistance R changes based on the charge/discharge status and SOC. Parameters K1 through K4 are identified as matching parameters, which will be determined through battery testing procedures, as indicated in [179]. Considering all the three-model equation and combining the resultant equation is shown in (4).

$$y = E_0 - Ri_k - \frac{K_1}{x_k} \tag{1}$$

$$y = E_0 - Ri_k - K_2.x_k \tag{2}$$

$$y = E_0 - Ri_k - K_3 \ln(x_k) + K_4 \ln(1 - x_k) \tag{3}$$

$$y = E_0 - Ri_k - \frac{K_1}{x_k} - K_2.x_k - K_3 \ln(x_k) + K_4 \ln(1 - x_k) \tag{4}$$

To clarify the electrochemical behavior of batteries for use in electric car applications, more sophisticated models have been developed. Fotouhi et al. conducted a discussion on a few of these models that relied on diffusion processes [180]. On a microscopic level, electrolytic models can offer a mathematical explanation of battery operation; nevertheless, the identification of parameters and the complicated nature of the differential equations present substantial obstacles. As a result, in order to overcome these challenges, several academics have thought of making these models simpler. Electrolytic models are distinguished by their high accuracy and precise equations that effectively capture battery behavior characteristics. However, their main drawbacks include high computational complexity under specific operating conditions and suboptimal performance due to limited flexibility.

5.1.2. Battery mathematical model

A comprehensive mathematical model of a battery typically consists of several smaller component models. Among these, the voltage–current model is fundamental for understanding the relationship between the battery's terminal voltage and current, making it essential for evaluating electrical systems. The Shepherd model is the most widely known voltage–current model used for analyzing constant-current discharge conditions [181]. The flowchart for mathematical design of battery is depicted in Fig. 16.

$$V_{bat} = E_0 - K\left[\frac{Q}{Q - \int idt}\right]i - R_0 i \tag{5}$$

Where E_0 denote the full capacity OCV of the battery, Q denote capacity of the battery (AHr), K is coefficient of polarization resistance (ω), i is current in the battery (A), R_0 is the battery internal resistance (Ω). In (5) the final term indicates the internal resistance loss, while the second term pertains to the polarization ohmic voltage loss.

$$V_{bat} = E_0 - \left[\frac{K}{SoC}\right]i - R_0 i \tag{6}$$

Incorporating SoC into Eq. (6) allows Eq. (5) to be rewritten, demonstrating that the polarization ohmic voltage is inversely proportional to the state of charge. Compared to Shepherd's model, numerous contemporary voltage-current models exhibit greater complexity [182,183].

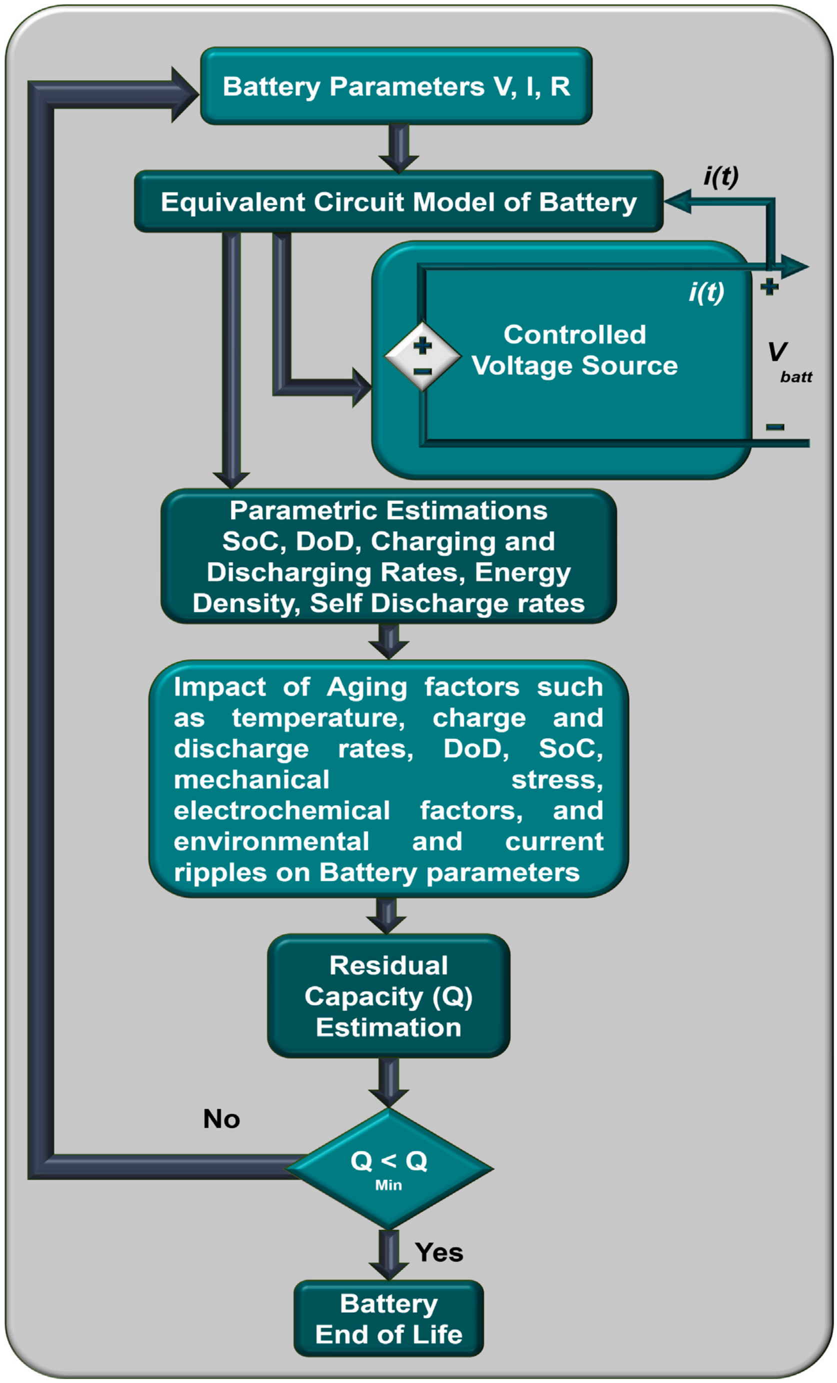

Fig. 16. Flowchart for mathematical battery design.

These models typically start with a foundation resembling the Shepherd model, subsequently modifying and adding terms to:

- better align with observed charge and discharge curves
- relax the assumptions inherent in the Shepherd model

Eqs. (7) and (8), which are based on the Shepherd equation and the battery model using SimPowerSystems, offer revised models for the discharge and charge processes of lead–acid batteries.

$$V_{Dis} = E_0 - K_{DR}\left[\frac{Q}{Q - \int idt}\right]i^* - R_0 i - K_{DV}\left[\frac{Q}{Q - \int idt}\right]\int idt + exp(t) \tag{7}$$

$$V_{Ch} = E_0 - K_{CR}\left[\frac{Q}{\int idt + \lambda Q}\right]i^* - R_0 i - K_{CV}\left[\frac{Q}{Q - \int idt}\right]\int idt + exp(t) \tag{8}$$

In these equations the second term is incorporates a filtered battery current i^* to simulate to better the slow voltage response typically seen during a step current event. The resulting ohmic voltage loss due to polarization differs between charging and discharging. The coefficient λ in Eq. (8) accounts for the change in polarization resistance that happens the charging phase of the battery [184]. The internal resistance in the third term has different values for charging and discharging. The fourth term addresses the polarization overvoltage. When combined with E_0, this term provides a more precise representation of the non-linear OCV interaction with the SoC. An exponential dynamic voltage

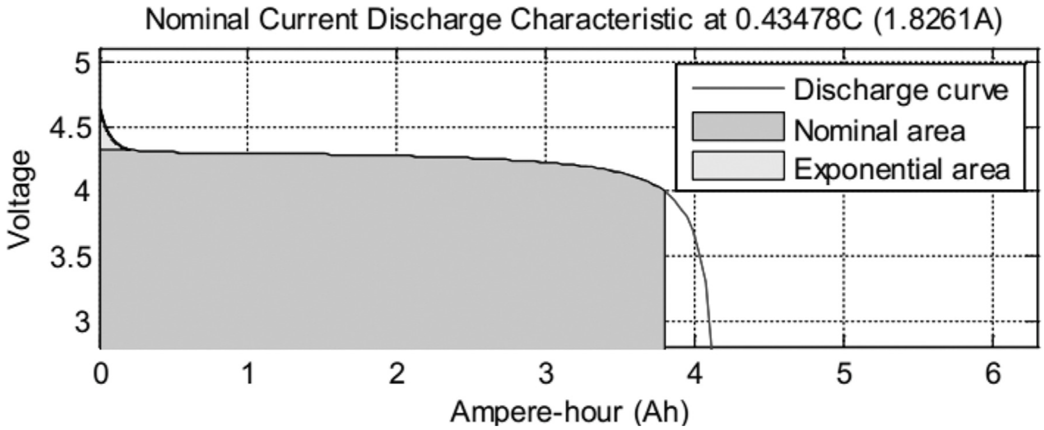

Fig. 17. Discharge curve of the battery [185].

is represented by the final equation, exp(t), in Fig. 17 to illustrate a non-linear hysteresis phenomenon between charge and discharge.

Eq. (8) calculates Exp(t) for lead–acid batteries, with u(t)=0 for discharge and u(t)=1, for charge. Eqs. (7) and (8) can be rewritten using SoC. For example, incorporating SoC into Eq. (7) results in Eqs. (9) and then (10), which shows that as SoC decreases, the voltage drops due to polarization ohmic and overvoltage effects increases during battery discharge. Additionally, Eq. (10) indicates that the impact of polarization overvoltage is minimal near the battery maximum capacity but becomes significant as the SoC decreases.

$$V_{Dis} = E_0 - K_{DR}\left[\frac{1}{SoC}\right] i^* - R_0 i - K_{DV}\left[\frac{1}{SoC} - 1\right] \int idt + exp(t) \tag{9}$$

$$SoC = S0C_{initial} - \int_0^t \left(1 - max(i_{gas}, i_{sd})\right) \frac{d\tau}{Q} \tag{10}$$

where SoC is the State-of-Charge, K_{DR} is the coefficient of Polarization resistance (ohms), and K_{DV} is the coefficient of Polarization Overvoltage ($\frac{V}{AHr}$).

The main drawbacks of Eqs. (7) and (8) are as follows: the battery's capacity Q is assumed to be independent of the current amplitude; the model does not account for temperature effects; battery aging is not considered; and self-discharge is ignored. A more comprehensive mathematical battery model, as depicted in Fig. 16 [186], can incorporate these variables. In this model, various battery parameters change throughout the battery's lifespan, providing an aging profile and performance degradation influenced by multiple additional factors (Fig. 16) [187,188]. The parameter changes are calculated at each simulation time step. For example, using Eq. (10), which includes the effects of self-discharge current i_{sd} and gassing current i_{gas}, the SoC can be determined more precisely at each time interval. The battery is deemed to have reached the end of its lifespan when its capacity drops below the specified threshold One advantage of mathematical modeling is its capability to swiftly assess and evaluate the internal state of the battery, reducing or eliminating the complexity associated with physical comprehension. However, the accuracy and results are significantly influenced by the size of the dataset and the training techniques used, which are major drawbacks. Additionally, computational inaccuracies can lead to issues such as underfitting and overfitting.

5.1.3. Equivalent circuit design (ECD)

As stated previously, scientists and researchers has been investigating new approaches for battery modeling in electric vehicles (EVs) because their electrolytic designs are complicated. The Equivalent Circuit Modeling, which is built using capacitors, resistors, and voltage sources, is one such method [171]. As seen in Fig. 18, the internal resistance model is the most basic version of the ECM for battery modeling. An alternative method for accounting for polarization features in a circuit is to include a RC element. Fig. 18.a shows the Thevenin Model. The Laplace domain equations for Thevenin's model was given in Eq. (11). Model parameter determination is an important task in the ECD framework, and there are a number of efficient ways to accomplish this. One noteworthy technique is Electrochemical Impedance Spectroscopy (EIS), which was first introduced by Haran et al. in 1998 and subsequently used by [172,173]. The electrochemical impedance from the equivalent circuit which is the electrochemical system's reaction to an applied potential is the essential building block of this method. Eq. (12) describes the equivalent impedance.

$$V_t(s) = V_{OC} - I_L(s)\left[R_0 + \frac{R_p}{1 + R_p C_p s}\right] \tag{11}$$

$$Z_{Eq} = R_0 + \frac{R_1}{1 + j\omega R_1 C_1} \tag{12}$$

The RC circuit's components are R_1 and C_1, the variable R_0 stands for the internal resistance and ω for the angular frequency. Edward Randles introduced the first electrical circuit design It represented each cell element with its matching component by means of electrical interconnections. This is the Randles circuit shown in Fig. 18.b. ECD models offer the advantages of easy comprehension and straightforward access to model parameters, and they typically require a moderate amount of time to implement. However, the downsides include the need for extensive experimental procedures and costly equipment for parameter estimation. Additionally, these models do not consider the internal properties of the battery.

5.2. Real-world solutions of DT technology in batteries

To help mitigate climate change, many academics have proposed employing DTs for renewable technologies and ESS. It is imperative to emphasize that specific elements are critical to battery systems; the BMS is one such component. As the central element, the BMS protects, oversees, and ensures the battery's dependability, efficiency, and safety [189]. In addition to estimating the SoC, SoH, and Depth of Charge (DOC), the BMS measures cell voltages, pack voltages, and pack temperatures [190]. Using a battery data storage platform, the digital twin (DT) functions in tandem with the integrated BMS.

Two researchers investigated the application of digital twins in battery systems. The first, by [191], was to determine the present State of Charge (SOC) and State of Health (SOH). The second study, done by Wu et al. [192], provided an overview of data-driven techniques in conjunction with vehicle diagnostics and battery modeling. The paper by Wu et al. introduces the usage of hybrid models, which make use of real-time data from the Internet of Things to combine the benefits of both data-driven and physics-based models. Physics-based models are quite beneficial, especially when it comes to predicting anode potential for fast charging algorithms, and they use differential

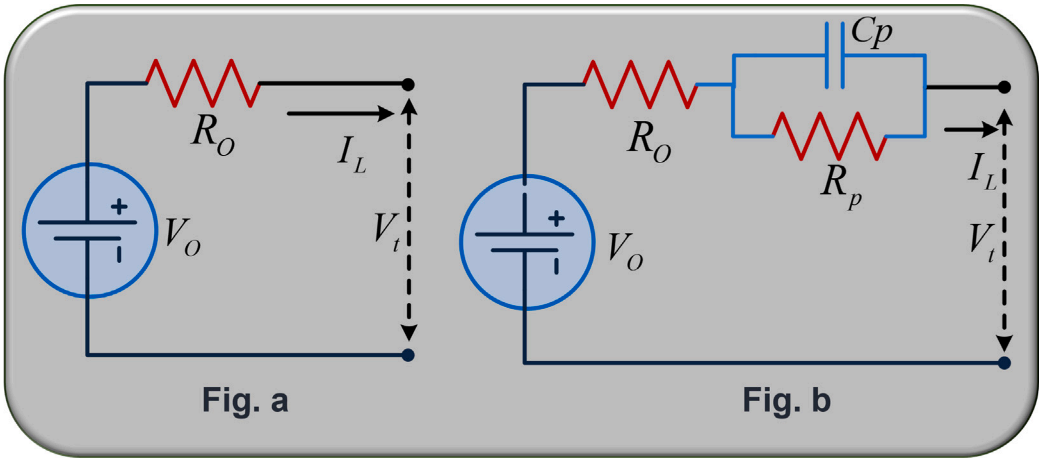

Fig. 18. (a) Thevenin's Equivalent circuit representation of battery with open circuit voltage (VOC), internal resistance (R_0) and terminal voltage (V_t). (b) Thevenin's Equivalent circuit considering RC Parameters.

equations to represent the battery's physical deterioration. The main benefit of hybrid models and artificial neural networks (ANNs) together is the speedy optimization and improved algorithmic correctness. It is also critical to investigate upcoming prospects [172], some of which are listed below:

5.2.1. Consistent and accessible data in digital twins

Digital twin systems can better represent real-world situations by using normalized data collecting and preprocessing procedures. This allows for more accurate forecast and monitoring of system performance, resulting in better decision-making and optimization. Validation and data preprocessing are critical components of the modeling, data storage, and database management procedures in digital twin applications. Standardizing these practices ensures that data is consistent, trustworthy, and accessible, which is critical for accurate and transparent diagnostics. For instance, in battery systems, reliable data on cell voltages, temperatures, and charge/discharge cycles are required to accurately estimate SoC and SoH proper data preparation, including noise filtering and sensor error correction, enables more trustworthy diagnostics and prognostics.

Furthermore, transparent data practices promote collaboration among various stakeholders, including researchers, engineers, and manufacturers. When information is gathered and processed in a consistent manner, it is easier to share and compare results, resulting in collective advancements in technology and methodology. In the context of DT for batteries, normalized data standards could also facilitate to integrate modern analytical approaches like machine learning and artificial intelligence. These technologies rely on high-quality, well-structured data to create reliable models that can anticipate battery performance under a variety of scenarios and detect possible problems before they arise [43,193]. Finally, consistent and accessible data standards improve the effectiveness and dependability of digital twin systems, allowing for more precise diagnostics, better performance optimization, and better overall system management [194].

5.2.2. Enhancing model precision: Convergence of multiscale physics and machine learning (ML)

Multiscale physics models address the difficulty of determining how processes at different scales interact. For example, in materials science, these models may replicate nanoscale interactions like atomic bonding and deficiencies while also predicting macroscopic qualities like strength and thermal conductivity. Multiscale models depict real-world systems with great fidelity by combining data from several scales. Machine learning algorithms, on the other hand, are highly effective at identifying patterns and forecasting outcomes using large sets of data. When integrated with multiscale physics models, ML can improve prediction skills by learning from previous data and adjusting model parameters. ML algorithms can examine complicated datasets generated by multiscale models, revealing insights that standard analytical methods might ignore [195,196].

Synergistic Benefits: The synergy between multiscale physics models and machine learning methods offers various benefits.

- *Enhanced Accuracy:* By combining comprehensive, scale-specific data from multiscale models with ML's pattern-recognition power, the overall forecast accuracy improves. ML can refine physics-based models by modifying parameters and correcting errors using actual data.
- *Improved Data Fidelity:* Multiscale models create high-resolution data at several scales, which may be analyzed by machine learning algorithms to produce more exact and reliable findings. This combination enables for more accurate depiction of complicated processes like material fatigue and thermal stress.
- *Optimized Performance:* ML algorithms can optimize the performance of multiscale models by identifying the most important variables and optimizing computational operations. This allows for more efficient simulations and speedier analysis.
- *Predictive Power:* Integrating machine learning with multiscale physics models improves the ability to forecast future system behavior using historical and simulated data. This is particularly useful in applications like predictive maintenance and process optimization.

The combined method of multiscale modeling and machine learning is rapidly being used in domains such as materials science, aerospace engineering, and energy systems. For example, digital twins, or virtual versions of physical systems, benefit substantially from this integration. They use real-time data to constantly update and modify models, resulting in precise simulations and predictions of system behavior.

5.2.3. Innovative approaches for estimating battery lifespan

Recent advancements in battery technology have led to the development of hybrid models that combine physical approaches with data-driven methods. These techniques show great promise for achieving real-time forecasts, which seek not only to extend the lifespan of battery systems but also to introduce novel operating tactics. According to current research, integrating complete electrochemical insights with data-driven approaches is a substantial problem due to the high level of accuracy required by these models. One significant example is the work of Li et al. [191], who developed a cloud-based Battery Management System. This method improves the estimation of the State of

Charge (SOC) and State of Health (SOH) by utilizing cloud computing, which considerably increases computational power and data storage capacity [197]. This method enables more accurate and dependable management of battery systems. The methodology comprises the use of advanced algorithms and real-time data processing to provide exact estimates and enhanced battery performance.

The use of Digital Twin (DT) technology expands the capabilities of these hybrid architectures. Digital twins generate a virtual picture of the actual battery system, enabling continuous monitoring and predictive maintenance. This technique aids in detecting possible problems before they become critical, improving the overall dependability and efficiency of the battery system. For example, using a DT, operators can simulate alternative operational scenarios and anticipate their impact on the battery's lifespan, allowing for more informed decision-making. The use of hybrid models and Digital Twin technology provides a comprehensive approach to battery management. These techniques enable a more in-depth understanding of battery behavior under different settings by combining sophisticated physical models with real-time data analytics. This not only helps to improve the battery life but also optimizes performance and operating methods.

5.2.4. Cloud-based BMS

A digital twin emerged by applying the ideas of cloud computing and the Internet of Things (IoT) to improve the Battery Management System's (BMS) processing speed, dependability, and data storage capacity. Six essential subsystems make up this sophisticated system [134,198].

- *Data Generation Subsystem for Battery:* The generation of real-time data from the battery, including voltage, current, temperature, and other crucial characteristics, is the responsibility of this subsystem.
- *BMS-Slave Data Acquisition Module:* The responsibility of sensing and gathering data from the battery cells falls to the BMS-Slave subsystem. It guarantees quick and accurate data acquisition, which is essential for effective management and monitoring.
- *IoT-Based Data Acquisition Component:* This component gathers data from the BMS-Slave by using Internet of Things technology. It makes data transfer to the cloud smooth and guarantees that the data is always up to date and available.
- *Cloud Data Repository:* Huge volumes of data can be safely stored in the cloud subsystem. It provides scalable storage options, allowing the system to manage large datasets produced over time by the battery system.
- *Data Analytics and Interface API:* The backend data analytics and the user interface are connected by the API. Through system interaction, data retrieval, and sophisticated analytics, consumers can learn more about the health and performance of their batteries.
- *Visualization of Data by User Interface:* The UI offers a framework for data visualization that is easy to use. Its user-friendly structure makes it easy for users to monitor battery health and make well-informed decisions by displaying important data and analytics.

With its use of the digital twin concept, this cloud-based BMS has many benefits. It increases the accuracy of SOC and SOH estimations, permits real-time monitoring and predictive maintenance, and boosts the effectiveness of battery management as a whole. Advanced energy storage solutions are made possible by the digital twin framework, which integrates these subsystems to guarantee the dependable and efficient operation of battery systems.

5.2.5. Modeling of the battery

An essential component of comprehending and controlling the lifespan and performance of batteries in a variety of applications is battery modeling. The Equivalent Circuit Design (ECD), which was utilized in this study to simulate the battery dynamics, is one often used method. The State of Charge (SOC) and State of Health (SOH) of the battery can be accurately estimated using the extended Thevenin model, which forms the basis of the ECD. In order to replicate the behavior of a battery under various conditions in real life, the expanded Thevenin model includes a number of components, including resistors and capacitors. The model uses an adaptive extended H-infinity filter (AEHF), which is well-known for its adaptability against both model uncertainties and outside disturbances, to improve the accuracy of SOC and SOH calculations. Furthermore, the model parameters are optimized through the application of particle swarm optimization (PSO) [199]. PSO is a computational technique that improves the potential solution iteratively in relation to a specified quality measure in order to optimize a problem. The model can adjust to changing conditions and produce more accurate battery performance estimates by merging AEHF and PSO. For example, precisely determining the state of charge (SOC) in electric vehicles helps avoid deep draining or overcharging, two critical actions that endanger the safety and health of the battery. Similar to this, understanding the SOH aids in the planning of replacements and maintenance for renewable energy systems, which ensures an uninterrupted supply of electricity [200].

5.2.6. Estimations of SoC and SoH

A number of thorough aging experiments were carried out on both hardware and software platforms in order to evaluate the effectiveness of the Adaptive Extended H-infinity Filter (AEHF) and particle Swarm Optimization (PSO) algorithms in estimating the SoC and SoH of batteries. These experiments were crucial to confirming the algorithms' correctness and dependability in a range of scenarios and battery life stages. An Uninterruptible Power Supply (UPS) system and a cloud-based BMS prototype were included in one of the validation settings. Data on battery performance could be monitored and analyzed in real time with this setup. Large volumes of data could be gathered, stored, and processed by the cloud BMS, which offered a reliable setting for confirming SoC and SoH estimations [191].

A battery test bench made especially for lead–acid and lithium-ion batteries was also linked to the cloud BMS. The PSO and AEHF algorithms could be thoroughly tested thanks to this test bench's simulation of various operational circumstances and aging processes. For example, deep discharges, frequent cycling, and temperature changes all important variables influencing battery health and charge status might be replicated on the test bench. Through these testing, it was discovered that the PSO algorithm successfully adjusted the battery models parameters, producing SOC predictions that were more accurate [199]. In a similar vein, the AEHF algorithm proved its flexibility in responding to shifting circumstances and reducing the influence of model uncertainty while delivering accurate SOH estimates. For instance, the cloud BMS used AEHF and PSO to accurately track the decrease in battery capacity and forecast the remaining usable life in a situation where a lithium-ion battery experienced rapid aging due to high discharge rates. For applications like electric vehicles and renewable energy storage systems [201], where precise battery management can greatly improve performance and safety, this level of precision is essential.

5.3. Optimizing battery management with digital twin technology

A ground-breaking study by Singh et al. in 2021 demonstrated the use of a Battery Digital Twin (DT) and its many advantages as well as future uses. The study focused on how an onboard Battery Management System (BMS) and a Battery Digital Twin can work together to provide a complete battery management solution. The study's most important findings included the following benefits [115,202].

- *Battery Performance Evaluation:* Accurate tracking and evaluation of several performance indicators are made possible by the Battery Digital Twin's real-time and predictive analytics. For example, in electric vehicles, the DT can monitor trends of energy use and forecast when the battery needs to be recharged.

- *Aging Indicators:* The DT is able to track the battery's aging process and discover important markers of wear and tear. This involves monitoring shifts over time in efficiency, internal resistance, and capacity. Comprehending these aging signs, for instance, can facilitate the scheduling of prompt maintenance and replacements in renewable energy storage systems.
- *Optimum Charging Strategy:* To improve battery lifespan and efficiency, ideal charging methods can be designed using data from the Battery DT. This involves finding out the most effective charging cycles and techniques to avoid deep discharging and overcharging. To guarantee that a fleet of electric buses is always ready for service while preserving battery health, the DT, for example, can recommend the best charging schedule.
- *Thermal Management:* By simulating and analyzing the battery's thermal behavior, the digital twin can aid in the development of efficient thermal management systems. This is essential to ensure safe operation and avoiding overheating. For instance, the DT can assist with the design of cooling systems for consumer devices that maintain battery temperatures within acceptable ranges throughout extended operation.
- *Fault Diagnosis:* The BMS capacity for fault detection and diagnosis is enhanced by the integration of a Battery DT. Proactive maintenance is made possible by the DT ability to recognize and anticipate potential issues before they result in serious malfunctions. In industrial applications, this translates to early problem solving to reduce downtime and save expensive repairs.

5.3.1. Impactful innovations of DT implementations

A thorough understanding of the numerous features and advantages of combining an onboard Battery Management System (BMS) with a Battery Digital Twin (DT) was given in this study [189,203]. The major contributions are given below:

- *DT Deployment and Operational Features in Battery Management*
  The study demonstrated that the advantages of the Battery DT are embedded into both the mechanism and operating system, offering significant benefits in performance estimation, optimization strategies, and enhanced representation from an electrical or electrochemical perspective. For instance, the DT can allow real-time data on battery performance, admitting for precise monitoring and predictive analytics to optimize charging cycles and enhance overall battery efficiency.
- *Innovative Strategies and Barriers*
  The study proposed an innovative approach shifting from a conventional battery model to a Battery Digital Twin. This method is structured around five essential steps:

  1. Identification of Experimental Parameters for Model Formulation: Collecting data from experimental setups to identify key parameters necessary for accurate model creation.
  2. Charge/Discharge Cycle Data Collection: Gathering detailed data from multiple charge and discharge cycles to understand the battery's behavior under various conditions.
  3. Model Parameter Update Estimation: Regularly updating the model parameters using the acquired data to ensure ongoing accuracy.
  4. Adaptive Model Refinement: Continuously refining the model to adapt to new data and changing conditions.
  5. Quantification of Key Performance Indicators (KPI): Measuring and quantifying the performance indicators of the DT to evaluate its effectiveness.

  The study also highlighted the differences between a traditional battery model and a Battery Digital Twin, providing a comprehensive literature review of DT applications in both industrial and academic contexts. Two primary challenges were recognized, the accessibility of operational data for the model and the strategy for updating its parameters.
- *Emerging Research for future investigations*
  The research identified several areas where further research is needed to enhance the functionality and accuracy of Battery DTs. Key areas for future exploration include

  1. Improving Fidelity: Enhancing the DT's accuracy in representing electrical, thermal, electrochemical, and aging aspects of the battery to reduce operational costs.
  2. Technical Deployment and Life Cycle Evaluation: Overcoming obstacles in the docking process, sensor installation, and production to guarantee smooth integration and sustainability over time.
  3. Enhancing Predictive Accuracy: Improving the DT's predictive capabilities by reducing the percentage error in estimates, which remains a critical focus for the research community.

- *Practical Applications*
  The practical applications of these contributions were demonstrated in various scenarios:

  1. Real-Time Performance Monitoring: In EV, the DT provided continuous updates on battery status, allowing for optimal charging strategies and extended battery life.
  2. Proactive Maintenance: In industrial energy storage systems, the DT enabled early detection of potential faults, preventing costly downtime and repairs.
  3. Thermal Management: For consumer electronics, the DT helped design efficient cooling systems, ensuring safe operation even under heavy use.

A solid grasp EV and ESS technologies is crucial not only for optimizing battery performance but also for identifying future trends and opportunities in the energy market. For instance, comprehending the intricacies of lithium-ion batteries, which currently dominate the EV market, can lead to improvements in their energy density and charging speed, thus enhancing vehicle range and reducing downtime for users. Furthermore, understanding ESS technologies can highlight opportunities in grid storage solutions, such as using second-life EV batteries for renewable energy storage, which can stabilize energy supply and demand. This dual knowledge is essential for staying ahead in a rapidly evolving industry where technological advancements and market dynamics are closely intertwined.

6. Discussions

The DT concept involves feeding real-world data into virtual environments to enhance model accuracy, bridging the gap between the real and virtual worlds for effective simulations. This approach is crucial in addressing significant challenges in EV networks, particularly the shortage of infrastructure and the need for cost-effective maintenance. The DT model allows evaluation before deployment, reducing maintenance costs and making it a financially viable option. Future advancements in EV transportation systems should prioritize ensuring data accuracy and scalability to maintain safe operation across diverse conditions. Data visualization is crucial for EV users when planning travel of long distances. DT technology combines 3D visuals and sound with physical objects through the use of IoT and AI, allowing for improved monitoring and management of EVs. This convergence improves efficiency during and after the design process. One major hindrance to the growth of the EV industry is the long charging time, despite various charging systems. DT simulations can analyze virtual model data to optimize charging infrastructures and efficiency. Additionally, research into wireless charging could benefit from DT advancements, further reducing charging times.

Security is a critical concern in EV and self-navigating vehicle (SNV) networks, and DT technology offers significant improvements. It supports the creation of highly accurate models for real-time systems by utilizing large amounts of operational data and expert insights. DT frameworks are capable of efficiently identifying intrusions or irregularities in EV networks. Various studies have explored DT applications in industrial settings, utilizing data analytics and machine learning technologies to enhance security. For instance, DT models have been used to enhance the predictive power for cyber–physical energy systems and detect faults in vehicle production lines. Applying these technologies to EVs and SNVs can significantly enhance security and operational efficiency, paving the way for safer and more reliable smart mobility solutions The convergence of ITS with cutting-edge technologies and communication tools through DT concepts is pivotal. Digital twin technology is increasingly being utilized to simulate and validate experiments, resulting in technological advancements and improved performance. Researchers are continuously exploring efficient methods for vehicle monitoring and tracking, as well as improving battery and automotive technologies to optimize energy usage, reduce charging durations, and extend driving distances. Although initial integration was slow due to underdeveloped complementary technologies like IoT, wireless connectivity, and AI, the readiness for DT technology is now significantly higher. This section will explore the various benefits and major obstacles in the realm of smart and green mobility, emphasizing the future directions necessary to integrate modern technologies effectively.

DT technology facilitates the effective advancement of eco-friendly EV technologies, spanning from design to operation. It is essential for predictive mobility, autonomous movement control, driver support systems, vehicle condition monitoring, battery supervision, smart charging, of electric powertrain systems. However, substantial challenges remain, particularly in engineering, technology, and big data integration. Ensuring data security in human–computer interactions within smart vehicles is crucial, especially for real-time applications like health monitoring. Advancements in global wireless technologies and signal transmission are necessary to address issues such as connectivity loss and power outages, which affect prediction model accuracy. The next decade will be critical for overcoming these challenges and advancing towards cleaner and sustainable transportation solutions.

Future studies should prioritize creating technologies and solutions tailored for connected and intelligent EV fleets, where vast amounts of data must be securely transmitted and processed instantly. Data-driven methodologies will be crucial, leveraging battery models and employing technological tools like Simulink. Implementing machine learning algorithms for evaluating battery degradation and predictive maintenance will be prioritized. Digital twin technology, despite its challenges, offers the potential to reduce physical testing costs and enhance vehicle safety and efficiency. This study establishes the foundation for Battery Energy Storage System (BESS) modeling and the creation of a digital twin for battery systems, supporting fault diagnostics and predictive maintenance. The continuous evolution of IoT and AI technologies and the growing demand for smarter, more efficient vehicles underscore the significant future impact of digital twin technology in achieving sustainable transportation.

CRediT authorship contribution statement

Uma Ravi Sankar Yalavarthy: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **N Bharath Kumar:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Attuluri R Vijay Babu:** Visualization, Methodology, Investigation. **Rajanand Patnaik Narasipuram:** Writing – review & editing, Writing – original draft, Supervision, Investigation. **Sanjeevikumar Padmanaban:** Writing – review & editing, Supervision, Investigation, Conceptualization.

Declaration of competing interest

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

We, the authors confirm that we have made substantial contributions equally as authors and coauthors in each section of the paper submitted for publication and reviewer process.

Data availability

No data was used for the research described in the article.

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